Université Paris Nanterre
200 av. de la République
92001 Nanterre Cedex
www.parisnanterre.fr

École doctorale 396 : Économie, organisation, société
EconomiX - UMR7235

Membre de l'université Paris Lumières

Édouard Civel

The Red and the Green

Essays on the economics of information in the sustainable habitat market

Thèse présentée et soutenue publiquement le 05/07/2019
en vue de l'obtention du doctorat de Sciences économiques de l'Université Paris Nanterre
sous la direction de M. Marc Baudry (Université Paris Nanterre)

Jury :

Rapporteur :	M. Jean-Christophe Poudou	Professeur des Universités, Université Montpellier 1
Rapporteure :	Mme. Katheline Schubert	Professeure des Universités, Université Paris 1
Membre du jury :	M. François Creuzet	Docteur d'État, Directeur Scientifique, Saint-Gobain Recherche
Membre du jury :	M. Laurent Denant-Boémont	Professeur des Universités, Université de Rennes 1
Membre du jury :	Mme. Meglena Jeleva	Professeure des Universités, Université de Paris Nanterre

What absurd fellows you are, both of you! I wonder who it was defined man as a rational animal. It was the most premature definition ever given. Man is many things, but he is not rational. I am glad he is not, after all.

—Oscar Wilde, *in* The Picture of Dorian Gray.

Remerciements

Mes premiers remerciements vont à Marc Baudry, mon directeur de thèse. Merci à lui pour sa patience et sa disponibilité, sa rigueur scientifique et son sens de l'humain. Il m'est impossible de résumer en quelques lignes tout ce qu'il m'a appris. Encadrer la thèse en économie d'un chimiste n'est pas chose évidente, et je lui suis extrêmement reconnaissant d'avoir pris le pari d'expérimenter cette transmutation.

Je tiens également à exprimer toute ma gratitude à Jean-Christophe Poudou, Katheline Schubert, François Creuzet, Laurent Denant-Boémont et Meglena Jeleva pour me faire l'honneur de constituer mon jury de thèse. J'admire le travail de chacun d'entre eux, et j'espère qu'ils auront trouvé le mien digne de leur intérêt.

Je remercie Nathaly Cruz et Laurent Denant-Boémont pour nos collaborations fructueuses et qui se prolongeront je l'espère. Merci à Nathaly, qui m'a toujours aidé et soutenu dans mon travail de thèse, tout en étant une coautrice bienveillante et vigilante. Merci à Laurent pour nos nombreux échanges, toujours passionnants, faisant de mes voyages à Rennes un véritable plaisir.

Je remercie chaleureusement Saint-Gobain, qui m'a apporté le financement permettant la réalisation de ce doctorat, mais également bien plus. Merci à Pauline Lavagne d'Ortigue d'avoir permis le démarrage de cette thèse en économie alors que ce n'était pas une coutume de l'entreprise, et de m'avoir toujours soutenu dans sa réalisation. Merci à Hélène Subrémon pour son écoute toujours attentive et bienveillante, ainsi que pour ses conseils toujours lumineux, sur la thèse et sur tant d'autres choses. Merci également à François Creuzet, à Lucien Figuié, à Pierre Hébert et à Jean-Marie Thouvenin d'avoir participé assidûment à mes 'points de thèse' à Saint-Gobain, et de m'avoir fait bénéficier de leur expérience. Enfin, merci à mes designers préférés qui m'ont suivi depuis le début, Simon, Germain et Cécile, et merci à la branche grandissante des sciences sociales à SGR: Nathalie qui démarra avec moi, Thibault depuis maintenant deux ans, et Esther qui prendra ma suite. Je tiens également à remercier ma directrice de stage lorsque j'étais à Saint-Gobain Northborough, Sarah L. Clark, qui m'a tant appris sur la recherche.

Je souhaite également remercier la Chaire Économie du Climat, pour son accueil durant les trois années et demi de cette thèse, pour son soutien financier à chaque fois qu'un besoin s'est manifesté, pour les personnes formidables qu'elle m'a permis de rencontrer. Je n'ai pas choisi l'économie de l'environnement par hasard, et j'ai eu grand plaisir à travailler avec des femmes et des hommes qui partagent la passion de la science et la conviction écologique. Je pense évidemment en premier lieu à Christian de Perthuis, qui m'a tant appris sur le rôle du chercheur dans la société. Je remercie également Jéremy Elbeze de m'avoir recruté en premier lieu à la Chaire, et de continuer à me soutenir depuis le CSTB. J'ai ainsi rencontré à la Chaire de nombreuses personnes qui ont pu m'écouter, me conseiller et m'aider. Merci à Raphaël Trotignon, à Boris Solier, à Jacques Percebois, à Olivier Rebenaque, à Bénédicte Meurisse, à Clément Bonnet, à Camille Tevenart, à Valentin Lignau, à Anouk Faure, à Côme Billard, à Claire Berenger, à Simon Quemin et à Anna Creti pour tous nos échanges. Je sais la dette que j'ai envers chacun d'entre eux.

Je remercie également les membres d'EconomiX pour m'avoir conseillé et aidé dans cette thèse, notamment lors des séminaires. Je pense en particulier à Meglena Jeleva, Johanna Etner, Gilles de Truchis, Valérie Mignon, Olivier Renault et Cécile Couharde. Je tiens à remercier également Lesly Cassin et Stellio Del Campo, qui ont été, malgré la distance physique, de formidables compagnons de thèse.

L'écriture d'une thèse requiert également de conserver un bon équilibre. Cet équilibre je l'ai trouvé en marchant, et je remercie très chaleureusement toutes les personnes qui m'ont permis de ne pas tomber. Merci à Gilles, pour avoir toujours crû en moi et pour m'avoir aidé à faire le bon choix. Merci à Pierrick pour son soutien en toute chose. Merci à Jean-Emmanuel, à Sébastien, à Hélène, à Alain et à Théo pour les grands moments vécus ensemble et tous ceux à venir. Merci à Thomas P., à Julien, à Bérengère, à Karim, à Danaé, à Rémi, à Thomas S., à Stéphane, à Ludovic, à Angèle, à Youssef, à Almahdi, à Sophie et à Hanane pour leur amitié.

Merci à mes amis fidèles de l'ESPCI, Baptiste, Emeric, Romain, Dounia, Sacha, Lucie, Anthony, et Élise, tellement patients et attentifs avec moi. Voyez également dans ce titre un hommage.

En dernier lieu, je tiens à remercier ma famille, en particulier mes parents, Éléonore, Alain, Laurent et Élisabeth, et ma grand-mère, Renée, pour leur soutien infaillible tout au long de mes études. Merci à Zoé, Marie et Gabriel pour la joie qu'ils m'apportent. Merci à Marie-Thé de m'avoir éveillé à la recherche. Merci enfin à Valentin, pour m'avoir appris qu'il y avait autre chose que la thèse dans la vie. Le meilleur reste à venir.

The Red and the Green,

Essays on the economics of information in the sustainable habitat market.

Abstract

A decade ago, Energy Performance Certificates have been introduced by the European Union to bridge the energy-efficiency gap. As informational failures are blamed for plaguing the development of greener buildings, energy labels could fix these failures by reducing both uncertainty on energy quality and information asymmetry between sellers and buyers. However, economic research has shown that information is a complex economic good, often imperfectly used or valued by real economic agents. This dissertation investigates the value of information in the context of the economics of green buildings, by combining theoretic, empirical and experimental approaches.

First, the perception of Energy Performance Certificate is studied through an artefactual field experiment on a representative sample of the French population. We point up a mixed cognitive efficiency for the label. A significant part of the population ignores it, however attentive subjects do use the label to revise their prior beliefs on energy quality. Second, we provide evidence of the capitalization of this information into real estate prices over two French regions. Low-consumption houses exhibit, *ceteris paribus*, a significant green premium that matches with techno-economic estimations of associated renovation costs.

However, despite this 'green value', the pace of energy renovations remains slow in the French market: the energy label information does not reduce uncertainty on the outcomes of the renovation process. In a third time, we show through a strategic option model that the lack of reliable information about renovation quality can delay investment decisions, and even inhibit their diffusion. Recently, several innovations have opened the possibility of producing reliable information on quality in the building industry. Then, fourthly, we explore with a laboratory experiment people's Willingness-To-Pay for information. Its magnitude is evidenced as significantly higher than information theoretic value. Nonetheless, pricing information has overall mixed effects on behaviors, inducing more strategic thinking but also some cognitive biases. A careful design of information markets is thus required.

Keywords: Information, Behavior, Energy efficiency, Innovation.

Le Rouge et le Vert,

Essais sur l'économie de l'information dans le marché de l'habitat durable.

Résumé

Afin de combler le 'fossé' de l'efficacité énergétique, l'Union européenne a introduit les Certificats de Performance Énergétique. Face aux multiples défaillances informationnelles entravant le développement de bâtiments plus sobres en énergie, cette étiquette énergie permettrait de réduire d'une part l'incertitude sur la qualité énergétique et d'autre part l'asymétrie d'information entre vendeurs et acheteurs sur le marché immobilier. Cependant, l'information demeure un bien économique complexe, imparfaitement utilisé par les agents économiques réels. Cette thèse examine la valeur de l'information dans le marché de l'habitat durable, en combinant des approches théoriques, empiriques et expérimentales.

Tout d'abord, la perception du Diagnostic de Performance Énergétique est étudiée à travers une enquête sur un échantillon représentatif de la population française. Nous mettons en évidence une efficacité cognitive nuancée pour l'étiquette. Une partie de la population l'ignore, mais les sujets attentifs utilisent bien l'étiquette pour réviser leurs croyances sur la qualité énergétique. En second lieu, nous apportons la preuve de la capitalisation de cette information dans les prix de l'immobilier sur deux régions françaises. Les maisons à basse consommation énergétique présentent, *ceteris paribus*, une prime verte significative qui correspond aux estimations technico-économiques des coûts de rénovation associés.

En dépit de cette 'valeur verte', le rythme des rénovations énergétiques reste lent sur le marché français : l'information véhiculée par l'étiquette énergie ne réduit pas l'incertitude sur les résultats des opérations de rénovation. Dans un troisième temps, nous montrons à travers un modèle d'options stratégiques que cette incertitude peut retarder les décisions d'investissement, voire empêcher leur diffusion. Ainsi, quatrièmement, nous étudions via une expérience en laboratoire la disposition-à-payer des individus pour obtenir de l'information, mettant en évidence qu'elle pourrait dépasser largement sa prédiction théorique. Néanmoins, les effets positifs d'une information payante pourraient être annihilés par plusieurs biais cognitifs, nécessitant une régulation des marchés de l'information.

Mots Clés : Information, Comportement, Efficacité énergétique, Innovation.

Table of Contents

List of Figures

List of Tables

* * *

General Introduction

In *The Red and the Black* (1830), Stendhal chronicles the life of Julien Sorel, a son of carpenter who strives to upgrade his social class. In this psychological novel, Julien pursues with consistency his own interest, using a clever blend of intelligence and deception. Nevertheless, both his lack of knowledge about high society's customs and his impulsive nature will prove fatal to him. In economic words, Julien Sorel's utility maximization is constrained both by information asymmetry and by his own cognitive failures. The present dissertation aims precisely at deciphering how people interact with information, specifically regarding energy efficiency in the real estate market. Our research thus applies concepts drawn both from information economics and behavioral economics to the issue of sustainable habitat. Whereas we evidence that energy classes ranking can structure green buildings economics, we also spotlight several failures related to information, deriving both from rational behaviors and from cognitive biases.

The economics of information

The seminal article published by Hayek (1945) emphasized the key role of information in optimizing the use of resources in society through signaling by the price mechanism. Since then, an extensive part of the economic literature has gained interest in the economics of information. In his landmark article "The Economics of Information", Stigler (1961) focuses more specifically on the consumers difficult search for information about products. While his article targets the task of gathering information on existing sellers and their prices, Stigler already warned economists about the thorny issue of products' quality in his conclusion: *"The search for knowledge on the quality of goods, which has been studiously avoided in this paper, is perhaps no more important but, certainly, analytically more difficult. Quality has not yet been successfully specified by economics, and this elusiveness extends to all problems in which it enters"*. If the research piece of Arrow (1963) gives some intuitions on the issue of uncertain quality (within the specific subject of medical care), the question raised by Stigler was more generally addressed nine years after his publication by two others contributions.

A first but partial answer was brought out by Nelson (1970), who initiated the distinction in economic analysis between a search and an experience good. On the contrary to a search good, which quality can be easily evaluated by consumers before purchasing it, an experience good's quality will be assessed by consumers upon their consumption of the good. If the purchase price is low enough, like for food, consumers will tend to 'buy and try' products. But if the purchase price is higher, making choice is more costly and complicated. It is the point of the second answer to Stigler, published by Akerlof (1970).

Akerlof takes the example of used cars to enlighten the failures of markets with asymmetric information between sellers and buyers. In this key contribution to the economic literature, Akerlof evidences that a market suffering from quality uncertainty might collapse. With this article, Akerlof modelizes an older economic concept, the Gresham's law stating that 'bad money drives out good money'. He considers buyers in the used cars market: when facing a car, agents cannot *a priori* know if its quality is good, *i.e.* the car is a 'peach', or bad, *i.e.* the car is a 'lemon'. As sellers' discourse on used cars quality cannot be trusted, and in the absence of any credible certification, uncertainty will lead buyers to only accept paying a price below the true value of a 'peach'. Progressively, peaches will then be removed from the used car market, which will only be left with the bad quality cars, *i.e.* the lemons. Solutions to this adverse selection phenomenon cover all measures aiming at delivering information to buyers. With an increasing level of reliability, we can mention branding, licensing and guarantees for instance. In the decade following Akerlof's work, Michael Spence and Joseph Stiglitz published several major contributions on the analysis of markets with asymmetric information, highlighting two mechanisms which can reduce information asymmetry, namely signaling and screening.

The concept of signaling is introduced for the first time by Spence (1973) in his analysis of the job market. Indeed, hiring a new employee is an uncertain investment for a company, as it is in a situation of asymmetric information about the prospective employee productive capacities. Spence's paper develops a model where potential employees signal their skills by acquiring education degrees. As this acquisition is more costly for less skilled people, employers will accept to pay higher wages to candidates with higher degrees as they will be statistically more productive. The signaling theory thus describes how an information asymmetry can be reduced by a costly information disclosure. The agent (*i.e.* the seller in Akerlof's model, who benefits from an informational advantage) voluntarily incurs a cost to reveal some relevant information to the principal (*i.e.* the buyer in Akerlof's model, who lacks information about quality).

In his introduction to a symposium on the economics of information, Spence (1976) also highlights a second kind of solutions to adverse selection: the theory of screening. Stiglitz

(1975) also uses the example of education for screening strategies. The key idea of screening is that principals force agents into revealing their private information. The buyer, who lacks information, can offer a menu of contracts to the seller. When the seller chooses the contract, he reveals some of his private information. For instance, an employer ignoring the productive capabilities of an employee can offer to him two different contracts: a first one with a fixed level of wage, and a second one with a lower base salary but with important potential bonuses if the employee is productive. If we consider that prospective employees know their level of productivity, then efficient ones will select the second contract while inefficient ones will choose the stable and certain wage. As underlined by Spence (1976), screening and signaling are *"opposite sides of the same coin"*. While signaling refers to a strategy undertaken by the more informed agent, screening refers to an action engaged by the less informed agent. But both of those approaches aim at solving the adverse selection phenomenon occuring for the 'lemons' of Akerlof (1970).

Stiglitz following contributions highlight the importance of informational failures across various markets. Among others, we can cite Rothschild and Stiglitz (1976) who focus on the insurance market screening processes, Grossman and Stiglitz (1980) about the inefficiency of capital markets when information failures are present, and Stiglitz and Weiss (1981) on credit rationing. Stiglitz (1985) synthesis underlines that the emergence of the economics of information since the 1970s reshapes the way economists analyze markets. This new research field for economic science, ushered by Akerlof, Spence and Stiglitz, has also given birth to several important branches of modern economic analysis, such as mechanism design or contract theory.

In his retrospective on the economics of information in the twentieth century, Stiglitz (2000) gives clues to economists interested in markets' informational failures about the way forward. From a methodological point of view, he emphasizes the need to extend empirical works on the role of information within markets, and to integrate more closely other social sciences. Stiglitz specifically mentions psychology, which could contribute to enlighten how individuals process information, but also sociology, to study the creation of social knowledge. From a theoretic point of view, Stiglitz draws attention on two areas. First, the dynamics of information should be more thoroughly explored, especially to understand how new information is absorbed and modifies behaviors. Second, economists should investigate how different institutional designs affect the creation and use of information. The present dissertation focuses on the economics of information applied to energy efficiency in the housing market, and attempts to draw recommendations for a faster transition to 'greener' buildings.

Behavioral and experimental economics

While the previously mentioned literature evidences that asymmetric and imperfect information can plague the functioning of markets where rational agents interact, it actually underestimates the extent of inefficiencies due to informational failures. Indeed, in parallel with the development of information economics, started the fruitful collaboration between Amos Tversky and Daniel Kahneman. Applying the methods and results of cognitive psychology to standard economics, these pioneer scholars spotlighted how numerous reasoning biases of real economic agents lead to important deviations in observed behaviors compared to the theoretic rational ones.

In their first seminal contribution, Tversky and Kahneman (1974) evidence three heuristics that are used by people when making decisions under uncertainty. Heuristics are judgmental shortcuts, simple information-processing rules, commonly used by people to ease the making of many decisions. While heuristics have several advantages which explain their widespread use in every-day life, such as reducing the cognitive efforts and fastening decisions, they sometimes induce errors. Interestingly, several of these errors induced by heuristics appear to be systematic: these are cognitive biases. It means that, beyond producing noise in economic behavior, which was expected by economists, cognitive failures can trigger off regular behaviors which patterns differ significantly from the one of the *'homo economicus'*, *i.e.* a perfectly rational agent. A common feature of the three heuristics named by Tversky and Kahneman in their article is that they highlight cognitive biases related to the misuse of information by people. The first one, representativeness heuristic, drives people to rely on archetypes to form their beliefs on the likelihood of an event or a characteristic. The bias lies in the fact that people overestimate the relevance of relying on such archetypes. The second heuristic identified is the availability heuristic. When forming a decision on a subject, people tend to rely too much on the first memory related to this subject that will come easily into their mind. People then give too much importance to more recent information for instance. The third heuristic is anchoring: people overweight the first piece of information offered in comparison to the following information received.

Together with the key article on prospect theory by the same authors (Kahneman and Tversky, 1979), *"Judgment under uncertainty: Heuristics and biases"* marked the irruption of psychology in modern economic analysis. The development of behavioral economics is especially key in the field of information economics as it evidences that people do not use information fully rationally. This point is underlined in the first book published by Richard Thaler (1992). Gathering his series of publications in the *Journal of Economic Perspectives* entitled *"Anomalies"*, Thaler describes how real economic behaviors deviate from the predictions of standard economic theory. He emphasizes that *"The new theory will retain the idea that individuals try to do the best they can, but these individuals will also have the human strengths of kindness and cooperation, together with the limited human abilities to store and process information"*. Intrinsic limits of human mind in the treatment of information have since been increasingly studied, not only to tackle the important failures it can induce in markets with tiny transaction costs, but also as an opportunity to induce better decision-making at a low cost compared to traditional public policies. This is the concept of nudge, which won its spurs with the publication of the eponymous book by Thaler and Sunstein (2008). The key idea of Thaler and Sunstein is that we can significantly modify both individual and collective decisions through small changes in the choice architecture. As many human decisions rely on the cognitive shortcuts we previously mentioned, and more thoroughly detailed by Kahneman (2003, 2011), we can use heuristics and cognitive biases to help people make 'better' choices, for themselves and/or for society.

The traditional example of nudge is to modify position of salads and fries in school cafeterias. To improve the choice of healthy food, one can highlight it by putting it in front compared to pizzas for instance. A nudge does not compel people to change their choice, it suggests it. As underlined by Thaler and Sunstein (2008), *"To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting fruit at eye level counts as a nudge. Banning junk food does not"*. Virtues of this so-called *'Libertarian Paternalism'* are nonetheless heavily discussed by numerous scholars as nudges can be seen as a kind of psychological manipulation, raising the question of their philosophical legitimacy. Energy efficiency remains an interesting field of experimentation for behavioral interventions as its benefits are not very controversial, either for households or for society. Allcott (2011) for instance evaluates the effects of a randomized natural field experiment, where treated households received reports of energy use of their neighbors. This 'social comparison' nudge significantly reduced those households' energy consumption.

Some governments have today set up 'Nudge Units' to develop the use of behavioral approaches in the design of public policies. A main example is the United Kingdom, which set up in 2011 the Behavioural Insights Team (BIT). Houses energy consumption is its pet subject. One of the first recommendation of BIT was about facilitating loft insulation, by proposing to households a combination of services (cleaning the attic and insulating it). Even though this supplementary service had an additional cost for households, a threefold increase of insulating decisions was observed within weeks. Since then, this Nudge Unit has also proposed an improvement of Energy Performance Certificates design, and conducted another field experiment on default options in heating control systems[1].

[1]See `https://www.bi.team/`

Behavioral economics, using empirical evidences based on many and various experiments, have shown in the past decades the importance of information design in decision making by real economic agents. This means that, when one tries to improve a market by removing some informational failures, one should pay attention to the real behaviors induced by the new information disclosure. If badly designed, response to the market failure might just replace it by a behavioral failure. However, a well designed informative device could significantly improve decisions of people, even if it does not fix completely the information asymmetry or imperfection.

The present dissertation attempts to keep this balance through the analysis of green building economics. Energy efficiency looks indeed as an interesting playground for behavioral information economics, as literature has underlined that the associated markets suffer both from information asymmetry and from some 'alleged' behavioral failures. Which are the informational failures preventing the development of more energy efficient houses? How do policy-makers try to fix these failures?

Energy efficiency: the gaps and the role of information

The numerous advantages of energy efficiency investments have long been underlined by policy-makers but their achievement has become a pipe dream. Indeed, energy efficiency could trigger off benefits in many dimensions to society. First, energy savings for households would translate into a higher purchasing power. Second, a smaller energy consumption would mean a lower dependency on exporting countries for the government. Last but not least, environmental externalities could be curbed by a reduction in fossils consumption. However, despite the development of efficiency technologies, their adoption rate, or at least their take-up rate, is considered as too low.

This chronic underinvestment has been observed by economists for a long time. Early contributions attribute this surprisingly low level of investment to the use of relatively high implicit discount rates by households. Hausman et al. (1979) for instance elicited discount rates about 20%, even though recognizing a large heterogeneity among households. The review on 'anomalies' in observed inter-temporal choices by Loewenstein and Thaler (1989) also underlines important variations in the discount rates used by households, based on various evidences. Discount rates vary according to many factors, such as the time delay, the magnitude and sign of the discounted amount of money, the framing of the choice... Sutherland (1991) adds that the use of high discount rates could be justified as energy efficiency investments are illiquid, thus implicitly referring to an irreversibility effect (Henry, 1974; Arrow and Fisher, 1974) and to real options (Dixit et al., 1994). However Loewenstein and Thaler mention themselves limits to this explanation for low adoption rate of energy efficiency measures, by acknowledging the existence of information failures regarding energy efficiency. Sutherland adds that even though high discount rates could be justified from an individual point of view, the social perspective justifies the use of lower discount rates to compute the benefits of energy efficiency, and then advocates for State intervention to foster more investments in conservation measures. Sutherland mainly mentions the 'external costs' of energy consumption and production, referring both to energy security issues and to environmental ones, even though, by the early nineties, global warming was not yet a major concern for policy-makers.

The conceptual framework to analyze the difference between observed and theoretic optimal adoption of energy conservation measures was drawn by Jaffe and Stavins (1994). In the present dissertation, we will prefer the terminology 'energy efficiency gap' to 'energy paradox' which is also used in the literature. Indeed, the definition of the latter is quite ambiguous as an economic paradox refers to a situation which cannot be explained by classic economic theory, whereas we saw previously that important discount rates could explain a low uptake rate of energy conservation measures. By contrast, the energy efficiency gap is a more appropriate denomination of the divergence between hypothetic energy efficiency investments and actual ones. Several theoretic optimums of energy efficiency can be targeted. Forecasted energy conservation level could thus either be the one simply profitable to their adopters (private optimum), the one predicted by an engineer's approach (technologic optimum), or even the one wished by economists who want to correct for environmental externalities (social optimum).

By distinguishing between the different kinds of obstacles to the accomplishment of the full energy efficiency potential, Jaffe and Stavins pave the way for future research. They underline that the energy efficiency gap can be explained by several important failures of the energy efficiency technologies markets, but also by modeling flaws of the engineer's approach which neglect heterogeneity in individuals' preferences, and by failures in the energy supply market (which for instance does not internalize environmental externalities of energy production). As shown by Gerarden et al. (2017), in their extensive review of the literature that followed the seminal contribution of Jaffe and Stavins (1994), this conceptual framework remains highly relevant in today's analysis of the energy efficiency gap. The only concept missing in 1994, which has been introduced since then, is the role of behavioral failures.

On Figure A we propose a simplified visualization of these different failures undermining energy efficiency, as inspired by the previously cited articles. The first gap between energy efficiency investments in the business-as-usual scenario and an ideal one is due to various failures of the energy conservation market. Most of them are linked with informational issues. Asymmetric and imperfect information indeed plague the energy efficiency market. For instance, in the real estate market it is difficult for the buyer to know the energy efficiency of a house before living in it. This is typically the 'lemons' issue that was spotlighted by Akerlof. As the buyer will not accept to pay a surplus for an energy efficient house if he does not have guarantees, homeowners have a disincentive to invest in an energy retrofit of their house. Agency issues, moral hazard and adverse selection deriving from information asymmetry thus cap investments in energy efficiency. Other market failures can also limit the upgrade of energy efficiency, such as informational externalities (learning-by-using, learning-by-doing, which can delay adoption) and capital market failures (mainly liquidity constraint for households, as some energy efficient technologies require an important upfront investment). Fixing market failures of energy efficiency markets can thus improve both energy efficiency and economic efficiency for agents, this is the first "private optimum".

The second gap that could be bridged by policy interventions lies in some behavioral failures. As discussed previously, cognitive shortcuts of human's mind can lead to systematic errors in the decision making process. As underlined by Gillingham et al. (2009), heuristic decision making by agents can lead them to choices that violate some axioms of rational choice, even when they are perfectly informed. Experiments lead by Kempton and Montgomery (1982), and by Kempton et al. (1992) especially show that consumers make systematic errors in the computation of energy needs and potential savings, leading both to an underinvestment in energy efficiency and to an overconsumption of energy. Another obstacle to rational choice is the *status quo* bias (Hartman et al., 1991), which can prevent households from switching to a more efficient technology, even in the absence of transaction costs. Just as for energy efficiency market failures, fixing behavioral failures can thus improve both energy efficiency and economic efficiency for agents. We call this new theoretic optimum the "rational agent optimum".

A third gap can be defined as the one separating the level of energy efficiency of this "rational agent optimum" to the one theoretically computed by a pure engineer's approach. Indeed this last method to calculate energy efficiency investments that should be profitable to agents neglect several rational explanations of lower than expected investments. Like Gerarden et al. (2017), we will call them modeling flaws, as they ignore the economic rationale behind using higher discount rates, neglect heterogeneity between consumers' preferences, hidden costs, rebound effects, but also forget that energy efficiency investments present an option value which can justify to postpone them. This "technologic optimum" achieves a higher level of energy efficiency but is less efficient from an economist perspective.

The three first gaps of energy efficiency we defined above were limited to the analysis of

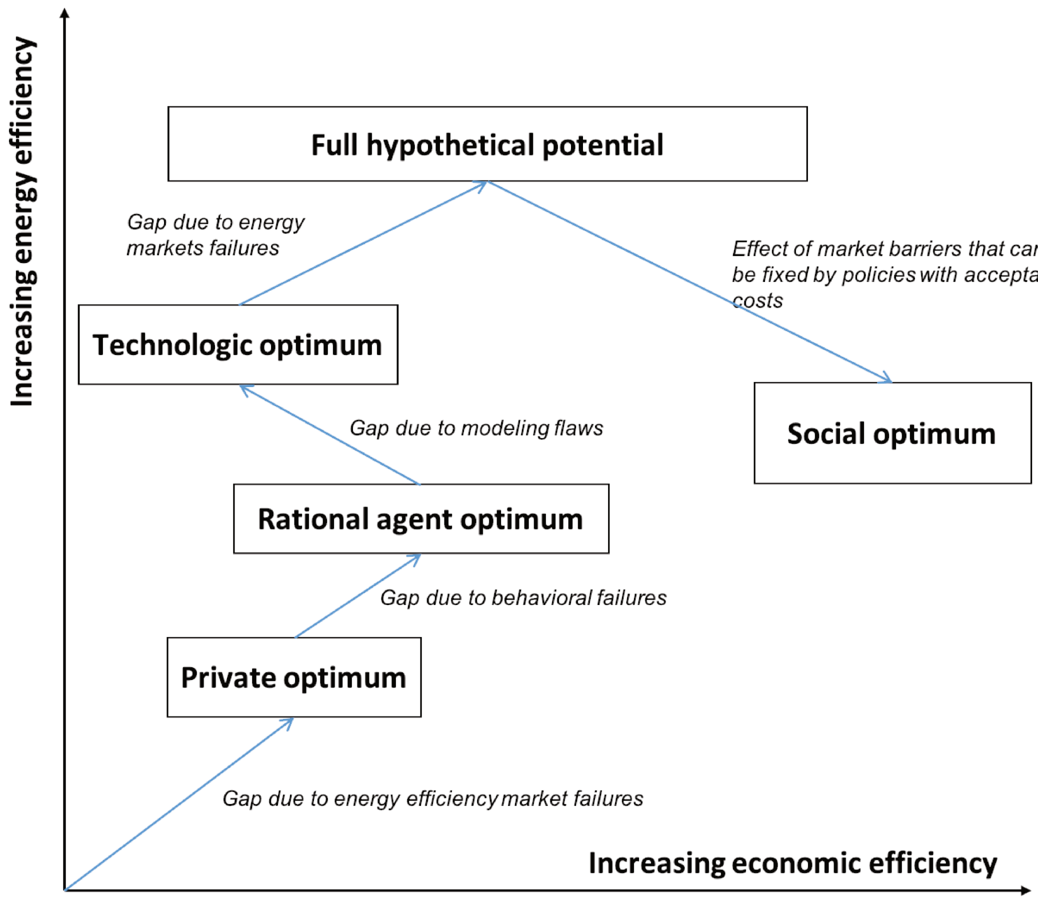


Figure A: Energy efficiency gaps

efficiency investments optimization within the energy efficiency market. However, energy supply markets also suffer from several failures which, if corrected, would induce higher energy prices for consumers, and thus more energy conservation measures. Market failures of energy markets include average-cost electricity pricing for consumers, energy security issues, and environmental externalities. Correction of these failures would lead to a higher level of energy efficiency in the economy, called the "Full hypothetical potential" in Figure A. However public policies to correct the four gaps described above will not all pass a cost-benefit analysis. "Social optimum" will thus imply a lower level of energy efficiency than the "Full hypothetical potential", but a maximized economic efficiency for society. The relative importance of the 'modeling flaws' gap compared to the three other ones is heavily discussed in the literature. Indeed if this gap was the most important one, today's equilibrium of energy efficiency investments would not be far from the social optimum. Recent literature reviews tend to disprove this theory. Despite the misevaluations of pure engineer's approach, Gillingham et al. (2009), Allcott and Greenstone (2012) and Gillingham et al. (2013) highlight that the energy efficiency gap remains significant and deserves policy-makers attention, notably on the grounds of the important environmental externalities.

Nonetheless, designing efficient public interventions to improve energy efficiency is today a major challenge as most of them seem to have limited impacts. The large field experiment conducted by Fowlie et al. (2015) evidences that even powerful public programs offering to households an entirely funded renovation of their house have a low take-up rate. Authors underline the importance of non-monetary costs in the adoption of energy conservation technologies. The contribution of Jacobsen (2015) also stresses the limits of the price signal to trigger off investments in energy efficiency. Common feature among those recent contributions lies in shifting economists attention towards other type of policies. Gillingham and Palmer (2014) outlines three main type of policies that should be more thoroughly explored: information programs, behavioral interventions and targeted policies.

First, information programs are necessary as the energy efficiency market is plagued with asymmetric information. For instance in the case of housing, there is an information asymmetry between the buyer and the seller on the energy quality of the house to be traded, which can cause adverse selection (the lemons issue). But there is also asymmetric information between a household and a craftsman: quality of the warmth insulation performed by the latter cannot be observed by the former, leading to a moral hazard situation. Even the split incentives issue occurring between landlords (who are in charge of energy retrofitting but do not pay energy expenditures) and tenants (who cannot renovate but have to pay for energy bills) could be solved if reliable information was disclosed to both parties, as proposed by Gillingham et al. (2012). Lastly, informational externalities which slow down the development of new technologies (Bollinger and Gillingham, 2012) could also be reduced with information programs. But the introduction of informational tools is not always efficient, and Dharshing and Hille (2017) show the importance of consumers' perception in the evaluation of labels.

The second type of policies which should be an area of research, and which are not disconnected from information programs, are behavioral interventions. In recent years they have been increasingly more studied in the context of energy efficiency and recent studies have proved the great potential of some nudges. Newell and Siikamäki (2014) evidence that different design of the same information regarding energy efficiency imply different choices. Furthermore Gillingham and Tsvetanov (2018) highlight that nudges are strongly cost-effective and constitute efficient policies to increase adoption rate of energy efficiency.

The third area to which researchers should pay more attention, and which is also connected to information programs and behavioral interventions, is the design of targeted policies. Indeed, all previously mentioned studies point out significant differences among the population in the response to information programs and nudges. This is consistent with the results of Newell and Siikamäki (2015) who spotlight the importance of individual discount rates, heavily dependent on individual characteristics, in the attitude towards energy efficiency investments.

As regards buildings efficiency, warmth insulation could enable important energy savings, both for households and firms but also, at the macro-scale, for countries. Energy savings would be associated to important cuts in CO_2 emissions. Indeed, worldwide, the building sector accounts for 36% of final energy consumption, and for nearly 40% of total direct and indirect greenhouse gas emissions[2]. This share is even higher in Europe, where buildings account for 40% of final energy consumption. Over two-third of this consumption is dedicated to space heating (European Commission, 2017). In order to address the climate change challenge and insure energy security and competitiveness, the European Union attempts, since the early 2000s, to significantly improve energy efficiency. Following the European directive 2002/91/EC of the European Parliament, Member States had to implement Energy Performance Certificates, which should be made available when buildings are constructed, sold or rented out. This directive was transposed in Member States legislations, and came into force by 2008 for most countries. This regulation aims at enabling any investor, household or company, to evaluate a building's energy quality. In the long-run, this policy is expected to favor green buildings by a differentiation in real estate prices according to energy-efficiency. Such a differentiation would testify that the 'lemons' issue is at least partly solved, as information about quality is conveyed to buyers. Nonetheless, it does not necessarily mean that the energy efficiency gap is bridged. To say it in a nutshell, in the light of the literature review above, credible information about energy quality is necessary to bridge the gap but might be not sufficient.

The present dissertation precisely aims at studying the informational failures of the sustainable habitat market, some of which are addressed by Energy Performance Certificates, and some of which need further interventions. Chapter 1 studies the perception of Energy Performance Certificates by households, while Chapter 2 investigates their effect on real estate prices. Whereas those two first chapters evidence a significant impact of this informational tool, take-up rates of deep renovations remains low. Chapter 3 proposes the analysis of another informational failure which could slow down energy renovations, through the option value of these uncertain investments. In order to close this 'informational gap', third-party producers of information could be included in the market, but this raises the issue of households Willingness-To-Pay for more information, and of their ability to handle this supplementary information. Chapter 4 details a laboratory experiment conducted to examine these points.

[2] https://www.iea.org/topics/energyefficiency/buildings/

Perception of information

Energy Performance Certificates were introduced a decade ago in France. Yet, as far as we know, no large scale study has assessed their perception by households. The previous literature has mainly attempted to assess efficiency of energy labels through their effect on market prices, but results are puzzling. Nevertheless, little effect on market prices does not mean that Energy Performance Certificates are inefficient. As discussed above, the energy efficiency market is undermined by numerous market failures, including other informational failures. It is then important to estimate the effect of energy labels upon their primary goal, namely enabling people to discriminate labelled goods. A weak effect on people's perception of energy quality could indeed explain the low uptake of energy efficient renovations, and request a complete overhaul of this information device. But a stronger effect would indicate a need to undertake other policies to induce more investments in energy efficiency.

The Energy Performance Certificate (EPC) is a complex informational tool. Although it aims at providing an objective information, the primary energy consumption of the house, this highly technical information is not very salient to households. Indeed, it is very complex to translate it into energy bills. Anticipating this challenge, European policy-makers have given a very specific design to the EPC, dividing typical energy consumptions into several classes. From the least efficient to the most efficient buildings, these classes are characterized using colors (from red to green), letters (from G to A), and arrows of different sizes. Each Member State in Europe has selected its own details, specifying differently the efficiency of a house. For instance, in the United-Kingdom, EPC also indicates which class could be easily achieved for the dwelling through a cheap renovation, and the ranking given to the building is based on a mark from 0 to 100. In France, the information displayed is the primary energy consumption, in [kWh/m^2/year], and classes do not cover equivalent ranges of consumption. When classes get greener, the range of consumptions covered gets narrower. We display an example of the French EPC versus the English one in Figure B. One should not disregard the important effect of this visual specification. As discussed above, the framing of information is important and might have implications in the way people appropriate this information.

The originality of our evaluation of energy label's efficiency lies in this cognitive approach. How do people treat the information conveyed by this complex design? In Chapter 1, we study this perception through an artefactual field experiment on 3,000 French subjects. The experiment consisted in the presentation of a real estate advert where the EPC has been randomized, followed by a questionnaire. By studying both attention subjects paid to the EPC and how EPC modifies their perception of the house energy quality, our results

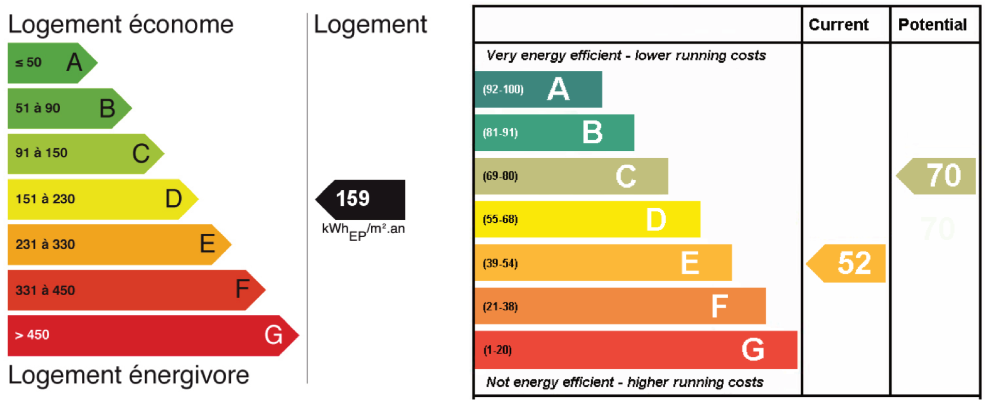


Figure B: French versus English Energy Performance Certificate

evidence several strengths of this design but also some unexpected weaknesses.

Regarding the capacity of EPC to convey information to subjects, we find that, while the EPC draws the attention of a large majority of subjects, still 24% of them did not pay attention to the label. We isolate a few socio-demographic characteristics which are decisive in this changing attention, namely gender and the owner-occupant *versus* tenant status. Gender effect is explained by the selectivity hypothesis. Previous psychology and marketing literature has shown that men and women do not select the same information when facing a large amount of it with a varying level of accessibility. The design of EPC, visually salient thanks to colors, based on a comparative scale but also displaying a very technical information, makes it more appealing to male subjects. The changing attention between tenants and owners could also be due to the poor handiness of EPC intrinsic information. Switching the information on primary energy consumption to a monetary information could then be more effective to also draw the attention of tenants.

Among attentive subjects, we use beta regressions to investigate energy labels' efficiency to transmit information, more specifically to induce a change in the ranking of a house on a scale of perceived energy efficiency. Our findings underline that EPC has a strong effect on subjects perception of energy efficiency, and that subjects do identify separately each of label's classes. The reading process of EPC is globally homogeneous within the population, with one exception. We find that older subjects slightly shift down their rating of the energy quality of the house, whatever the class indicated, whereas they do not when the label is not displayed. This effect is especially strong within the age class which has faced and experienced the introduction of EPC. It might be linked with negative prior beliefs regarding the EPC's reliability, as its outcomes is publicly known as volatile and depending on the assessor.

The in-depth analysis of subjects perception of energy quality through this energy label evidences that people base their judgment on the deceptive visual design of EPC rather than on its intrinsic information. They follow the 'nudge' rather than the objective information to make up their opinion on the energy quality. However, we also highlight that EPC information is not perceived as perfect. Subjects have a Bayesian reading of EPC: they use the label information to partially revise their prior beliefs on energy quality, but some uncertainty remains. EPC are thus efficient in the reduction of information asymmetry between sellers and buyers, but people do not blindly believe this label which credibility is often questioned. A resulting interrogation is whether this conveyed information is capitalized in real estate prices. Chapter 2 addresses this question through an empirical investigation on two French real estate markets.

Capitalization of information

To what extent is the information conveyed by EPC capitalized into real estate prices? While several studies on various European countries evidence a capitalization of Energy Performance Certificates into home prices, these studies disagree on the magnitude of this green premium. Moreover, they also diverge from engineer's estimations of theoretic green values. Thus, understanding the capitalization of EPC in real estate prices requires more than the traditional hedonic estimation, it involves a comparison with associated renovation costs and expected savings for households. This is the research question addressed by Chapter 2 in the present dissertation.

We investigate the green value of French houses over two regions, Lyon metropolis and Brest area, in order to see the impact of market tightness. The Lyon metropolis is a densely populated and urbanized zone, whereas Brest area in Brittany is mostly rural with a much lower density of inhabitants. In a first step, the traditional hedonic analysis of transactions in those regions is coupled with Geographic Information Systems to regress prices on the intrinsic characteristics of dwellings and on the distance to various public amenities, such as parks, city center or public transport facilities. A spatial econometric model is estimated to control for unobserved spatial heterogeneity. Results evidence a significant green value in both areas. Relative premium turns out to be much higher in Brittany, amounting to 29% of a house price, while representing only 11% in Lyon.

This large difference in the capitalization between rural areas and dense cities was already evidenced before. The present contribution to the literature lies in the fact that we selected those two regions because they share similar heating needs and energy prices. Consequently, savings on the energy bill associated to a greener EPC class are comparable in the two areas. Consistently, switching to absolute terms the green premiums previously mentioned evidences tantamount green values for each level of efficiency in the two regions, reaching about 35,000€ for low consumption houses. This result underlines that the green value should be considered as an absolute component of a house value.

Then, we use in Chapter 2 a dataset on warmth insulation costs together with a thermal model of energy consumption for space heating. Renovation investment costs required to upgrade an inefficient house to a higher EPC class are computed and compared with the premiums empirically evidenced by the hedonic analysis. We find that empirical estimations of the green premiums lie for each EPC class within the range of associated renovation costs. Green value is thus consistent with the capitalization of renovation costs. A potential explanation of these very close estimates is that a Bertrand-type competition occurs between home sellers on the energy quality component of the house value. Indeed, the production cost of energy efficiency, *i.e.* the required investment to turn an inefficient house into a more efficient one, is homogeneous over France. For instance, let's consider a seller of an efficient house who tries to charge more than the investment cost that is required to renovate this house. Then, *ceteris paribus*, the potential buyer will prefer either choosing an equivalent house with the same label, for which the seller proposes a lower price, or buying an inefficient house and invest by herself in the renovation. Equilibrium premium of an EPC class will then be the investment cost required to convert an inefficient house into this class.

Chapter 2 also compares green premiums with expected energy savings. Beyond the smallest renovation, from the F-class to the E-class, green premiums appear to be substantially higher than expected savings. Indeed, reduction of the heating bill could match green premium for low-consumption houses only if households' time preferences are strongly oriented to future gains, with discount rates smaller than 5% and time horizons over 20 years. However such time preferences of households are usually discarded by the empirical findings of economic literature, which evidences shorter time horizons and higher implicit discount rates. We can thus guess that ancillary advantages of low-consumption houses, especially improved thermal comfort, constitute an important part of the benefits that households derive from an efficient house.

Nonetheless, if Chapter 2 highlights that French households do value energy efficiency, the pace of housing energy renovation in France remains too slow with regard to public policy objectives. Over three years (2014-2016), a recent survey by the French National Agency for Environment and Energy Management (ADEME, 2018) has found that, even if over 5 millions houses were renovated, less than 5% of those were concerned by deep energy renovations. It corresponds to less than 90,000 houses per year. As policy-makers aim at turning all buildings into low consumption ones by 2050, the pace required to meet public objectives is then five times superior to the current one.

This large report on the renovation of French houses also gives insights on the drivers and obstacles to the renovation decision in France. In accordance with findings of Chapter 2, households appear to value both energy savings and thermal comfort. But this survey also underlines that the missing keystone to scale-up renovations is the confidence in their results. As energy renovation contracts today rely on an obligation of means and not of results, households might wait for positive feedbacks from their relatives before launching a renovation. Households action on energy efficiency thus heavily depend on 'word-of-mouth' processes. This is an informational externality.

Dynamics of information

In Chapter 3 we investigate potential outcomes of uncertainty and informational externalities on households behavior. Even though the added-value of an efficient house is recognized by the market, the renovation process is hazardous. Numerous defects due to poor workmanship plague construction industry in France, and threaten energy performance post-renovation. On the one hand, moral hazard can lead to poor workmanship in energy renovation, as evidenced by Giraudet et al. (2018): as long as there is no *ex-post* measure of energy efficiency, quality of craftsmen work is unobservable by households. On the other hand, beyond moral hazard, craftsmen training in installing efficiency devices is not satisfactory, which also lead to faulty works (CGDD, 2015). Asymmetric information thus lead to uncertainty in renovation quality, undermined by adverse selection (asymmetric information regarding craftsmen skills) and by moral hazard (asymmetric information regarding craftsmen efforts). As the decision to invest in energy renovation can be delayed, in Chapter 3 we choose to model this investment under uncertainty as a real option problem.

When people face uncertainty, sociologists underline the importance of word-of-mouth processes. Social influence, herding behavior, informational cascades... Following the early contribution of Rogers (1962), the idea that innovation diffusion, and its standard representation of the S-shape curve, depends on information sharing has spread across all social sciences. In a context of uncertainty, people make their decisions upon information they can gather from sources they consider as reliable, whether it is their relatives, rating websites or consumers or professional associations. In this social learning perspective, positive feedbacks are critical in order to induce adoption. The previously mentioned survey by ADEME on French renovations emphasizes the importance of positive feedbacks to trigger the renovation decision: word-of-mouth is underlined as the key driver of households action.

Nonetheless, in this perspective, the adopter becomes also a part of the process. When she adopts a new practice or product, she produces knowledge on its quality. Is it efficient or not? Her knowledge is something she will share with her relatives. Then, information about innovation quality can be seen as a public good. While information is a by-product ensured by costly private decisions, information consumption is free and can be enjoyed by all agents. This strategic stake is embodied in Chapter 3: agents who choose to exercise their option (*i.e.* invest in the renovation) costlessly produce public messages about result's quality. But agents also anticipate that they will benefit from messages produced by others if they postpone their decision. A free-rider problem thus arises.

However, information is not perfect, *i.e.* its production is noisy. If we consider that, in theory, a renovation is an efficient way to improve the energy performance of a house, it is still possible to receive a negative message regarding the quality of renovation outcomes. This error in the nature of the message can be due to two kinds of factors. Either the renovation really was inefficient, and the negative message is consistent with it, or the renovation was efficient but the message is inconsistent.

On the one hand, previous sociologists' field investigations, like the ones of Renauld-Giard (2014), underline the lethal effect of faulty works on the diffusion of inventions in the building industry, even when those inventions are effective and useful. The enlightening example of solar boilers is described by Renauld-Giard (2015). This green technology enables energy savings for households and reduces greenhouse gas emissions thanks to the use of solar energy. But the implementation of this technology at the beginning of 2010 in France was not a success, due to early failures. These failures were due to a too short training of craftsmen. As the first solar boilers were badly installed and did not work well, they got quickly a bad reputation and sales of solar boilers collapsed. This is an example of the 'teething troubles' that can encounter inventions. Broadly speaking, both of the previously mentioned informational failures regarding craftsmen (adverse selection and moral hazard) can significantly increase the probability that the renovation fails to achieve a high energy performance. On the other hand, even a performant renovation can trigger a negative message, again due to the lack of objective measure on house energy quality. For instance, a dissatisfied household can send a negative message even though renovation quality is good, either because the household expected higher energy savings or it faced delivery delays.

Whether it is the renovation that has failed or it is the household that is being picky about it, information regarding the benefits of energy retrofitting is not perfect. Thus, several messages are required to help the household in making its decision. Consistently with

Chapter 1 findings, which suggest that people update their prior beliefs thanks to public information, we include in the strategic option model a Bayesian learning.

Chapter 3 model can be more broadly applied to any innovation diffusion, in the construction industry or in other sectors. We exemplify in Chapter 3 several stylized facts to underline how our framework can be applied to the analysis of other new products or services. We develop a dynamic game where heterogeneous agents have the option of adopting an invention of uncertain quality or postponing their decision to benefit from others' experience through Bayesian learning. Information produced by adopters about the invention's nature is public but the messages sent are noisy. Our modeling thus departs from standard real option models (Dixit and Pindyck, 1994) by its Bayesian basis and the role of strategic behaviors. We give microeconomic foundations to the S-shaped innovation diffusion curves, informational externality inducing strategic delay in agents' behavior. Moreover, consistently with stylized facts, noise can nip in the bud the diffusion of inventions with intrinsically high quality. The model thus highlights how 'teething troubles' may influence the fate of inventions. Numerical simulations underline a bi-modal distribution of steady states for the diffusion path of inventions of intrinsically high quality. They may be either stillborn or fully developed, bringing to light a reputational valley of death for inventions. This result is robust to an endogenization of the choice of its price before the firm launches the invention on the market.

In our model, the only way agents can become more informed is by delaying their decision, *i.e.* waiting for more information. The production of information is unintended and suboptimal. We then explain waiting strategies, due to the free-riding and teething troubles. Such informational externalities could significantly delay the renovation decision, and enlighten the slow pace of renovations observed today in France. This lack of information raises the question of information production by a third party. But how much is the value of information on the quality of a product? Are people ready to pay for information, and, if so, how will they use it? Those are the questions we attempt to address in the fourth and last chapter of this dissertation.

Value of information

Currently, several innovations are under development in the construction industry to enable a reliable evaluation of buildings energy quality. We can cite at least two technologies in France: the QUB method designed by Alzetto et al. (2018), and the ISABELE method developed by Thébault and Bouchié (2018). Contrary to the current method used to assess buildings efficiency (the 3-CL method, more thoroughly detailed in Chapter 2), which relies on a theoretic estimation and upon which is made the Energy Performance Certificate, those disruptive inventions enable experimental measures of buildings energy performance. This shift from an estimation-based method to a measure-based one will provide a much more reliable information, whereas today's EPC suffers from many errors as underlined by Hardy and Glew (2019).

The emergence of these technologies will enable the inception of *ex-post* check-ups on renovation quality for instance. They will also facilitate thermal audits and more efficient targeting of energy conservation measures. Obviously, future implementation of these informational tools will probably spur development of new kinds of contracts regarding energy renovations, and be a game changer in the building industry. But before these add-ons, some upstream questions deserve economists' attention. Indeed, this reliable information will imply more important production costs than the traditional Energy Performance Certificate. We choose then to investigate in Chapter 4 people's Willingness-To-Pay for information on quality and to compare it with information theoretic value.

In order to test both the Willingness-To-Pay for information and behavioral effects of information arrival, we choose an experimental approach. In Chapter 2, green premiums of energy efficiency are estimated using the hedonic method popularized by Rosen (1974). In this framework, the implicit price function derives from how agents value and bid for each characteristic of the house. However, if most of characteristics are objective and perfectly known by potential buyers before making their bid for the house (living space area, number of rooms, distance to environmental amenities, distance to city centre...), this is not the case for energy efficiency. They have some information about a house's energy performance, either drawn from public information (the EPC class of the house for instance) or from some 'private' expertise they can have. For example, it may be their own experience of living in roof-insulated dwelling that make them aware it is the most efficient way to reduce heating bills, or they may have noticed when visiting the house that windows frame was poorly airtight. Nevertheless, if energy performance of the house is uncertain, it creates the same added-value to all potential buyers, as underlined in Chapter 2. Consistently with this hedonic approach, we choose a framework to study people's bidding behavior when the auctioned good has a common value to all bidders but this value is imperfectly known. Moreover, as some inventions previously mentioned offer a reliable estimation of energy performance, we include this possibility of acquiring more information about the common value. We thus build a laboratory experiment where participants play a Common Value Auction (CVA) game obtaining the opportunity to bid for additional information about the intrinsic value of the auctioned good.

A classic outcome of CVA games, where the quality (*i.e.* the value) is common but uncertain to buyers, is the Winner's Curse (WC) phenomenon. This paradox is especially interesting in our analysis as it lies in the irrational use of information by real economic agents. Since the concept of winner's curse was firstly discussed by Capen et al. (1971), many economic studies have studied this phenomenon, but their early example remains a relevant way to explain WC principle. In the two decades preceding their publication, authors of the 1971 study find that Gulf of Mexico oil fields have paid off less than the local credit union, while those petroleum deposits' leases were acquired through a sealed competitive bidding. How do behavioral economists explain this puzzling result? Let's suppose several oil companies are interested in buying the drilling rights of an area suspected of harboring an oil field. If considered companies have equivalent extraction technologies, then the value of the oil field will be substantially the same to them. Nonetheless, the true value of this oil field is imperfectly known as the size of the deposit is uncertain. Each company will use its own experts to evaluate the volume of hydrocarbons, and the subsequent value of the oil field. As evaluations will vary, companies' bids for the land will be different as well. Of course, it is the company which experts have made the largest prediction that will place the highest bid and win the auction. However, this winner is likely to be a loser, as its estimate will probably be too high in regards to the true value of the oil field. Either the winning company is cursed through a smaller profit, as its high bid remains below the true value, or in the worst case scenario the profit can even become negative if it turns out that the oil field's value is below company's bid. Many experimental and empirical proofs of this phenomenon have been since brought out across various CVA. It is today manifest that the key error of bidding behavior which leads to winner's curse lies in the imperfect treatment of information. More precisely, in those CVA, bidders do not take into account the fact that winning the auction is informative. When a bidder wins the bid, it probably means that she has a higher signal about auctioned good's value, and she should then significantly shade her bid *ex ante*.

At first sight, the winner's curse could be considered as something we do not want to avoid as it could increase the green premium of efficient houses. Reality is more complex. When digging into at how the WC modifies bidding functions, it appears that this phenomenon could actually limit the differentiation between poorly and highly efficient buildings. Indeed, as shown by Holt and Sherman (2014), the 'naive' bidding function that is adopted by real economic agents, *i.e.* optimal bids when subjects do not take into account the fact that winning is informative, is much flatter than the Nash equilibrium bidding function. The reaction of the bidder to information is suboptimal, as she does not shade enough her bid when her signal on the auctioned good worsens. Therefore, the gap between bids for inefficient houses and performant ones will be much smaller, making the green premium less important than it would be if bidders avoided the Winner's Curse. Figure C illustrates our rationale.

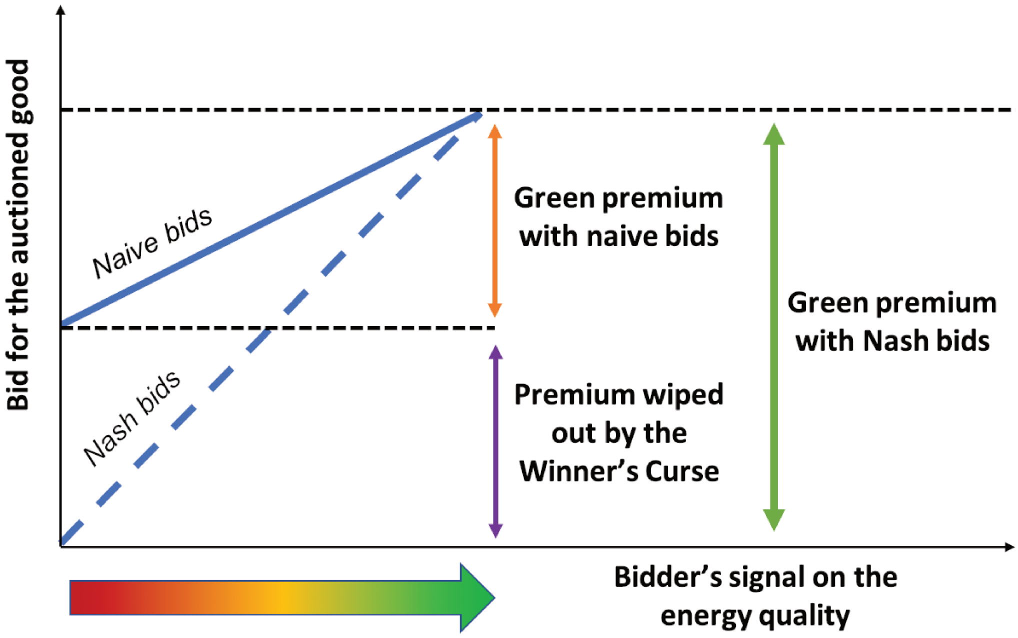


Figure C: The Winner's Curse and the Green Value

We underlined in Chapter 2 that, at a first glance, green premiums were consistent with investment costs required. One could then argue that there is not much space left in the French market to improve green value. Nevertheless, we can object two points. First, in Chapter 2 we estimate a range of potential investment costs to upgrade a house from an energy class to superior ones. If empirical premiums of the different classes systematically belong to their corresponding range of renovation costs, we can note that, as the label gets 'greener', the premium shifts towards the lower bound of the renovation costs. While for the E-label the premium is at the upper bound of this price range, the B-label premium is at the bottom of corresponding range of investment costs. The gap between the two premiums could then be widened even if premiums still matched the investment costs.

Second, these estimations of renovation costs only include material and labor costs. However, it is widely recognized that engaging in a renovation imply many other hidden costs. It takes time to find craftsmen, and the investment required has opportunity costs. Moreover, these hidden costs of the renovation are obviously more important when the renovation targets a higher level of efficiency. For instance, upgrading a house from the F-label to the E-one will simply require to insulate the attic. Investment is relatively small and a single craftsman can do it within a day. In contrast, a warmth insulation to reach the B-label level of efficiency will require walls, attic, floor and windows insulation. Thus much more money will be needed, different craftsmen with various skills will have to work for several weeks, and the house might be uninhabitable for some time. Transaction costs of a highly efficient renovation are then more important than the ones associated to a small renovation, and could justify a premium beyond investment costs for low-consumption houses. Those two points advocate for a potential stronger differentiation of green houses than the one empirically observed today in France. This differentiation could be achieved through a more reliable information on energy performance, especially if providing more information reduces the Winner's Curse.

In the light of the previous discussion, we want to investigate three specific questions in our experiment. First, regarding the winner's curse, we want to investigate if being more thoroughly informed could change subjects' bidding behaviors and bring them closer to a Nash equilibrium that would translate into higher premiums for high quality goods. Second, we have underlined the appearance of new information tools, and we want to test people's Willingness-To-Pay for more information on the quality of a good. Third, regarding the price of information, it is interesting to compare the arrival of a free information compared to a costly one. Indeed today's EPC is freely available to the buyers as it is mandatory and paid by the seller. Does putting a price on information change the way it affects subjects behaviors?

In our CVA game, groups of 2 bidders obtain free and private information about the true value of a Prize and should bid repeatedly for buying it as additional information may be provided throughout the bidding process. In a *benchmark* treatment, free information occurs and could result in various information structures for bidders. In the other *'Buy'* treatment, after obtaining some free information, participants bid for buying an additional signal before bidding again for the good. This treatment implies in particular that information asymmetry may be endogenously created between bidders, while it is exogenously created in the benchmark. We had 260 participants for which we control for cognitive abilities and risk aversion. We observed the Winner's Curse (WC) phenomenon consistently across the different information structures. Overbidding occurs both for the Prize but also for costly information. We give statistical evidence for explaining overbidding as the consequence of various well-known behavioral biases.

Results of the experiment evidence that pricing information helps subjects understanding information value and acting more strategically with it, which reduces the winner's curse. However this effect comes along with three new cognitive failures in the bidding behavior for the good: a sunk cost fallacy, a placebo effect, and a second-level winner's curse on information. Subjects Willingness-To-Pay for information appears to be much higher than information theoretic value. Those cognitive failures overshadow subjects' behavioral improvements, and thus the treatment does not improve overall profit of subjects. As regards disclosure of more and better information about energy quality, various solutions can be formulated in the light of Chapter 4. While it is useful to make households pay to signal them that information has a value, this price should be regulated by policy-makers. A first possibility is to allocate information production to a public authority. A second option is to set a flat rate pricing to energy audits, and to let private actors produce information. These insights on the behaviors of real economic agents under imperfect and asymmetric information can be useful to design more efficient policies, not only regarding energy efficiency, but also about many markets that can suffer from informational failures.

* * *

«Le style doit être comme un vernis transparent : il ne doit pas altérer les couleurs, ou les faits et pensées sur lesquels il est placé.»

—Stendhal.

* * *

Chapter 1

Green, yellow or red lemons? Artefactual field experiment on houses energy labels perception

* * *

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

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

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

* * *

This Chapter is an adaptation of a collaboration with Nathaly Cruz.

1.1 Introduction

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

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

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

1.2 Literature review: labels efficiency

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

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

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

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

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

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

1.2.2 Labels: the case of food

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

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

1.2.3 Labels: the case of energy

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

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

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

1.2.4 Conjectures

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

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

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

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

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

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

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

1.3 Experiment, data and empirical methods

1.3.1 Experimental design

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

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

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

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

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

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

1.3.2 Data analysis

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

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

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

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

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

1.4 Results

1.4.1 Data overview

1.4.1.1 Descriptive data

On Figure 1.1, we represent energy ratings' box-plots for the control group and the seven treatments. We observe that, as labels get "greener" (resp. "redder"), ratings shift towards good levels (resp. bad levels). In both ways, box-plots' width increases when labels become more extreme. Moreover, the median of the control group ratings is close to the scale center, just like the median of D-label treatment group ratings. This suggests that our real estate ad did not in itself strongly bias judgments on house energy quality. Between treatments, medians are correctly ordered: G is rated better than F, which is rated better than E, etc. Nevertheless we can note a small inversion between the medians of A-label and B-label groups. It seems also that G-label ratings are much more concentrated on the inferior boundary of our scale than A-label ratings are on the superior boundary.

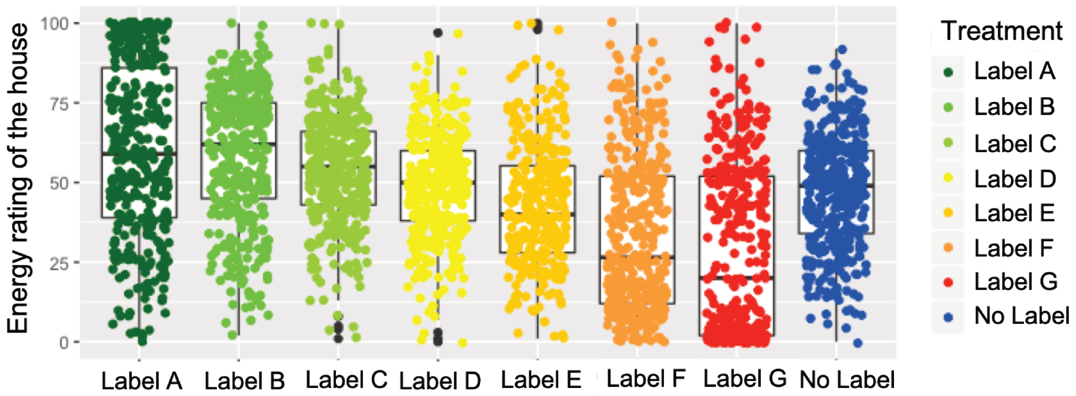


Figure 1.1: Box-plots of energy ratings

On Figure 1.2 we draw the empirical densities of energy ratings. Three main features can be drawn from these distributions. First, we can observe that distributions' modes are correctly ordered: they increase when shifting from label G to label A, and the mode of the central label D distribution is similar to the one of the control group (no label). Secondly, distributions are not "clear-cut": on the whole, people's perception of energy labels is not exact, distributions overlap each other. Thirdly, distributions which are not central exhibit a second mode, in the center of the rating scale. Thanks to the fourth step of our experiment, we were able to differentiate people who noticed the energy labels when watching the real estate advert to those who did not. We count overall 614 subjects who declared not remembering anything about the information displayed by energy label, instead one was present on the advert. There were similar numbers of inattentive subjects in the different treatments groups, with respectively 87 subjects for label A, 98 for label B, 92 for label C, 89 for label D, 75 for label E, 83 for label F and 90 for label G. When withdrawing from the samples those subjects, the second mode of distributions (located in the center of the scale) softens strongly in each distribution (see Appendix 1.B). This result is consistent with the control group results: when people do not face an energy label or do not pay any attention to it, their energy ratings form a distribution centered in the middle of the scale. This corresponds to subjects' prior: this is the distribution of beliefs on energy quality before (or without) seeing the EPC but posterior to seeing the rest of the add.

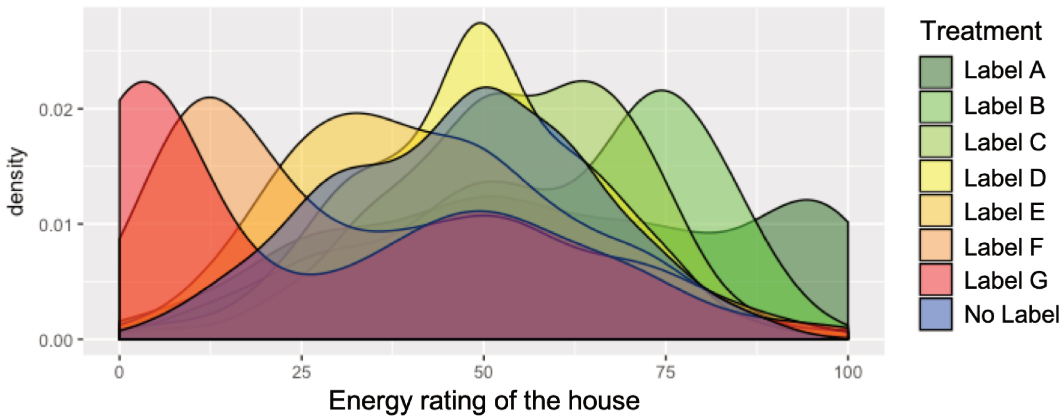


Figure 1.2: Distributions of energy ratings, all subjects

1.4.2 Determinants of attention to energy label

Another interesting result of our experiment is that 24% of subjects in the treatment groups did not take heed of the energy label displayed on the real estate advert. This information is available thanks to the analysis of subjects' answers to the question *"Which was the energy* *performance expressed by the energy label?"*. One quarter of treated subjects declared not remembering anything about the energy label which was displayed on their advert, even though remembering it was present. In order to test if energy labels had an unconscious impact on rating for these respondents, we replicate on the subset of these subjects the analysis of the previous section (see appendix 1.C for the corresponding distributions). In Table 1.1, the Kolmogorov-Smirnov test shows that we cannot significantly differentiate ratings given by subjects submitted to different treatments but who reported they did not take heed of the energy label. These tests demonstrate that there is no significant unconscious influence of energy labels. When subjects declare they did not pay attention to the energy label, their energy ratings of the house are unbiased by the energy label, and are not significantly different from the ones of respondents in the control group.

Table 1.1: Labels induced no significant difference between ratings of inattentive subjects

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

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

A relevant point for public policies is to estimate if some socio-demographic characteristics of subjects have an impact on the probability of being attentive to the energy label. To answer that question, we built a probit model, with a stepwise procedure minimizing the Akaike Information Criterion; we control the goodness of fit with the McFadden statistics and we check the relevance of explanatory variables using the Wald test. Selected variables are significant with a level of confidence of 90% or higher. Coefficients of the model can be found in Table 1.2.

Table 1.2: Determinants of the attention to the energy label

	Binary dependent variable:
	Attention to the Energy Label
Gender: Woman	**−0.292******
	(0.055)
Owner-occupant	**0.157******
	(0.058)
Housing search after EPC introduction	**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	**−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	**0.781******
	(0.110)
Observations	2,609
Log Likelihood	−1,430.782
Akaike Inf. Crit.	2,891.564
Note:	*p<0.1; **p<0.05; ***p<0.01

Four socio-demographic characteristics have a significant impact on the attention given to the energy label: gender, owner-occupant/tenant status, the fact of having been involved or not in a housing search since the introduction of EPC, and the region where lives the subject. Factors which appear not being significant deserve some comments: age, socio-professional category, revenue and education level do not exhibit a significant impact on the attention to energy labels (in Appendix 1.D we list all tested variables).

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

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

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

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

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

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

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

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

1.4.3 Evidences of EPC impact

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

1.4.3.1 Statistical evidence of EPC impact

As descriptive data underline that all distributions overlap, and that several distributions have almost the same means and close modes, a legitimate question arises: are these distributions significantly different? In order to answer it, we use the nonparametric Kolmogorov-Smirnov test on attentive subjects. Results shown in Table 1.3 exhibit that all energy ratings distributions drawn from the treatments are significantly different. However distribution derived from attentive subjects who received the treatment "label D" is not significantly different from that of the control group.

Table 1.3: Significance of the difference between ratings of attentive subjects

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

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

1.4.3.2 Beta regression model

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

$$E[y] = \int_0^1 yf(y;\alpha,\beta)dy = \frac{\alpha}{\alpha+\beta} = \mu \tag{1.1}$$

$$Var[y] = E[(y - E[y])^2] = \frac{\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)} = \frac{\mu(1-\mu)}{1+\Phi} \tag{1.2}$$

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

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

We implement the beta regressions proposed by Cribari-Neto and Zeileis (2010) in an ascendant stepwise applied to our two groups of subjects, isolated thanks to the previous section. The first group gathers subjects whose real estate ad did not display an energy label, *i.e.* the control group. The second group gathers subjects who did face an energy label and were attentive this information : we call them "attentive subjects". The first group counts 391 subjects, the second group counts 1,968 subjects. Tables 1.4 and 1.5 present beta regression results when we authorize 10% level of type I errors in the selection of explanatory variables. Tested variables are the ones used in the previous section and presented in Table 1.D1 (see Appendix 1.D).

1.4.3.3 Econometrical evidence of EPC impact

We apply beta-regressions to two groups of subjects: the control group, who faced not any EPC, and attentive subjects in the treatments (who faced an EPC and paid attention to it). Table 1.4 presents regressors selected for their significance in the mean model for the control group. No significant variables were found for the precision model applied to the control group. Two variables exhibit significant impacts on subjects rating of the house energy performance: education level of the subject and the climate indicator of his county. Education level has an impact for one category: subjects with the highest level of education tend to underrate the energy performance of the house, while subjects with lower education levels (e.g. bachelor levels) or subjects with an education level below the baccalaureate do not rate differently the house energy quality. The climate indicator, depending on the county where the subject lives, corresponds to the annual need for heating due to the climate, expressed in degrees. The negative coefficient for this variable means that when subjects live in colder counties, they tend to underrate the energy quality of the house all other things being equal. However the explanatory power of this model is quite low: pseudo-R^2 is evaluated at 5.5%. These two effects are then not sufficient to explain the centered symmetric distribution of energy performance ratings made by subjects in the control group (see appendix 1.C). This heterogeneity in ratings does not result exclusively from the systematical biases identified (education and climate) but also from idiosyncratic reading of the real estate ad: each subject perceives and treats differently the various pieces of information (as the pictures and information about heating system and windows).

A similar procedure is applied to subjects exposed to an energy label and attentive to it. However, there is a non-random selection for this group, as we have shown in Table 1.2 that some variables have a significant impact on the probability of paying attention to the energy label. We use the Heckman correction in two steps to control for this selection bias: the inverse Mills ratio is calculated from the probit model discussed in section 4.2 and

Table 1.4: 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	

used as a control variable. Results are reported in Table 1.5. The EPC displayed on the real estate ad and the age category of the subject are both significant at a 1% level, the dummy for having been looking for housing since the introduction of EPC is significant at a 5% level in the mean model. In the precision part of the model, only EPC is significant. The inverse Mills ratio does not exhibit significance at common levels, we then reject the hypothesis of a sample selectivity effect. Analysis of these regressions is threefold: EPC is highly informative and its reading is consistent with the design, but older generations, more exposed to this label, might be more skeptic. Moreover, label A perception stands out as noisier.

Firstly, EPC is highly informative for attentive subjects: the EPC grade is the main driver of energy ratings. Moreover, variables which were influencing the mean of energy ratings of the control group (see table 1.4) are cleared out for attentive subjects. Indeed in table 1.5, education level and climate show no influence on subjects' perception of energy quality. Hereof we can consider houses energy labels as efficient: when they are processed, subject characteristics which influenced their perception are pushed aside. When giving a look at model's coefficients, results evidence a reading consistent with the design. As labels worsen, the mean of energy ratings decreases, while upgrading labels increases energy ratings. Together with results of section 4.3.1, we can validate the conjecture 2.

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

Secondly, the model reveals that age category and temporal proximity of a real estate research have an impact on labels reading. Age seems to evidence a generational effect in energy performance certificates reading. Subjects in the mid-life and superior age categories (35-49 years old, 50-64 years old, and over 65 years old) exhibit a lower perception

Table 1.5: 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

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

A third lesson from our econometric analysis comes from coefficients analysis. In Table 1.5, coefficients point out a peculiar treatment of the top-graded EPC, the A-label, obvious at all significance levels. Given the proximity of A-label and B-label estimated coefficients in the mean model, we test the significance of the difference between all labels coefficients by building instrumental variables. It appears that {A;B} is the only pair of labels which coefficients are not significantly different in the mean part of the beta regression, while remaining strongly significantly different in the precision part of the beta regression. If labels A and B are perceived differently by subjects, in terms of mean the label A is not perceived as better than the label B, while in terms of dispersion label A reading is much less precise than label B reading. This stronger dispersion of energy ratings for the A-labelled EPC could either be due to a noisier perception of this grade, and/or to a weaker confidence in this grade. A potential explanation of this phenomenon is the relative scarcity of A-labelled houses in the French real estate market, which may raise skepticism among subjects when they see this specific label in view of the house's pictures displayed on the ad.

1.5 Treatment of Energy Performance Certificate information

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

1.5.1 Hypothetical readings of EPC

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

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

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

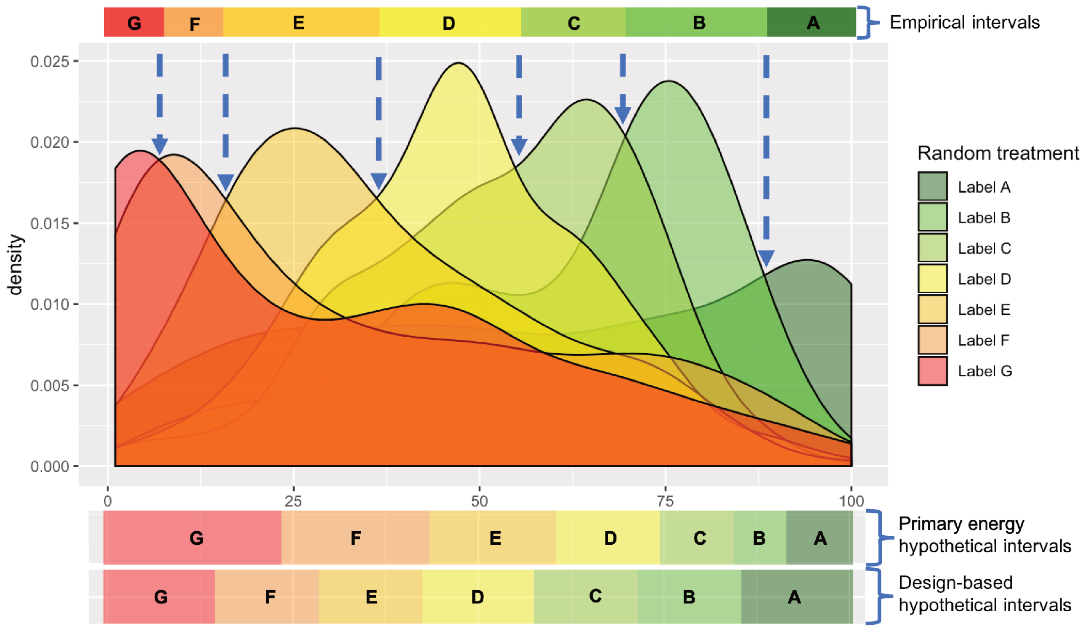


Figure 1.3: Hypothetical vs Empirical readings of EPC grades

On Figure 1.3 we represent those hypothetic intervals below the actual ratings made by subjects. In order to understand if subjects reading is based on the primary energy or on the visual design, we show upon the figure the empirical intervals. These empirical intervals are built using a stochastic dominance criteria which computes for each rating (from 0 to 100) which EPC grade has most probably been shown to the subject. For instance, the D-label is associated to the interval [60; 74] in the primary energy reading, to the interval [43; 57] in the design-based reading. Empirically the interval [38; 53] is the one where ratings are more probably given by subjects who faced the D-label in our experiment.

Comparison between empirical intervals and hypothetical ones evidences that subjects reading is closer to a design-based one: indeed intervals for the same grade systematically overlap when considering empirical results and the design-based hypothesis. On the contrary, intervals deduced from the primary energy hypothesis are disjoint from empirical ones for a majority of grades (labels C, D, E and F). This result confirms the conjecture 3: reading of

EPC is based on the label design and not on the intrinsic information on primary energy conveyed by it.

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

Nevertheless, we observe that ratings distributions are not confined to their hypothetical intervals: on the opposite they overlap each other largely and dwell on the whole scale. This observation weakens the conjecture 4 which stated that EPCs were treated as perfectly informative. In Table 1.6, we compute the part of ratings made by attentive subjects belonging to the three kinds of previously built intervals: empirical intervals based on the stochastic dominance criteria, energy-based intervals built according to an hypothetical reading of EPC following its intrinsic information, and design-based intervals consistent with an hypothetical reading of EPC following its visual design.

Table 1.6: Dominance intervals cover a minority of actual ratings

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

Overall, empirical intervals gather 37% of the ratings corresponding to their grade, while it is 32% for design-based intervals and only 20% for energy-based intervals. Empirical intervals systematically gather less than 50% of subjects ratings, no matter which treatment is considered. Together with the precision model of the beta-regression presented in Table 1.5 (which shows that when labels get more extreme, the ratings tend to be more disperse), this result evidences that EPC are not perfectly informative for subjects. We hypothesize that these distributions could be explained by a bayesian inference of EPC information.

1.5.2 Simulation of a Bayesian reading of EPC

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

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

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

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

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

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

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

In the previous definition, υ is a reliance level: the higher υ, the most informative is EPC. For instance, if x belongs to the dominance interval of the label i $[x_i^{inf}; x_i^{sup}]$, then when υ increases, $Pr_x(i)$ increases as well, and for any other label $j \neq i$, $Pr_x(j)$ decreases. In our simulation, we calibrate $\upsilon = 10$ to illustrate the Bayesian reading. Figure 1.4 represents resulting distributions.

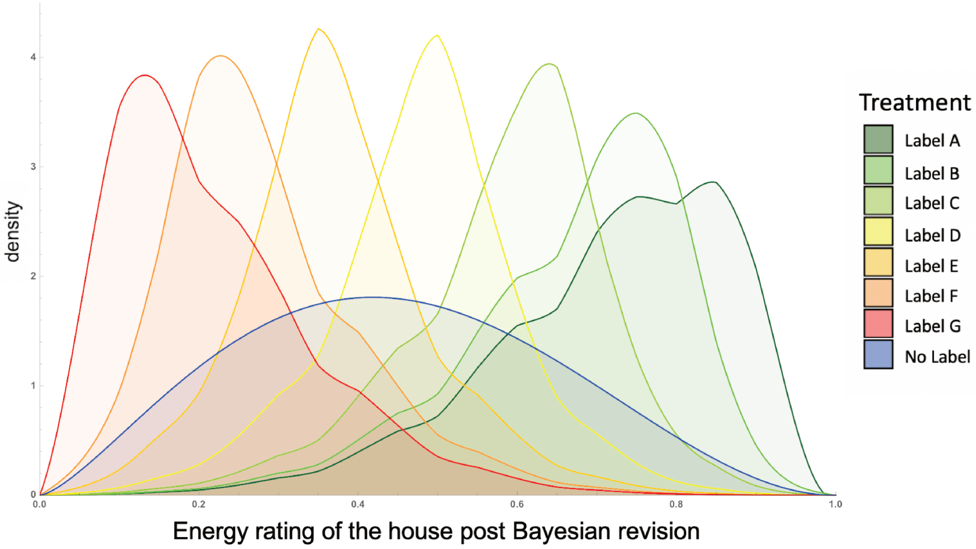


Figure 1.4: Simulations of ratings distributions based on a bayesian revision of prior beliefs

The blue curve (prior beliefs of subjects facing a no label ad) is modified into the colored ones according to the message received (EPC class, from A to G). Those counterfactual distributions are consistent with the ones empirically observed (see appendix 1.B). Labels distort the prior beliefs, modes of the revised distributions are correctly ordered, following the logical hierarchy of labels. Moreover, this Bayesian inference gives rise to strongly skewed distributions as label's class gets more extreme, similarly to empirical distributions. The A-label reading stands out again: its mode is significantly lower than the ones of other labels, and the distribution is more disperse. This is explained by prior beliefs: even though they were only slightly shifted towards bad ratings compared to the scale center, this anchoring is sufficient to decrease substantially the informative power of the A-label. In accordance with our simulations results, we disprove conjecture 4 in result 4.

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

1.6 Conclusion

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

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

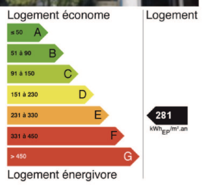
This chapter approach is novel by treating information as continuous: subjects are neither perfectly informed or totally ignorant, they have a signal which is processed into usable information for the economic decision. We open the debate on the limits such a perception could cause to the green value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

Appendices of Chapter 1

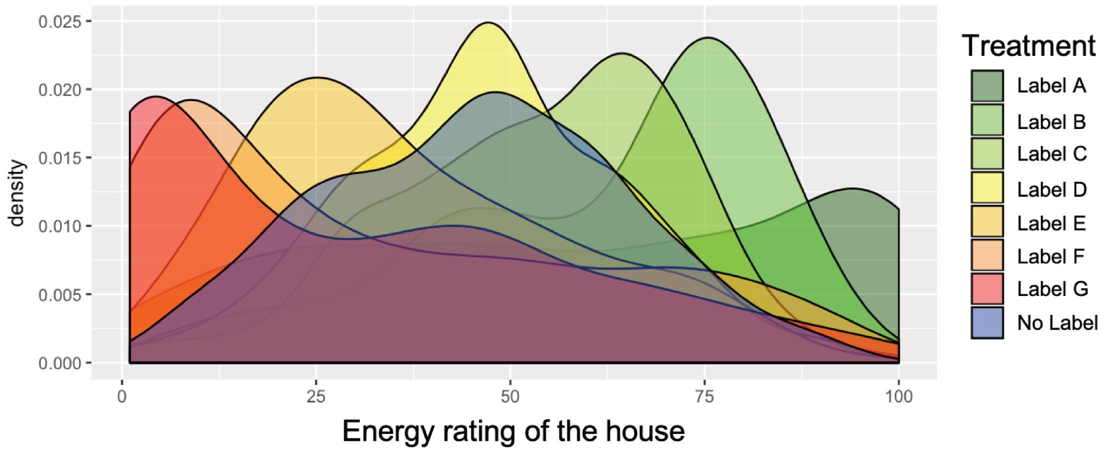
1.A Real estate advert, Energy label E displayed

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

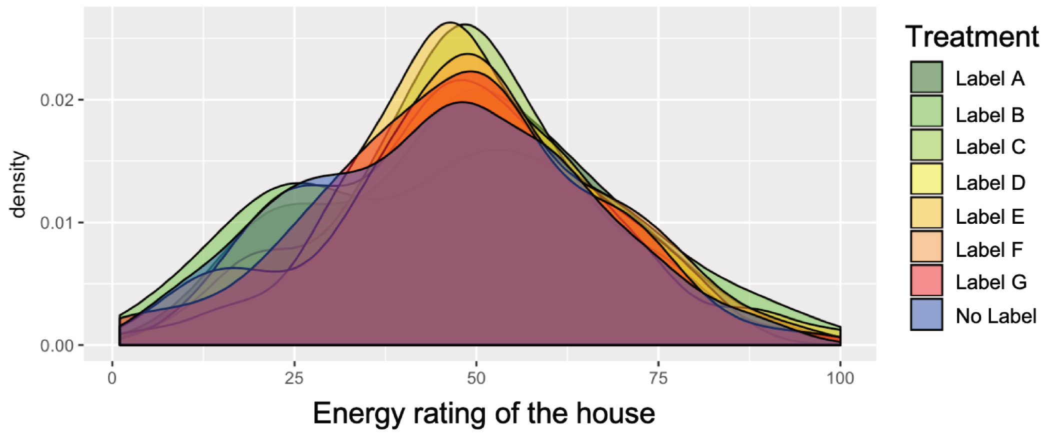
Charmante maison traditionnelle au rez-de-jardin donnant sur une ruelle piétonne. Belle pièce de vie lumineuse de 45 m^2, avec cheminée, exposée sud/ouest. Deux étages distribuant 4 chambres et 2 salles de bains avec WC séparés. Cuisine attenante entièrement équipée. Bureau à l'entresol. Huisseries alu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



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



1.C Distributions of energy ratings, subjects inattentive to energy labels and subjects in control group



1.D Tested variables

Table 1.D1: Tested variables for econometric analyzes

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

* * *

* * *

«Je voudrais savoir si le château est logeable, et si les environs sont aussi jolis qu'on le dit. Il y a tant de réputations usurpées !»

−Stendhal.

* * *

Chapter 2

Capitalization of energy labels versus Techno-economic assessment of energy renovations.

* * *

While a growing number of studies evidence the existence of a green value associated to energy labels, these studies disagree on the magnitude of this green premium and lack comparison with associated renovation costs and expected savings for households. This chapter investigates the green value of French houses in two regions: one urban area, the Lyon metropolis, and one rural are, the Brest area in Brittany. In a first step, the traditional hedonic analysis of transactions in those regions is coupled with Geographic Information Systems to regress prices on the intrinsic characteristics of dwellings and on the distance to various public amenities, such as parks, city center or public transports. A spatial econometric model is estimated to control for neighborhood effects. Results evidence a significant green value in both areas. If relative premium is higher in Brittany, switching to absolute terms evidences tantamount green values for each level of efficiency in the two regions, reaching about 35,000€ for low consumption houses. In a second step, using a dataset on warmth insulation costs, the chapter highlights that green premiums match with the investments required to improve energy efficiency. Green value is thus consistent with the capitalization of renovation costs. Comparison with expected energy savings suggests that households' time preferences need to be strongly oriented for the future, with implicit discount rates smaller than 5% and time horizon over 20 years, to favor low-energy houses.

* * *

2.1 Introduction

Since the introduction of real estate energy labels during the last decade, economic literature has regained interest in the application of hedonic methods to the housing market. Indeed, if those labels meet their goal, namely reducing information asymmetry between buyers and sellers on energy quality of traded houses, we should be able to observe a capitalization of the energy savings associated to a 'greener' house. The Energy Performance Certificate (EPC), progressively introduced in the European Union since 2002, is especially interesting: on the contrary to Energy Star label or LEED certification in the United States, it has to be realized for any building sold or rented out. The EPC, which came into force a decade ago for most Member States, ranks dwellings into seven classes, each of them identified by a letter, from A for almost zero-energy buildings to G for energy-greedy ones.

Most of recent hedonic investigations have found a significant green premium for energy-efficient buildings. In the United States, Eichholtz et al. (2010) found increased selling prices for energy-efficient office buildings. Kahn and Kok (2014) also evidenced a small premium for green-labelled houses in California. In Europe, hedonic analyzes have been applied in several countries that have adopted the EPC, estimating the sales premium at a few percents of a house price: Brounen and Kok (2011) identified a premium of 3.7% in the Netherlands, Hyland et al. (2013) found a premium of 9% in Ireland, just as Fuerst et al. (2015) in England. In Germany, Cajias and Piazolo (2013) estimated that a 1% increase in energy efficiency lead to a 0.45% increase of the market value. In France, a working paper by Leboullenger et al. (2018) identifies also a premium between 1 and 3% for green houses. However those hedonic approaches of the green value lack a detailed description of associated costs and savings. Indeed the 'engineer's approach' of the green value suggests that the premium should be more important, and is generally calculated in absolute terms rather than in percentage of the market value, as stressed for instance the techno-economic optimization of renovations made by Ferrara et al. (2013).

The present research innovates from the existing literature on two aspects: first it analyzes separately two different real estate markets with strongly different levels of prices, one densely populated (the Lyon metropolis, center of France) and one with low density and vast rural spaces (the Brest region, in Brittany). Second, it couples the analysis of the green premium with a dataset on renovation costs, and with a thermal model enabling the estimation of associated energy savings. Results evidence that the 'green premium' should be considered in absolute terms rather than relative to the house price. Indeed, absolute premiums associated to each grade of the EPC are closely similar in the two regions investigated, despite the important differences between each market. Moreover, those premiums are consistent with corresponding renovation costs, suggesting that green value results from a Bertrand-type competition between sellers. Lastly, comparison of each label premium with its associated energy savings underlines the importance of taking into account households' time preferences to design efficient public policies and meet energy goals of the building stock.

Section 2.2 details the hedonic method implemented and the specification used for the spatial error model. Summary statistics of the datasets used are also presented: characteristics of traded houses, material and labor costs for warmth insulation and energy costs. A thermal model is also built to assess renovation costs to upgrade a house and associated energy performance. Section 2.3 presents the econometric results and the estimates of the green premium. The green value of a B-labelled house compared to a F-labelled house *ceteris paribus* is estimated at 29.7% of the price in the Brest region, against 11.1% of selling price is the Lyon metropolis. In absolute terms, both green premium amounts to 34,000€. Section 2.4 evidences that this consistent green value in both regions corresponds to the required investments to upgrade a house from the F-class to the B-class. A comparison with expected energy savings follows, discussing the importance of time preferences in the renovation decision. Section 2.5 concludes with the main findings and potential extensions.

2.2 Data and methods

2.2.1 Hedonic regression and spatial error model

A hedonic model is used in order to evaluate the effect of Energy Performance Certificate on house prices. Hedonic regression is a widespread method to evaluate the determinant characteristics of complex goods pricing. Indeed, as goods with multiple and heterogeneous characteristics offer various services to consumers, pricing of a given good depends on the level of each service it can provide. Following the seminal contribution of Rosen (1974), this method has been extensively used to estimate the role of various characteristics in housing prices, as underlined by the review of Sirmans et al. (2005). Indeed, dwellings vary by multiple intrinsic characteristics (such as size, number of rooms, presence of a pool...) but also locational advantages (proximity to the city centre, to environmental amenities, attractiveness of the neighborhood...). More recently, this method has also been used in papers addressing the issue of the green value in the residential sector.Brounen and Kok (2011), Hyland et al. (2013), Kahn and Kok (2014), Fuerst et al. (2015) or Ramos et al. (2015) are illustrative of this kind of literature.

To test the impact of energy label's various classes on the price of a houses, the natural logarithm of transaction price is regressed on houses' characteristics as specified in the following equation:

$$ln(P_i) = \alpha + \beta * X_i + \gamma * L_i + \delta * EPC_i + \xi_i \tag{2.2.1}$$

$$\text{With} \quad \xi_i = \lambda * W * \xi_i + \epsilon_i \tag{2.2.2}$$

In equation 2.2.1, P_i is the transaction price of house i. X_i and L_i are respectively vectors of intrinsic characteristics (size, number of rooms, construction period, etc.) and of locational variables (distance to city centre, to the nearest underground station, to the seaboard, etc.) of house i. EPC_i is a categorical variable indicating to which Energy Performance Certificate class the dwelling i belongs. Those variables are either available in our transactions dataset (for X_i and EPC_i) or built using Geographic Information Systems (for L_i). α, β, γ and δ are vectors of coefficients to be estimated. δ is our interest vector of coefficients. ξ_i is a spatially correlated error term, whereas ϵ_i is an *i.i.d.* Gaussian random term (see equation 2.2.2). W is the spatial weights matrix, which terms are defined as follows:

$$w_{ij} = \frac{exp(-dist_{ij})}{\sum_{k \neq i} exp(-dist_{ik})}$$

The Euclidian distance between i and j is expressed in kilometers. This spatial specification of errors in our model aims at capturing the effects of unobserved spatial variables, such as neighborhood effects. This log-lin model can be easily interpreted: an increase of 1 unity of a variable z contributes to increase the price by a percentage corresponding to the estimated coefficient of the variable z.

2.2.2 Transaction prices, houses characteristics and geographic variables

The model detailed in the previous section is estimated separately for two French regions: first the Brest area in Brittany, gathering about 430,000 people over 2,100 km^2, and second the Lyon metropolis, gathering almost 1,400,000 inhabitants over 553 km^2. The '*Pays de Brest*' is a mostly rural area, while '*Grand Lyon*' is a dense and urban area. Those two regions were specifically chosen in order to compare the green value in two real estate markets unevenly tense, but with similar heating needs. Indeed the $D_{h.ref}$, a climatic indicator which measures the number of degrees-hour needed to heat a dwelling during a year, are similar in those regions: respectively $D_{h.ref}^{Brest} = 55000\ K$ and $D_{h.ref}^{Lyon} = 54000\ K$, while $D_{h.ref}$ ranges from $30,000$ to $71,000\ K$ in France (the kelvin K is the base unit of temperature in the International System of Units).

Another advantage of treating those areas is that their respective local authorities have made publicly available an important volume of geographic data. It enables a detailed geographic analysis of the role of various environmental and public amenities in the formation of prices.

Transaction details were obtained through the French association of notaries, PERVAL. Those datasets include the precise dwelling location, transaction price, and many characteristics of the house, including total floor area, garden area, number of rooms, construction period, presence of a swimming pool, presence of a parking, month of the transaction, and the Energy Performance Certificate of the dwelling. Our dataset covers more than 70% of the transactions realized in 2016 in the two areas of interest. Transactions of "exceptional properties", such as castles, are removed from the sample. We restrict this analysis to houses, which represent 60% of dwellings in France. We choose this market as a house-owner can independently choose to renovate her house, while a condominium-owner have to agree on the renovation process with the homeowners association. In the end, the Brest sample gathered 1,242 houses transactions, with a mean price of 160,636€, and the Lyon one 1,094 houses transactions with a mean price of 365,481€.

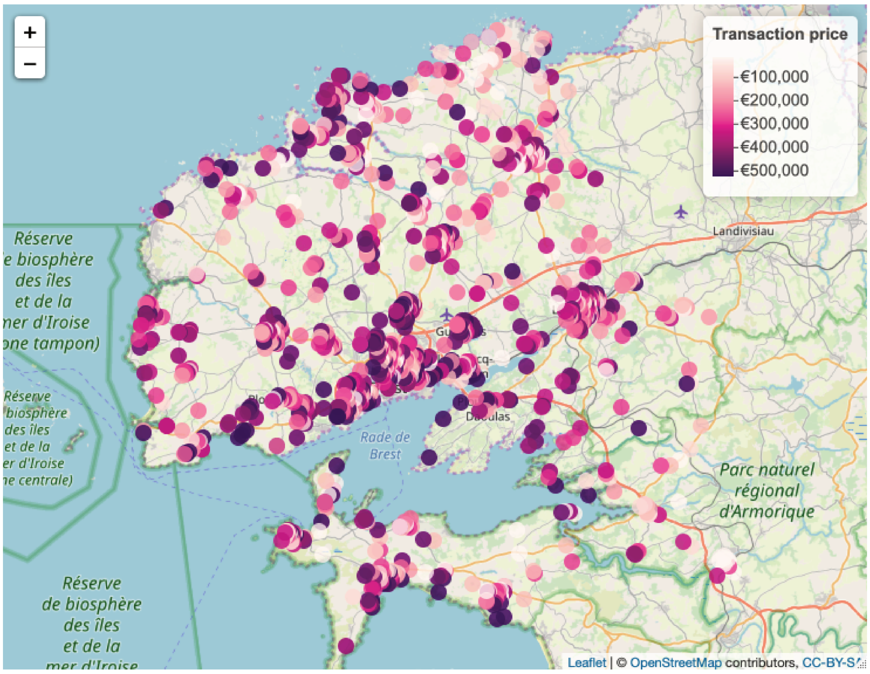


Figure 2.21: Map of observed prices of transactions in the Brest region

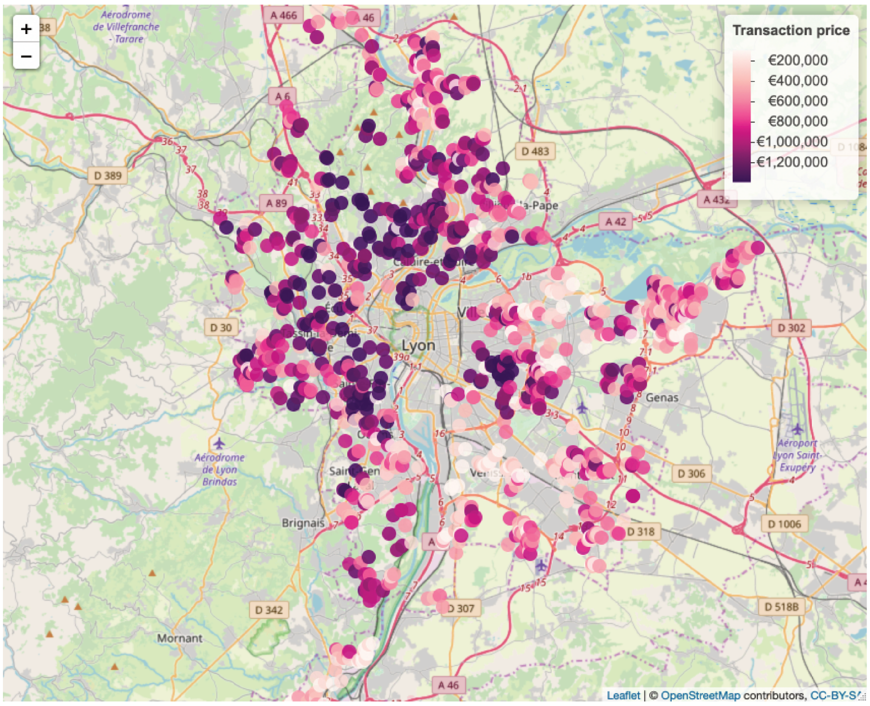


Figure 2.22: Map of observed prices of transactions in Lyon metropolis

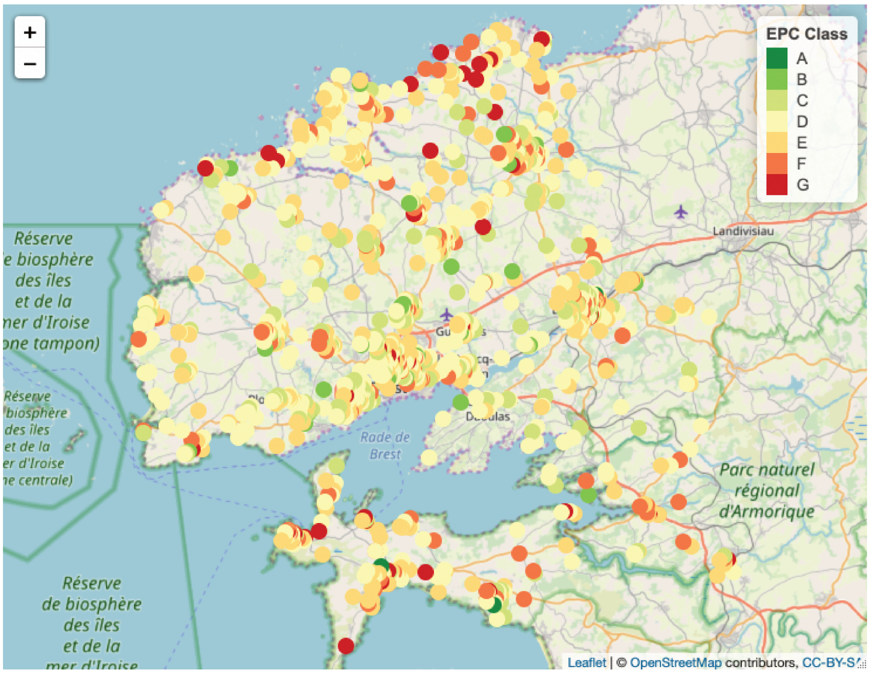


Figure 2.23: Map of observed Energy Performance Certificates in the Brest region

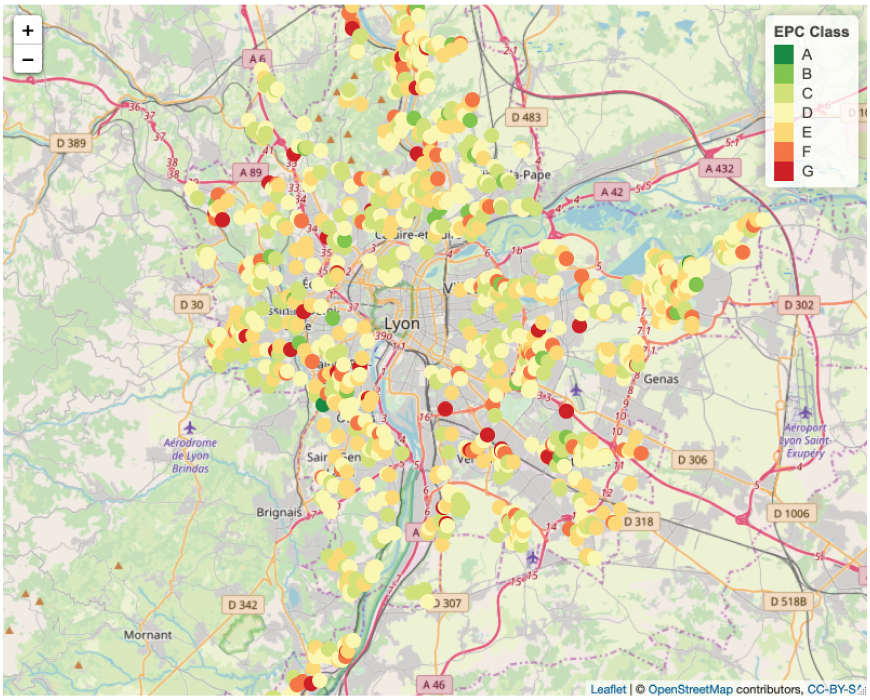


Figure 2.24: Map of observed Energy Performance Certificates in Lyon metropolis

Location and prices of transactions investigated are plotted in Figure 2.21 for Brest area and in Figure 2.22 for Lyon's one. We can already observe that neighborhood is a key driver of prices in the Lyon metropolis, while prices seem less dependent to location in the Brest region. Maps built with the price per meter squared is similar to those with total prices.

Figures 2.23 and 2.24 indicate the EPC grades of observed transactions. On the contrary to prices, which were heavily dependent on location in the Lyon metropolis, we do not observe strong spatial correlation for this variable. This varying spatial distribution of interest variables justifies the use of a spatial econometric model. Locations are used to compute several geographical variables for each house. Datasets on public amenities are available on the websites of the two local authorities, respectively `https://geo.pays-de-brest.fr/` for the Brest region and `https://data.grandlyon.com/` for the Lyon metropolis. Using the R software and Quantum GIS, a geographic information system, Euclidian distances (in kilometers) or travel time through the street/road network (in minutes), according to which is the more relevant, have been computed. When the public amenity presents more than one point of interest, the closest one to the dwelling is selected: for instance, the travel time to the underground in Lyon is the travel time to the nearest metro station.

Tables 2.21 and 2.22 describe statistical distributions of the samples key variables. As expected, the housing market is more tense in the urban area, with transaction prices over two times superior on average in the Lyon metropolis than in Brest region. One can note that the distributions of energy labels in the two areas are similar, and that A-labelled houses represent a very small part of the samples (3 in Lyon and 3 in Brest). The construction period variable has some missing values (7% of the sample in Lyon, 4% for Brest), other key variables are complete. Two variables describe the house size, respectively the total floor area and the number of rooms. Regarding geographic variables, in both areas the travel time to the city center (indicated by the city Hall) are computed. Travel time to the nearest train station and to the nearest tramway station are also computed for both areas. For Lyon specifically, travel time to the nearest park and metro station have been added. For Brest, distance to the seaboard, distance to the nearest wind turbine and travel time to the nearest hamlet are used as additional geographic variables.

2.2.3 Renovation costs and expected energy savings

In order to compare costs and benefits of energy efficiency, a technical-economic analysis is implemented using a description of typical French houses, a thermal model, a dataset on mature technologies and their costs for thermal renovations, and energy costs. This approach enables an estimation of the investment required to perform a warmth insulation of a house and upgrade its EPC class. The techno-economic analysis also provides estimates of energy savings associated to those insulation improvements.

Table 2.21: Summary statistics, key variables for Brest region (N = 1,242)

Continuous variable	Mean	St. Dev.	Min	Max
Price	160,636	61,766	16,000	520,000
Total floor area	110.501	32.143	34	252
Total land area	1,053	1,346	28	13,674
Number of rooms	5.465	1.387	1	12
Travel time to Brest center (min)	26.974	13.060	3.000	65.800
Travel time to the nearest tramway station (min)	19.081	13.364	1.100	60.200
Travel time to the nearest train station (min)	19.645	11.020	0.200	46.300
Distance to the seaboard (km)	3.262	2.768	0.000	11.727
Distance to the nearest wind turbine (km)	7.932	4.016	0.788	19.476
Travel time to the nearest hamlet (min)	3.890	2.683	0.000	13.200

Categorical variable	Categories	Number
Construction period	Unknown	53
	Before 1850	0
	1850 / 1913	18
	1914 / 1947	119
	1948 / 1969	318
	1970 / 1980	315
	1981 / 1991	148
	1992 / 2000	63
	2001 / 2010	194
	2011 / 2020	14
Energy performance Certificate	A	3
	B	32
	C	189
	D	455
	E	382
	F	132
	G	49

Table 2.22: Summary statistics, key variables for Lyon metropolis (N = 1,094)

Continuous variable	Mean	St. Dev.	Min	Max
Price	365,481	161,135	100,000	1,387,300
Total floor area	123.777	43.167	39	300
Total land area	802.237	718.665	27	5,757
Number of rooms	5.207	1.434	1	12
Travel time to Lyon center (min)	23.634	5.010	9.400	35.500
Travel time to the nearest metro station (min)	13.132	5.761	0.400	27.600
Travel time to the nearest park (min)	7.517	3.078	0.200	17.700
Travel time to the nearest tramway station (min)	11.471	6.887	0.400	28.700
Travel time to the nearest train station (min)	8.346	4.911	0.100	25.000

Categorical variable	Categories	Number
Construction period	Unknown	83
	Before 1850	4
	1850 / 1913	15
	1914 / 1947	124
	1948 / 1969	206
	1970 / 1980	202
	1981 / 1991	169
	1992 / 2000	113
	2001 / 2010	151
	2011 / 2020	27
Energy performance Certificate	A	3
	B	27
	C	304
	D	390
	E	259
	F	76
	G	35
Swimming pool	Yes	181
	No	913

2.2.3.1 Typical houses

An archetype of French house is defined using Insee (2015) statistics. Architectural characteristics and initial efficiency of each component of this typical house are described in Table 2.23. Architectural characteristics are assumed homogeneous within one period of construction. The thermal performance of the house is estimated through the mean U-value of its envelope. Envelope covers 4 components: external walls, roof, ground floor and windows of the house. The U-value is the heat transfer coefficient, expressed in $[W.m^{-2}.K^{-1}]$.

A component's U-value is then a measure of the quantity of heat leaked by this material. This measure is the key indicator on which the EPC is estimated (see Appendix 2.A for more details). When insulating a component, its U-value decreases. As thermal norms have become more demanding since their appearance in 1974, the U-values of building materials have become smaller, inducing less heat losses for more recent houses, hence smaller energy consumptions and better initial EPC classes. For instance old houses built before 1974 and not retrofitted have a mean U-value about $2.5W/(K.m^2)$, which corresponds to a primary energy consumption over $400kWh/(m^2.an)$ and an EPC class F. On the contrary, recent houses built after the introduction of 2005 French thermal norms have a mean U-value of $0.6W/(K.m^2)$, and consume about $100kWh/(m^2.an)$ for space heating (the corresponding EPC class is C).

Table 2.23: Architecture and performance of French typical houses

Characteristic	Value
Total floor area	$112m^2$
Number of floors	2
Height per floor	$2.5m$
Percentage of external walls covered by glass	30%

Construction period	<1974	74-81	82-89	90-2000	2001-2005	2006-2014
Share of the housing stock	53.29%	11.2%	10.3%	11.2%	5.9%	8.1%
Uwalls	2.5	1	0.8	0.5	0.47	0.36
Uwindows	4	3	3	3	2.3	2.1
Uroof	2.5	0.5	0.32	0.26	0.25	0.2
Ufloor	1.2	1.2	0.74	0.5	0.36	0.27

2.2.3.2 Dataset on material and labor costs for renovation

To evaluate investment costs for dwelling thermal renovation, we use Bâtiprix (2015), a French data base on prices in construction, including both material and labor costs, and a set of academic articles and official reports dealing with the costs of renovation (Lechtenböhmer and Schüring, 2011; Ferrara et al., 2013). We select mature technologies, widely available on the French market. All available options and associated costs are presented in Table 2.24. Costs are given with a VAT of 5.5%, which is the VAT applicable in France for thermal renovations, and include both material and labor costs.

For walls, the main technologies available are interior thermal insulation (ITI), using various thicknesses of glass wool, and exterior thermal insulation (ETI), using various thicknesses of rock wool or expanded polystyrene with coating. Interior insulation is less expensive, but also less efficient. The best solution for wall insulation is a combination of interior and exterior insulation. There is also the possibility of not acting on the walls (*statu quo*) : the price is then zero and the U-value is not modified. For windows, four options are available, including the *statu quo*: double-glazed windows, double-glazed windows with argon, and triple-glazed windows. Prices are significantly higher for these technologies. For the floor, the technology is an insulation with different thicknesses of rock wool, typically used on the underside of floor slabs. For the roof, house attics can be considered as uninhabitable or convertible, inducing higher insulating costs in the latter case. The main technologies available for uninhabitable attics are rolls of mineral wool (with various thicknesses) and blown granulated rock wool. For converted attics, the main technology is mineral wool between herringbones.

Table 2.24: Mature technologies for warmth insulation

Component	Technologies	U-value ($W/m^2.K$)	Prices (€/m^2)
Walls	Statu Quo	Unchanged	0
	ITI Glass wool 4cm	0.77	71.74
	ITI Glass wool 6cm	0.5	73.85
	ITI Glass wool 8cm	0.38	75.96
	ITI Glass wool 10cm	0.3	78.07
	ETI Exp. Polyst. with coating 14cm	0.27	180.405
	ETI Exp. Polyst. with coating 15cm	0.26	183.57
	ETI Rock wool with coating 16cm	0.23	200.45
	ETI(rock 20cm) + ITI(mineral 10cm)	0.11	288.015
Windows	Statu Quo	Unchanged	0
	4/16/4 double-glazing	2	380
	4/16/4 double-glazing argon	1.7	420
	4/16/4/16/4 triple-glazing	1.2	480
Roof	Statu Quo	Unchanged	0
	Mineral wool rolls 20cm	0.2	20.045
	Mineral wool rolls 30cm	0.13	22.155
	Blown rock wool 20.5cm	0.22	34.815
	Blown rock wool 29.5cm	0.15	53.805
	Mineral wool between herringbones 10cm	0.35	85.455
	Mineral wool between herringbones 12cm	0.29	86.51
	Mineral wool between herringbones 16cm	0.22	87.565
Floor	Statu quo	Unchanged	0
	Rock wool slab underside 10cm	0.34	128.71
	Rock wool slab underside 12cm	0.29	133.985
	Rock wool slab underside 14cm	0.25	139.26

2.2.3.3 Minimized renovation costs

For each construction period, an efficient cost function of thermal performance is computed by ranking the different technologies in increasing order according to their ratio U-value/Price and by cumulating their costs. The obtained curve is convex, consistent with decreasing marginal gains of efficiency when investments grow. Figure 2.41 in section 2.4 gives this efficient cost function.

2.2.3.4 Heating energy prices

Table 2.25 gives the distribution of the various energies used for space heating in French houses, and their associated costs (CEREN, 2018). The average energy cost in €/kWh of houses built before 1974 is lower than the global average cost for French houses: this is explained by a smaller share of those houses heated by electricity, in favor of natural gas and heating oil. In order to compare expected energy savings between a theoretic consumption and the real one (including a 'rebound effect'), the thermal model described in Appendix 2.A also includes a behavioral adaptation through the intermittence factor. In theory this factor is supposed to be constant regardless of the energy performance of the house. In reality, households living in poorly efficient houses limit their own consumption, while households living in efficient houses consume more than the theoretical prediction.

Table 2.25: Heating energy of French houses and associated costs in 2016

Energy	Share of all houses	Share of houses built before 1974	Costs (Cts of €/kWh)
Natural gas	34.5 %	41.1%	6.96
Electricity	39.1 %	23.8%	16.48
Heating oil	18.1 %	26.4%	9.17
Wood	7.4 %	7.8%	5.8
Heating coal	0.4 %	0.7%	17.0
Urban heating	0.5 %	0.2%	10.31
Weighted average of energy costs	11.1	9.8	-

2.3 Econometric evaluation of the Green Premiums

Table 2.31 presents results from the estimation of the two spatial econometric models. Linear regression models estimated with the same variables present fair explanatory powers (pseudo-R squared between 63 and 65%), but the Moran's test evidences spatial autocorrelation of residuals both for Lyon and Brest. Geographical variables used are thus not sufficient to control for spatial effects, justifying the use of a spatial error model. In Table 2.31, we can distinguish the effects of three kind of variables: the ones describing the intrinsic characteristics of houses, the ones related to their location, and the interest variable, namely the Energy Performance Certificate.

First, both in the Brest region and in the Lyon metropolis, we find as expected a strong significance and a positive impact of size variables: the total floor area, the total land area but also the number of rooms and of floors increase the price. Moreover in Lyon, the presence of a basement and especially swimming-pool increases the price. Among the intrinsic characteristics of houses, we also control for the construction period. It is important to control for this variable as it may be linked to the energy performance of the house. Indeed, after the first oil shock in 1974, the French government enforced thermal norms, which have been gradually tightened since then. Thus, as houses get more recent, they are naturally more efficient. However, the age of houses also captures other effects. For instance it might be a proxy for the house general condition. Identified effects are consistent with this hypothesis: houses built since the eighties are gradually more expensive, while houses built before the seventies are less. Nevertheless, this effect is not systematically stronger as houses get older, probably due to a 'vintage effect'.

Second, geographical variables also appear to have an important impact on the price of houses in both areas. The travel time to the city center impacts negatively the price, evidencing a premium for houses nearer to the city center, even though this effect is less significant in Lyon. The negative effect of the travel time to the nearest metrostation is stronger in Lyon. An alternative indicator of the presence of various services in the Brest region has a more unexpected effect: it is the travel time to the nearest hamlet. When this time increases, house's price increases as well. This suggests that in this rural zone, households value more houses located out of small town centers when keeping the same distance to the bigger city center. This is a probably due to the fact that when living in a rural zone, households have to take their car for almost any shopping activity. The travel time to the nearest rail station has a positive effect on prices in both areas, meaning that households prefer to be further from a train station. If this effect can be counter intuitive at first sight, the ambiguous effect of rail station on real estate prices has been deeply studied by Bowes and Ihlanfeldt (2001). They show that positive effects of train stations, such as reduced commuting costs or attraction for some retail activity, can be offset by several negative externality: primary the noise, and secondly an increase in criminality in the direct neighborhood. In those two particular cases, we can hypothesize that positive effect of reduced everyday commuting time can be small. Indeed those areas are well connected by various public transports (many bus lines are available for instance), and then those train stations are more used to travel out of the region. However, the noise externality associated to trains remains important, and might explain this overall negative effect of distance to the nearest train station. This rationale is especially relevant for the Lyon metropolis, and consistent with the hedonic result. The travel time to the nearest tramway station has a poorly significant effect: in the Lyon metropolis this effect is not evidenced, in line with some literature results about the impact of tramway on prices (see Papon et al. 2015 on the associated gains of light rail line for real estate in Paris). In the Brest region, this effect is significantly positive, meaning that households value more houses which are further from tramway stations. Similar drivers of the impact of train station can be summoned to explain this effect. One could shade this explanation by underlying that this effect could be different for houses and flats: indeed, tramways installation in cities takes up space on roads previously dedicated to cars. Households owning a car, as most households living in houses, might then fear an increase in travel time by car in the surroundings of tramway stations.

Regarding environmental amenities, interpretations of travel times are more straightforward, as a smaller distance to the seaboard is associated to a greater price in the Brest area, and a smaller travel time to a park is also associated to a greater price in Lyon. The last geographic additional variable in estimation for the Brest area (distance to the nearest wind turbine) evidences a highly significant and positive effect on price: households penalize houses close to wind farms. This effect is consistent with the results of Gibbons (2015) who showed that wind turbines impact negatively housing sales prices in England and Wales.

Last but not least, estimation results highlight a significant effect of Energy Performance Certificate class on the price of houses in both areas. The D-label is used as a reference category. On the one hand, lower classes (namely E, F and G labels) have a significantly negative effect on price, with a stronger effect as the label worsens. On the other hand, classes better than D gradually increase the price of houses, with the exception of the A-labelled houses which stands out in both areas. In the Brest region, the A-label does not have a significant effect compared to the D-label, and its effect is even negative in the Lyon metropolis. This effect roots in two possible sources. First our sample of A-labelled houses is extremely small (3 in both areas). Second, and more importantly, the French law allows to estimate the Energy Performance Certificate upon energy bills of the occupier for old houses. UFC, the national association of consumers in France, has shown that in some cases, poorly insulated houses have got an A-label as they were not occupied, and then energy bills were equal to zero.

Table 2.31: Hedonic spatial estimation for the Brest region and the Lyon metropolis

	Dependent variable: log(Price)	
	Brest region	**Lyon metropolis**
Energy Performance Certificate		
Class A	−0.010	**−0.335****
	(0.145)	(0.115)
Class B	**0.116****	**0.036****
	(0.048)	(0.022)
Class C	**0.032***	0.012
	(0.022)	(0.016)
Class D	Hold-out	Hold-out
Class E	**−0.090*****	**−0.055*****
	(0.018)	(0.016)
Class F	**−0.145*****	**−0.069*****
	(0.026)	(0.026)
Class G	**−0.280*****	**−0.073****
	(0.041)	(0.036)
Total floor area	**0.005*****	**0.003*****
	(0.0003)	(0.0002)
Total land area	**0.00004*****	**0.0001*****
	(0.00001)	(0.00001)
Number of rooms	**0.016****	**0.035*****
	(0.007)	(0.005)
Presence of a basement	0.029	**0.035****
	(0.018)	(0.014)
Presence of a swimming-pool	0.078	**0.143*****
	(0.102)	(0.017)
Construction Period		
Unknown	Hold-out	Hold-out
Before 1850	-	**−0.192***
		(0.101)
1850 / 1913	−0.003	−0.035
	(0.069)	(0.056)
1914 / 1947	−0.047	**−0.062****
	(0.042)	(0.029)
1948 / 1969	−0.061	**−0.070*****
	(0.038)	(0.027)
1970 / 1980	0.040	0.009
	(0.038)	(0.027)
1981 / 1991	**0.146*****	0.009
	(0.041)	(0.028)
1992 / 2000	**0.245*****	0.034
	(0.048)	(0.030)
2001 / 2010	**0.276*****	**0.071****
	(0.040)	(0.028)
2011 / 2020	**0.387*****	0.052
	(0.077)	(0.047)
Travel time to Brest/Lyon center	**−0.014*****	**−0.006***
	(0.005)	(0.005)
Travel time to the nearest hamlet (Brest) / Metrostation (Lyon)	**0.013*****	**−0.016****
	(0.004)	(0.006)
Travel time to the nearest train station	**0.004****	**0.012*****
	(0.002)	(0.004)
Travel time to the nearest tramway station	**0.008***	0.008
	(0.004)	(0.005)
Travel time to the seaboard (Brest) / nearest park (Lyon)	**−0.017*****	**−0.009****
	(0.005)	(0.004)
Distance to the nearest wind turbine (Brest)	**0.009*****	-
	(0.003)	
Constant	**11.314*****	**11.952*****
	(0.080)	(0.122)
Other control variables		
Month of the transaction	Not significant	Significant **
Number of floors	Significant *	Significant *
Observations	1,242	1,094
Log Likelihood	−32.929	195.213
σ^2	0.061	0.039
Akaike Inf. Crit.	147.859	−304.426
Wald Test	50.284*** (df = 1)	1,590.116*** (df = 1)
LR Test	45.138*** (df = 1)	323.638*** (df = 1)

Note: Standard deviations of estimated coefficients are reported within brackets *p<0.1; **p<0.05; ***p<0.01

To estimate the green premium of efficient houses, the B-label is considered as the Energy Performance Certificate of 'green houses'. This is a legitimate assumption as policy-makers in France have set the B-label as the 2050 target for the whole housing stock, designing both A and B-labelled houses as low consumption buildings. Owners of B-labelled houses comply then with the most demanding norms for energy efficiency for the next decades. The 'red' reference (*i.e.* inefficient houses) chosen for estimating the green premium is the F-label rather the G-label. The before last label is chosen for two reasons, even if it reduces the estimated green premium (as G-label is in both regions less valued than F one). First, classes of the Energy Performance Certificate cover varying intervals of estimated primary energy consumption (see Appendix 2.B). The case of the G-label stands out as it has no upper limit on consumption, and G-labelled houses can then present important heterogeneity in their respective performances. The second reason leading to the choice of the F label roots in the theoretic primary energy consumption of typical houses built since 1974. As shown in the following section, a typical French house built before the introduction of thermal norms should not have a performance worse than F. The G label then indicates the presence of important defects or architectural characteristics not referenced in our database and affecting the energy quality of the house, such as a pierced roof or a glass canopy. Measuring the green premium from this category of dwellings would be deceptive, capturing other effects than house insulation.

In relative terms, the green premium associated to the B label compared to the F label amounts to 29.7% in the Brest region and to 11.1% in the Lyon metropolis. However, energy costs are homogeneous between our two regions of interest: in France the price of electricity is the same across the country for households thanks to tariff equalization, while heating oil and natural gas prices are closely similar in the two regions (price differences are respectively below 1% and 2%). As the two regions share similar heating needs (see section 2.2.2), energy bills and expected savings associated to a more performant house should be similar as well, even if the urban market of Lyon is tighter than the rural one of Brest. It is then more relevant to estimate the green premium in absolute terms. Switching to absolute values, it appears that the green premium in Brest amounts to $35,300$€, while in Lyon it equals $32,300$€. Those two real estate markets, structurally different but sharing similar heating needs and costs, reveal close capitalizations of the green label. This result also holds when estimating the green premiums of intermediary classes. Keeping the reference as the F-label, the premium of more efficient houses, respectively in Brest and Lyon, is $6,500$€ and $4,100$€ for the E-label, $20,600$€ and $18,100$€ for the D-label, and $24,200$€ and $23,400$€ for the C-label.

This kind of result is consistent with the engineer's approach of the green value, which compares investment costs and expected savings associated to energy renovations. The following section mixes this hedonic estimation of the green value with a techno-economic assessment of energy renovation.

2.4 Techno-economic analysis of energy renovation

2.4.1 Renovation investment costs

Using the description of thermal and architectural characteristics of a French typical house built before 1974 (over the half of France housing stock), a dataset on material and labor costs for renovation, and the thermal model described in Appendix 2.A, the optimized renovation curve of F-labelled houses displayed on Figure 2.41 is obtained. On the abscissa is represented the level of investment in the thermal renovation. On the ordinate is represented the primary energy consumption which can be achieved by a renovation of this investment level. The range of the various energy classes of the Energy Performance Certificate is also displayed in order to highlight investment levels enabling to upgrade the energy label. The initial performance of the house corresponds to an investment level of 0€, meaning that the house has not been retrofitted and consumes over $400kWh/m^2/year$ of primary energy. This consumption lies in the range of the F-label. As investment level grows, primary energy consumption decreases. We can observe some important steps which correspond to the point where increasing the energy performance requires to insulate another component of house's envelope, or to switch to a more efficient but also expensive technology. The merit order of renovation actions starts with the insulation of the roof. Indeed, the roof is responsible for approximatively 30% of heat losses, and insulation technologies are relatively cheap. Then follows the internal wall insulation and floor insulation. Replacement of windows by double-glazed ones only occurs in the fourth position of the merit order, and the last technology to be chosen is external wall insulation, highly efficient but also much more expensive. Smaller steps of the renovation curve indicate that the same set of components are insulated, but with gradually more efficient technologies (*e.g.* switching from double-glazed windows to double-glazed with argon windows).

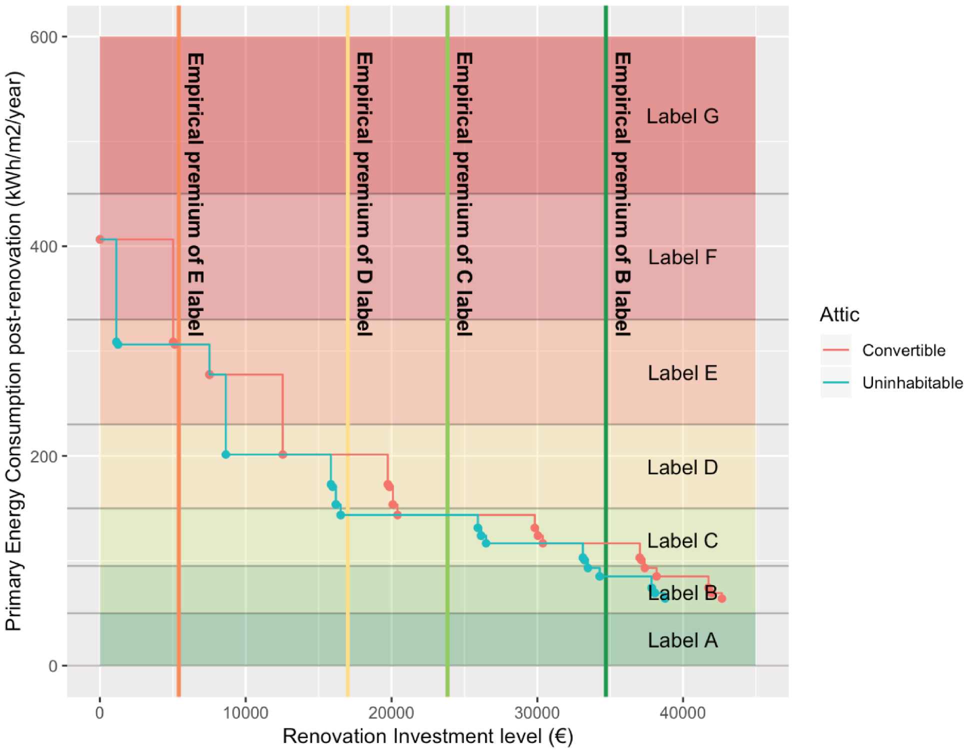


Figure 2.41: Renovation of a typical house built before 1974

Figure 2.41 also displays the empirical capitalizations of the different labels compared to the F-one, identified in the spatial econometrics section. This evidences that the green premium associated to low-consumption houses matches closely with the renovation investment level required to reach this performance level. Indeed, turning a typical house built before 1974 into a B-labelled one requires an investment of 32,000€, while the green premium estimated in the previous section amounts about 34,000€. Other intermediate premiums also fall within the range of investments required to reach corresponding levels of efficiency. A potential explanation of these very close estimates is that home sellers compete *'à la Bertrand'* in prices on the energy quality component of the house value. Indeed, the production cost of energy efficiency, *i.e.* the required investment to turn an inefficient house into a more efficient one, is homogeneous. Then, charging more than this amount will lead buyers either to choose another seller proposing a house with the same label at a lower price, or to buy an inefficient house and invest themselves in the renovation. This hypothesis is also consistent with the premium difference observed between the Brest region and the Lyon metropolis. Indeed, a previous study on the French market has found that, outside the Paris region, renovation costs are similar across the country, but slightly superior in rural areas compared to the urban ones. More precisely, observed prices are about 5% superior in rural areas (OCRE, 2015). Whereas the 'green' premiums of houses can be explained by a Bertrand type competition on energy quality, next section explores the associated energy savings that households can expect from more efficient houses.

2.4.2 Discounted energy savings

In order to ease comparison, energy savings and green premiums are plotted against on Figures 2.42, 2.43, 2.44 and 2.45 (respectively for an E, D, C and B-labelled house). Energy savings are computed as the sum of discounted savings on the energy bill (in €) which are expected by living in a house more efficient than the typical not retrofitted house built before the thermal norms of 1974. Using the thermal model, two cases can be distinguished. First the case of a household forecasting energy savings only on the basis of the theoretic energy consumption (dotted curves). Second, the case of a household taking into account the rebound effect (solid curves). The rebound effect can be decomposed in two sub-effects cutting excepted savings: first households living in poorly efficient houses restrict their energy consumption, second households living in low-consumption houses over-consume energy compared to the theory. Expected savings on the energy bill are then less important when the rebound effect is taken into account. Two time horizons which could be used by households to compute expected savings are also considered. The first one, 15 years (red curves), corresponds to the expected time the household will live in the house (our dataset provides this information, revealing a mean period of ownership of 13 years in Brest and of 14 years in Lyon). The second time horizon chosen, 30 years (blue curves), corresponds to the expected lifetime of energy efficiency technologies (technologies lifetime are available in the dataset on renovation costs). Obviously, a longer time horizon implies a more important sum of expected savings today.

On Figures 2.42, 2.43, 2.44 and 2.45, the abscissa represents the discount rate, and the ordinate represents the sum of discounted energy savings. Each of those figures also displays the empirical premium associated to its label by an horizontal line. For a given discount rate and time horizon, as label gets 'greener', the sum of energy savings will be more important, but also the premium associated. The intersection between savings curve and premium associated thus gives the implicit discount rate that equalizes for homebuyers the expected energy savings and the surplus paid to buy this house in comparison to a less efficient house. If the household's discount rate is below, then it gains a net positive surplus from buying this labelled-house. But if its discount rate is higher, the surplus would be negative: *ceteris paribus*, the household would choose the less efficient house.

For the E-label (Figure 2.42), matching the empirical premium with energy savings suggests that implicit discount rate used by households would be at most between 7 to 12% for an horizon of 15 years, or between 10 to 15% for an horizon of 30 years.

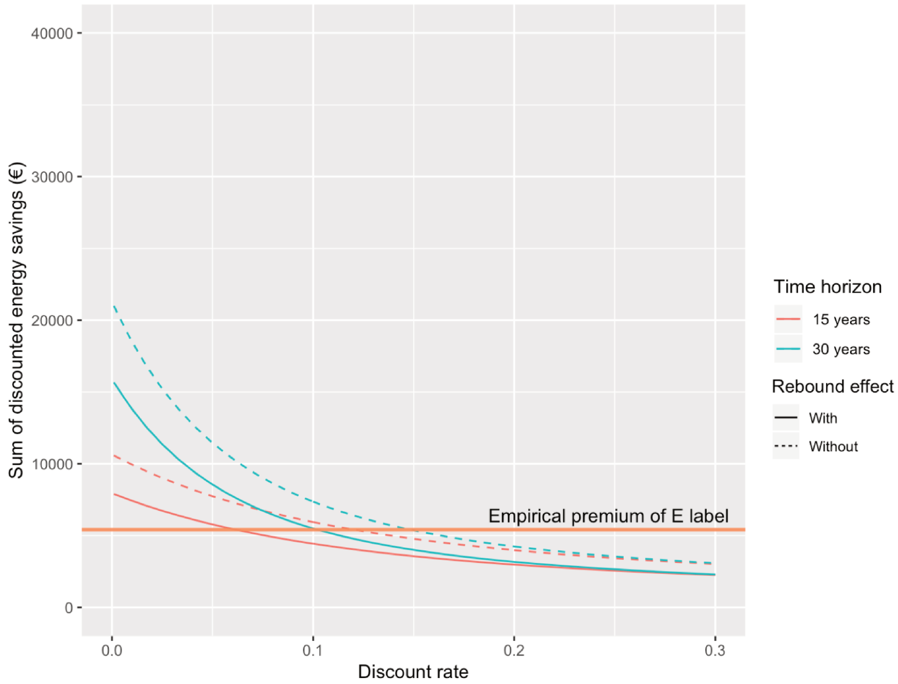


Figure 2.42: Energy savings versus Green premium for an E-labelled house

For the labels D and C, Figures 2.43 and 2.44 highlight smaller implicit discount rates, similar for the those two labels. Discounted savings with the 'short' time horizon (15 years) can equalize the premiums only when the rebound effect is not taken into account, and the resulting implicit discount rates are close to 0%. With the 'long' time horizon (30 years), implicit discount rates equalizing empirical premium and expected savings range from 4 to 7%.

Last but not least, the case of B-label furthers this trend. When the time horizon considered is 15 years, the green premium always exceeds the energy savings, no matter the discount rate. In the case of a 30 years time horizon, these savings can fully explain the green premium when the discount rate discount rate is low enough. In the case where subjects do not take into account the rebound effect, the green premium is superior to savings for all discount rates above 4%. This result is even more striking when the rebound effect is taken into account. The sum of discounted savings is then less than the green premium for all discount rates above 2%.

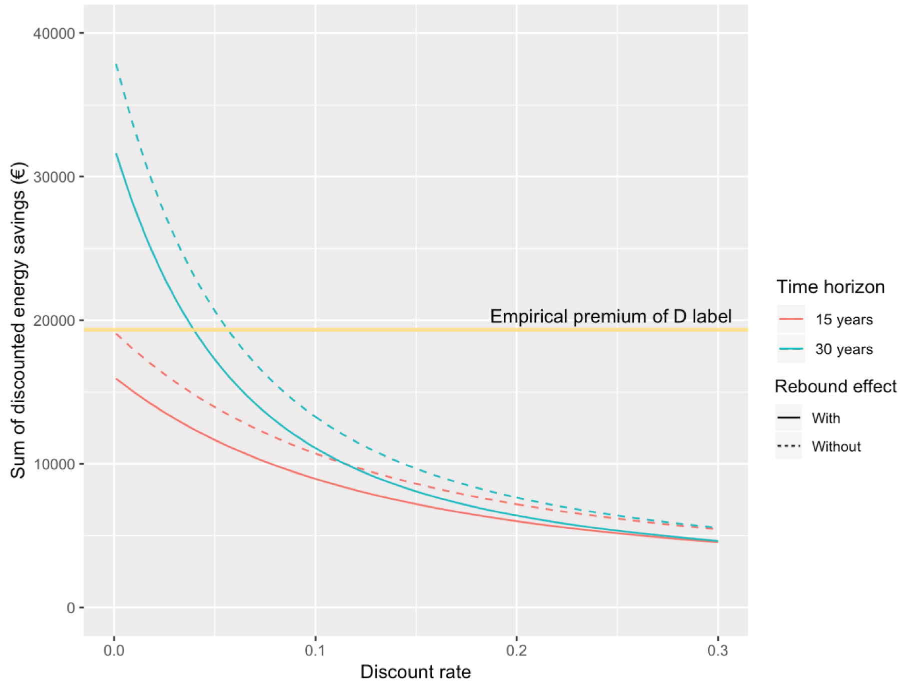


Figure 2.43: Energy savings versus Green premium for a D-labelled house

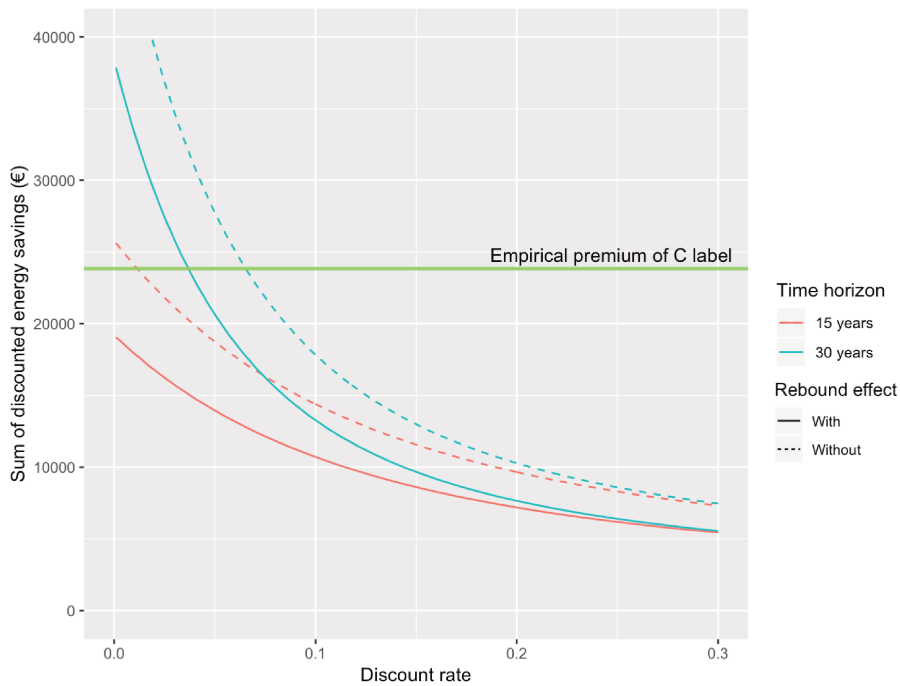


Figure 2.44: Energy savings versus Green premium for a C-labelled house

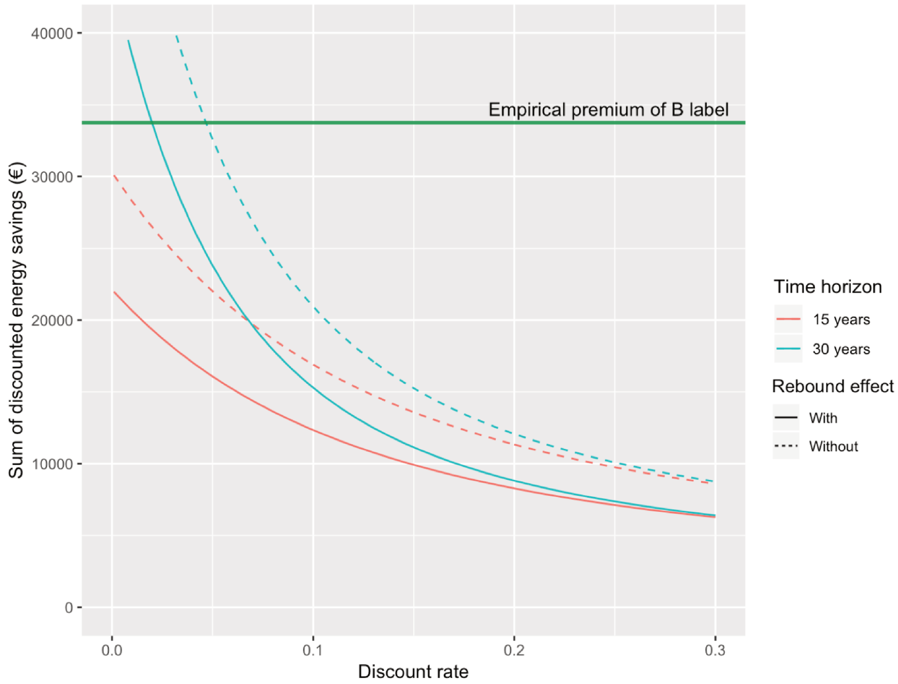


Figure 2.45: Energy savings versus Green premium for a B-labelled house

According to national statistics published by Banque de France, in 2016 mean effective interest rates on loans to households was about 4%. However many academic studies have shown that discount rates used by households are largely superior to what standard economic works assume as rational, namely the previously mentioned real interest market rate that amounts 4%. Hausman et al. (1979), Coller and Williams (1999) and Harrison et al. (2002), while using different empirical approaches (respectively observed choices for room air conditioners, a controlled laboratory experiment and a field experiment in Denmark), all reveal discount rates largely superior to 10% for households but also underline their large heterogeneity. In a recently published paper, De Groote et al. (2018) use a large sample of Belgian households to show that over 90% of implicit discount rates used by households to invest in photovoltaic panels fall within the range of 12% to 17%. This investment decision in energy production can be compared to the investment decision in energy renovation as return-on-investment time are similar. Using this range of discount rates, in all the scenarios considered (15 or 30 years time horizon, rebound effect taken into account or not), previous figures suggest that, in theory, only the E-labelled houses premium could be acceptable for home-buyers as the surplus associated would be positive. The magnitude of other premiums (D, C and B labels), significantly higher than savings when using previously mentioned discount rates above 10%, leaves room for different interpretations.

First, the gap between savings and premiums is probably smaller as time preferences of households are strongly disperse. For instance, the small sample of home-buyers who accept to pay the important premium of B-labelled houses probably have a marked preference for the future, with longer time horizons and smaller discount rates than other households.

A second and complementary interpretation of this gap between premiums and expected savings is supported by the study of ADEME (2018). This survey was conducted on an important sample of French house owners who proceeded to a warmth insulation between 2014 and 2016. It highlights that beyond energy savings, the thermal renovation presents important other advantages for households. Three main benefits can be cited to explain this green value beyond energy savings. First ancillary benefits, such as improved thermal comfort, reduced exposition to external noise and moisture issues, were targeted by the study of Jakob (2006) who hypothesizes that they could represent utility gains of the same order of magnitude than energy savings. Results of the present chapter could be consistent with this hypothesis: co-benefits could be as much valuable as energy savings for households. Second advantage of owning a house labelled as 'low-consumption', or at least labelled C or D, lies in the protection against future changes in public policies. French policy-makers have set the target for the whole building stock to be labelled as 'low-consumption' at the 2050 horizon. This target is not legally binding for now, policy-makers favoring rather incentives such as subsidies and zero-interest loans to motivate owners. However, a first attempt was made to make renovations mandatory for inefficient houses (labelled below D) in the 2015 French law for the energy transition. Whereas this article of the 2015 law has been censored by the constitutional council due to imperfect specifications[1], it remains an important signal that policy makers might, in the next decade, enforce a legislation on this topic to constrain owners of poorly efficient houses to invest in renovation. Therefore, buying a house already labelled D or higher is an efficient way to protect one's investment from the regulatory uncertainty. Third, a last potential root of the green premium is the 'moral value' of living in a more environmentally friendly house. Brounen and Kok (2011) showed in the case of Netherlands that the proportion of green voters in a given neighborhood modifies households' behavior regarding the Energy Performance Certificate, suggesting that the Willingness-to-Pay for energy efficiency could vary among households according to their environmental beliefs.

In their large study on the French renovations, ADEME (2018) also found that, whereas many French house owners retrofitted their houses in the 2014-2016 period, most of warmth insulations were limited to small interventions, such as the one enabling to upgrade from the F-label to the E-label. This observation on the French market strengthens the hypothesis that most of implicit discount rates used by households are too high to favor low-consumption houses (*i.e.* B-labelled ones), despite the fact that they constitute the

[1] See `https://www.conseil-constitutionnel.fr/decision/2015/2015718DC.htm`

target of French policy-makers. Until today, French public policies trying to incentivize energy retrofitting have mainly rely on tax credits rather than zero-interest loans. Given the capitalization of renovation investments in houses prices and the future preferences required to favor those investments, one could recommend to develop the use of interest free loans. For instance, a relevant measure could be to extend their repayment time, today constrained at 15 years, as we evidenced that this time horizon might be too short.

2.5 Conclusion

Existing literature on energy efficiency has often opposed the economic approach and the engineer approach. This opposition has been extensively documented in the studies on the energy efficiency gap and on the energy paradox, underlining differences between technologists', economists' and social optimal level of energy efficiency (Gerarden et al., 2017). This chapter suggests that the two approaches are not irreconcilable. Using a dataset on houses transactions in two French regions, it evidences that 'low-consumption' houses benefit from of a significant green premium on the real estate market. Capitalization of energy label information is more important in relative terms in the rural area, but in absolute terms rural and urban green premiums are similar, reaching about 35,000€ for low-consumption houses. These tantamount absolute green values correspond to the required investment in mature technologies to improve energy efficiency. A legitimate assumption is that a Bertrand-type competition occurs between sellers on the energy quality component of houses, preventing them from selling a low-consumption higher than its renovation cost. On the buyer side, our results highlight that this green value can only be fully explained by discounted energy savings if households preferences are strongly oriented towards the future. This result advocates for the development of zero-interest loans. The remaining green value, beyond energy savings, could be explained by various co-benefits of energy-efficient houses, such as improved thermal comfort or protection against regulatory uncertainty. Those ancillary advantages could be important motives to emphasize in order to trigger more investments in energy renovations.

Relevant extensions of this work could focus on disentangling the relative importance of the various co-benefits that could explain the 'green surplus' of efficient houses. Moreover, the dynamic dimension of the renovation decision should also be studied: as underlined by ADEME (2018), households decision rely heavily on word-of-mouth processes. Lastly, the extension of the use of free-interest loans raises other questions about energy labelling of houses, as this policy device involves a more advanced but also more expensive thermal audit than the Energy Performance Certificate.

Appendices of Chapter 2

2.A Thermal model

On the basis of a thermal model inspired by the 3CL-DPE method, a French official method to estimate building energy consumption for space heating (MEDDE, 2009, 2012) and using the PhD thesis realized by Allibe (2012), the performance of the envelope (represented by the mean U-value = U_G) is linked to the primary energy consumption for space heating: $Cons_{peh}$ expressed in $[kWh/(m^2.an)]$. This conventional consumption in primary energy for heating is the value used to attribute an EPC class to a house. The corresponding relation is stated in Eq. (2.A.1).

$$Cons_{peh}(U_G) = K_{final \to primary} * \frac{U_G * A_{envelope} * D_{h.ref} * I}{Boil_{eff} * L_s} \tag{2.A.1}$$

In the previous equation, U_G is the mean U-value, and main variable, of the building $[W/(K.m^2)]$. It is calculated by an algorithm on the basis of the architecture and materials of each building.

Other parameters are fixed. $A_{envelope}$ is the total area of the building envelope $[m^2]$. It is calculated by the program thanks to information on building's architecture. L_s is the total floor area $[m^2]$. In order to estimate the need per m^2, the total living space area in the house needs to be provided. $Boil_{eff}$ refers to the boiler efficiency. It depends on the particular heating system of the dwelling. The efficiency of a regular boiler is usually between 0.85 and 0.95 ; for this dissertation we will assume that this efficiency is equal to 0.9 for all houses. $K_{final \to primary}$ is computed as the mean standard transformation coefficient of final energy into primary energy. Given the distribution of heating energies in the French houses stock, we use $K = 1.6$. For more details on heating energy in French houses, see ADEME (2013).

$D_{h.ref}$ is the number of degrees - hour needed to heat up the space during a year (depending on the climate) $[K.h]$. The 3CL-DPE method[2] provides $D_{h.ref}$ for all French metropolitan departments ; these numbers are computed under the assumption that a temperature of 18^{o}C with the heating system is targeted, considering that other contributions (lighting, biological heat) will be enough to reach the setpoint temperature of 19^{o}C. In the model the average value across French metropolitan departments of Lyon and Brest, which have similar heating needs as detailed in section 2.2.2, is used. The $D_{h.ref}$ is thus set at 54500 $K.h$.

I is the factor of intermittence. As a house is not continuously occupied during the year, especially during working hours, heating systems can be turned off. The factor of intermittence is between 0 and 1, the reference value for houses is $I_0 = 0.85$. Contrary to the conventional consumption prediction model ($Cons_{feh}^{theoretic}$, which is used to estimate the EPC class of the house), the behavioral consumption model ($Cons_{feh}^{behavioral}$) integrates the behavior of households by allowing the variation of intermittence. On the one hand, when U_G is high, the intermittence is lower: households adopt strategies to reduce their consumption (decrease temperature setpoint in bedrooms, or turn off heating at night). But on the other hand, when U_G is small, the intermittence will be close to 1: a better insulated dwelling allows to choose a higher temperature setpoint higher. This is the "rebound effect": a gain in energy efficiency implies a lower cost for the same energy service and then demand for that service may increase. The expression of this $I = f(U_G)$ is inspired by Allibe (2012):

$$I(U_G) = \frac{I_0}{1 + 0.1 * (\frac{U_G}{U_{G_0}} * \frac{A_{envelope}}{L_s} * \frac{H_{c0}}{H_c} - 1)} \tag{2.A.2}$$

Where H_c is the ceiling height per floor (in $[m]$). $H_{c_0} = 2\ m$ and $U_{G_0} = 1\ W/(K.m^2)$ are references values. This thermal model is used to estimate the theoretical and behavioral consumption of a typical house. When comparing these consumptions to the average observed consumption in France (RAGE, 2012), it appears that the behavioral model gives a fair estimation of real consumption rates.

For instance, the prediction of total French energy consumption for residential heating is 30.6$Mtoe$. This estimation is obtained by combining the thermal model with the description of the French housing stock (see Tables 2.23 and 2.25). According to official figures given by CEREN (2018), residential energy consumption in 2016 for space heating was 28.1 $Mtoe$ in France. The real energy consumption is then 8% inferior to the calculated one. Two main factors explain this over-estimation. Firstly, already refurbished buildings are not taken into account. Secondly, in the last thirty years, the average area of houses has strongly

[2] See https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000026601023&categorieLien=id

increased, from $96m^2$ in 1984 to $112m^2$ in 2014 (see Insee, 2015). But this evolution is not represented in the model, resulting in an overestimation of the total area of old houses, which consume more, and an underestimation of the total area of recent houses, which consume less. This gap between predicted and real consumption is still significantly smaller than the ones found in the literature until now for space heating in France (22% for Mata et al. 2014, 18% for Ribas Portella 2012).

2.B Energy Performance Certificate design

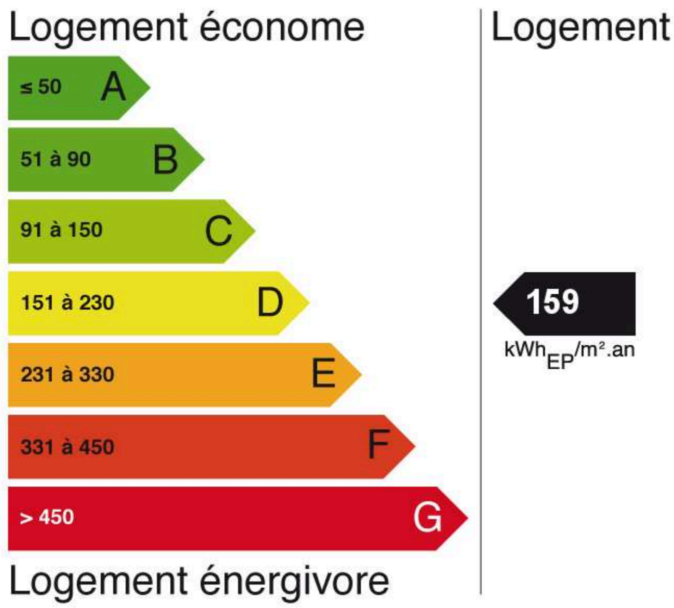


Figure 2.B1: EPC classes cover various ranges of energy consumption

* * *

* * *

«La tyrannie de l'opinion, et quelle opinion ! est aussi bête dans les petites villes de France qu'aux États-Unis d'Amérique.»

−Stendhal.

* * *

Chapter 3

The Fate of Inventions: What can we learn from Bayesian learning in a strategic option model of adoption?

* * *

We develop a dynamic game where heterogeneous agents have the option of adopting an invention of uncertain quality or postponing their decision to benefit from others' experience through Bayesian learning. Information produced by adopters about the invention's nature is public but the messages sent are noisy Our model thus gives microeconomic foundations to the S-shaped innovation diffusion curves, informational externality inducing strategic delay in agents' behavior. Moreover, consistently with stylized facts, noise can nip in the bud the diffusion of inventions with intrinsically high quality. The model thus highlights how *"teething troubles"* may influence the fate of innovation. Numerical simulations underline a bi-modal distribution of steady states for the diffusion path of innovations of intrinsically high quality. They may be either stillborn or fully developed, bringing to light a reputational valley of death for inventions. This result is robust to an endogenization of the choice of its price before the firm launches the innovation on the market.

* * *

This Chapter is an adaptation of a collaboration with Marc Baudry.

3.1 Introduction

Schumpeter (1911) defined innovation as *"the market introduction of a technical or organizational novelty, not just its invention"*, shedding light on the gap existing between a well-functioning invention, which can provide benefits to its adopters, and the actual market diffusion of this invention. In his book *"The Fate of the Edsel"*, Brooks (1963) describes for instance how the eponym Ford car, launched in the late fifties, failed to bridge this gap, despite the strong financial commitment of the company.

The challenge of an invention entering a market is to prove its value : when facing an invention, economic agents (households, firms or even governments) are in a situation of uncertainty. If the invention is effective and well-working, its adoption will generate profits or well-being ; but if the invention turns out being only a gizmo which benefits do not cover adoption costs, agents will loose their investment. Economic agents are then constantly on the lookout for information on these new products. As the most reliable information on invention quality is the experience of its users, agents rely on informational hubs, such as consumer associations, professional unions, private networks or one of the numerous rating websites, to exchange information and learn from others' feedback.

Information production by agents is then key to the full development of an invention. In this setting, information has the characteristics of a public good, and, consequently, the free rider problem arises. Each agent has an incentive to postpone her adoption of the invention to benefit from information generated by others' adoption. Thus, free riding delays adoption decisions and spreads over time the production of information. This strategic behavior leads only a few agents to adopt the invention at the time of its entry on the market, and then only a limited number of messages on the performance of innovation are generated.

However, when an invention enters a market, it often meets start-up problems. Even an effective invention can lead to failures in its first stages of development, by early mishaps, misuses or misunderstandings. These failures are commonly known as *"teething troubles"* and generate noise in the information produced by early adopters. This noise can put shade on the invention true quality and nip in the bud the development of a socially good invention. A recent article from *The Economist (2015)*[1] presents the example of frugal innovation, and attributes its delayed development to early mishaps which created people's mistrust.

The present chapter gives a rational framework to analyze this phenomena. We focus on agents' behaviors on the demand side, i.e. adopters' behaviors as a prerequisite to the analysis of inventors' behaviors. The research develops a microeconomic model enabling the analysis of an informational externality threatening the diffusion of an innovation. In the second section we expose some of the market-based examples which motivate our research question and modeling choices. The third section reviews the academic literature on innovation diffusion models, from holistic models of technological diffusion to informational cascade and social learning models. The fourth section describes the framework of our model, which consists in a strategic option representation of the invention adoption decision, in a context of Bayesian learning. We firstly study the interaction between two agents and then extend the model to n agents. Results from numerical simulations using this model are described in the fifth section, underlining the bimodal distribution of the steady state caused by the informational externality. The last section evidences that this result is robust to an endogenous determination of invention's price. We conclude by arguing that our model highlights some reputational investment decisions by firms that aim at avoiding falling due to a bad fate.

3.2 Stylized Facts

We present in this section two empirical economic facts which evidence both the importance of early reputation in an invention diffusion with the case of the Edsel car, and the variability of diffusion paths for similar inventions with the case of wind tubrines.

3.2.1 The Fate of the Edsel

In September 1957, on the "E Day", the Ford company launched its Edsel model which was one of the first large sedan car commercialized at an affordable price for most American households. With this new model, the Ford company was pursuing a vertical differentiation in the car market. But whereas the Ford Company had invested $250 Million on Edsel development, manufacturing and marketing, the car is today a symbol of commercial failure

[1] https://www.economist.com/business/2015/01/22/cheap-and-cheerful

(Bonsall, 2002). While various reasons are used to explain it, like the controversial design of its front grille, an interesting reading is the national survey conducted by *Popular Mechanics* when the car entered the market: this survey of Railton (1958) was published only six months after the "E Day". In this survey, 1,000 Edsel owners throughout the U.S. have been asked about their thoughts regarding the car. If owners enjoyed performance and ease of handling, surprisingly this survey emphasized one frequent complaint, about poor workmanship in assembly. More than 16% of the owners surveyed listed that default. In the report, Arthur R. Railton, the magazine's journalist in charge, underlines aptly that this kind of defaults does not show up in usual road test, and was unusual coming from a well-known brand. This poor workmanship in the first models which came out of the factory is explained by the Edsel industrial production management: the Edsel did not get its own assembly lines in Ford factories. It was assembled alternatively on lines of other Ford company cars, such as the Mercury, and then often unfinished (Brooks, 1963).

This illustrates why, when the Edsel entered the market, a joke on its name quickly spread: "Edsel stands for Every Day Something Else Leaks". Despite a powerful launching campaign, information produced and shared by consumers about poor workmanship plagued the reputation of the Edsel, and contributed to its historical failure: the Ford Motor Company lost about $300 million and stopped the production less than two years after Edsel's launch.

3.2.2 Turbines in the wind

More recently, the importance of new products early reputation has also been exhibited in the sector of low-carbon innovations, as illustrated by the peer-effect and social spillovers in solar panels adoption by Rode and Weber (2016). We chose to investigate the case of wind turbines, using *TheWindPower* database: it gathers technical information about 1,580 wind turbines from 219 different makers. The database also lists wind farms installed across the world, counting 26,869 farms. In Germany, this database covers about three quarters of the total wind power installed in 2017. We chose to study the diffusion of two specific wind turbines on the German market: the E-82 from Enercon and the V-90 from Vestas. We picked those two turbines for several reasons enabling their comparison. Firstly, they share almost exactly the same power performance (see power curves compared in annex 3.A) and rated power. Secondly, they were both introduced on the market in 2002. Thirdly their respective constructors, Enercon and Vestas, are comparable, as shown by Hau and von Renouard (2003): they both develop and produce all their turbines' components, both of them are major players in the wind turbines market with close market shares for Enercon and Vestas in Germany (respectively about 30% and 24% in 2017), and review from Hansen et al. (2004) shows that those companies were the two leaders in the world in 2002, when E82 and V90 turbines were launched. Last, diffusions of the two turbines are observed in the same country, Germany, a mature market, in order to control for legislation and economic conditions. We do not have the price for each commissioning contract, nevertheless we can reasonably make the assumption that the two turbines' prices are not strongly different: as underlined in the European Commission report on Wind Energy (Lacal-Arántegui, 2014), "*wind turbines are viewed as a kind of commodity, it is likely that non-technological factors will have a stronger influence in the onshore turbine price*", such as demand and public subsidies.

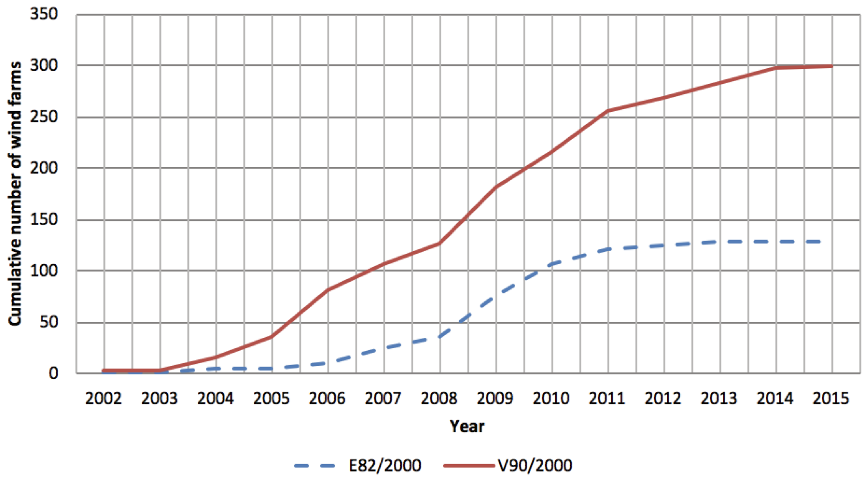


Figure 3.21: Diffusion of the E82 and V90 turbines in Germany

On figure 3.21 we represent the cumulative number of german farms equipped with the two models of turbines. Representing installed turbines number gives a similar graphic, nevertheless we chose to represent the number of farms. Indeed, as most of them are equipped with a unique model, the relevant economic decision to study is then which turbine the agent chooses to equip its farm. Figure 3.21 evidences the well-known S-shaped diffusion curves of new product, but steady states for the two turbines are not similar. The number of farms equipped with Vestas' turbine stabilizes at 300 in 2014, whereas the number of farms equipped with Enercon's turbine already stopped its growth in 2011, with about 130 farms. The earlier and lower steady state of the E82 turbine is interesting, as its power curve was similar to the V90 turbine, and happened on the same market. Morover, whereas Germany is the home market of Enercon and is not for the Danish firm Vestas, Enercon did not take advantage of a home market effect.

Sarja and Halonen (2013) investigated the determinants of new turbines adoption in Finland: their findings underline that reputation was the key driver leading to the choice of a wind turbine over other ones, ahead of other classical factors such as turbine's technical performance or costs. The second driver identified is the volume of electricity generated, which is similar for E82 and V90 as demonstrated on the power curves (annex 3.A). Costs are only listed as the third factor, and in these costs the turbine's price is poorly cited by the interviewees, strengthening our hypothesis that turbines with similar power have converging prices, at least in Europe, and then that prices do not strongly affect commissioning decision. In their survey, Sarja and Halonen underline that the reputation was not referring to production statistics, but "*interviewee's own past experiences and by sharing information with other companies*", which emphasizes the role of public information that accrues from private decisions made by farm owners.

3.3 Literature review: information and innovation diffusion

Whereas the S-shaped diffusion curves of innovation have been identified by economists in the fifties, and while this stylized-fact has for long been attributed to an information effect, we evidence in this section that the economic literature still lacks models based on rational agents decisions to explain this phenomenon.

3.3.1 Holistic models of innovation diffusion

Since Griliches (1957), many empirical analysis have highlighted the S-shaped curve of innovations diffusion. The Bass diffusion model, firstly exposed in Bass (1969), provides a good description of this dynamics phenomena, and has been widely applied to the diffusion of innovations in the last fifty years, including works on the diffusion of renewables, such as the one by Rao and Kishore (2010) and by Jenner et al. (2013). Nevertheless, these analyzes are holistic and lack microeconomic foundations, whereas social sciences widely recognize the key-role of information in this logistic diffusion of innovation, by word of mouth processes for instance as shown by the early contribution of Rogers (1962). Indeed microeconomic approaches on innovation diffusion focus either on network externalities (where frameworks similar to the one of Cabral (1990) have numerous applications for ICT) and on learning curves, as in the study by Beck et al. (2018). Our framework of social learning with an informational externality is linked to the concept of learning curve: indeed the invention adoption by some agents reduces the adoption costs (in terms of uncertainty) for the following adopters; this link was underlined by Baudry and Bonnet (2019). Those studies all suppose that in the end, after the S-shaped diffusion, an innovation always reaches its full potential development. By contrast, the aim of the present work is to build a microeconomic model eliciting the role of information in technology adoption and innovation diffusion. One of the main lessons from this model is that imperfection of information can randomly cap the diffusion of an innovation below its optimal level.

A first theoretic microeconomic model, taking into account the role of information and the agents' trade-off between adopting an innovation with uncertain outcomes and waiting for more information, was proposed by Jensen (1982). This model evidences that information could be a driver of the S-shaped curve of innovation diffusion, but still relies on an exogenous arrival of information. As shown in Hall (2004) and Peres et al. (2010), the economic literature still lacks models representing the rational choice of agents in interaction with their environment. As the individual decision rooting innovation diffusion is either to adopt immediately the invention or to postpone the adoption in the aim to obtain information arising from others' adoption, it is relevant to look at this decision as a real option problem. Moreover, as the action of an agent has an impact on the choice of others, and reciprocally, it requires a game theoretic approach, leading to our choice of a strategic option model.

3.3.2 Real options and game theory

Irreversible discrete decisions of investment in a situation of uncertainty have been firstly analyzed by Henry (1974). This analysis was then extended to the precautionary principle in a continuous choice framework by Gollier et al. (2000). Simultaneously to Henry's contribution, another seminal paper on irreversible decisions in a context of uncertainty was published by Arrow and Fisher (1974), where information arrival stochastic process left room for various interpretations, mainly Markov process and Bayesian learning. The first interpretation is privileged by the literature on real options theory, mainly known through thetextbook by Dixit et al. (1994). The Bayesian interpretation has been applied to climate economics by Kelly and Kolstad (1999) for instance, and the synthesis of real options theory with Bayesian learning applied to the precautionary principle is realized by Baudry (2008). However those works focus on the precautionary principle for policy-makers at a global level, avoiding the strategic dimension which has to be taken into account when focusing at the level of states, and *a fortiori* at the level of individuals.

Indeed, beyond the use of options to analyze choices under uncertainty, the invention adoption problem we described in the previous section requires to introduce strategic interactions between agents. Investment decision in an innovation becomes subject to a waiting game:

by delaying adoption, agents can learn from others' experience. A more recent literature has focused on strategic options: in the wake of Lambrecht and Perraudin (2003) and Smit and Trigeorgis (2006), research works such as the ones of Thijssen (2010), Mason and Weeds (2010) and Thijssen et al. (2012) have started modeling strategic behavior of firms facing an investment with uncertain outcomes, especially in the context of R&D. But, by focusing on the decision of inventors to develop and market their invention, their works exhibit situations where preemption strategies become dominant, whereas our model is interested in situation where potential adopters' waiting strategies are reenforced: agents are interested in others' experience. Such behaviors are usually described in models of herding and informational cascades.

3.3.3 Informational cascades, herding and social learning

Two seminal papers, independantly published the same year, exposed the fundamentals of informational cascades: Banerjee (1992) and Bikhchandani et al. (1992) describe a sequential decision model where each decision maker looks at the decisions taken previously. Herd behavior derives from the fact that some individuals have private information on the good decision to make, but can decide rationally to ignore their private information to mimic others' behavior. But these models rely on an exogenously determined order of arrival, which are made one by one. These restrictions were exposed by Shiller (1995), who outlines the limits of the sequentiality and the first movers' issue, namely the removal of strategic interplay. Gale (1996) underlines the issue of endogenous sequencing as one of the main limits of informational cascades models, but also outlines an important feature of informational cascades: the first best could be unreached due to the informational externality. In their article, Chamley and Gale (1994) implement an endogenous timing of decisions, but still rely on agents differing by their private information, whereas our problem relies on the public nature of information.

There is a wide brand of literature dealing with the social aspects of innovation diffusion. They usually acknowledge the key role to information sharing. Review made by Young (2009) evidences three types of models in the economic literature: contagion ones, where innovation spreads like epidemics, social influence ones, where innovation spreads thanks to a conformity motive (also called peer effects) and lastly social learning. The two first categories of informational effects are dug into by Xiong et al. (2016), but this research does not investigate the strategic aspect of delaying adoption. The last category, social learning, is underlined as the most relevant for economic analysis, as decisions made by actors are rational, people waiting for empirical evidence before adopting a new product.

However, Young (2009) does not introduce the notion of "teething troubles" which is key to us to explain some less evident diffusion patterns, and does not either explicitly model the waiting game in which agents could engage in. Our aim is then to fill this gap by modeling rational agents having the option of adopting the innovation immediately or postponing their decisions to benefit from social learning. As information transmission is not perfect, noise is introduced in our model, evidencing an alternative aborted diffusion path for new products.

3.4 Model Description

In the lights of the models reviewed above, we innovate on several aspects. We consider a framework where N agents face an invention of uncertain quality, and share information about this invention.

Agents are free to adopt the invention immediately or to postpone the decision to the following period. They differ by their preference for quality θ, and are in asymmetric information on others' preferences, that they treat as uniformly distributed between the minimal preference θ_m and the maximum one θ_M. Economic agents are rational, risk-neutral and in strategic interaction; moreover, they are one-period forward looking to capture inter-temporal choices. At each period, each agent decides to invest if and only if her expected gains from immediate adoption are greater than expected gains of postponing the decision to the next period.

Invention is a durable good of uncertain quality: effective Q_{sup}, or counter-productive Q_{inf} (with $Q_{sup} > Q_{inf}$), with a price P fixed by a firm that is assumed to have a monopoly power on it due to patenting or secrecy. Adoption is irreversible: the irreversibility arises, for instance, from a "market for lemons" in the case of product innovation, or from the specificity of assets mobilized in the case of other types of innovations.

Belief (X_t) in the invention nature is common and shared among agents, i.e. information about invention quality is public. This belief is revised by Bayes' rule according to messages produced by adopters: each time an agent adopts the invention, she produces a message on its nature, but information transmission is not perfect (e.g., adoption of an invention of effective quality can give birth to a negative message, and conversely for an invention of counter-productive quality). Noise is multi-sourced (teething troubles, measurement issues, Chinese whispers...), and captures the phenomena exposed in introduction.

Expected gains then incorporate the possibility of receiving messages of both types, and the possibility of postponing adoption if expected gains are negative. As they are in an information asymmetry, agents give a common probability p to other agents to invest, and they adopt a strategic behavior. Our game theoretic framework is solved recursively in pure strategies.

3.4.1 A basic two agents - two periods model: proof of concept

3.4.1.1 Framework of the game

We use the basic model of vertical differentiation developed by Shaked and Sutton (1982). The utility flow u_i of agent i is written $u_i = \theta_i * Q + Y$; her budget constraint is $Y + P = R_i$, where θ_i is the marginal rate of substitution of the agent i between the aggregate good and the differentiated good, Q is the quality of the differentiated good, Y is the quantity of the aggregate good, P the price of the differentiated good and R_i the revenue of the agent i at each period. Each agent is supposed to buy only one unit of the differentiated good, and we consider our good as a durable one[2]. By substitution, we obtain the following expression for agent i's utility flow:

$$u_i = \theta_i * Q - P + R_i \tag{3.4.1}$$

We consider 2 agents A and B who are facing the decision to adopt a same product. Quality preferences of the two agents are respectively $\theta_A > 0$ and $\theta_B > 0$; each agent knows her preference, but it is private information. Agents do not know the preference of their partner, they only know that quality preferences are in the range $[\theta_m, \theta_M]$. Prior adopting the invention, quality is normalized to $Q = 0$ obtained at price $P = 0$. Invention quality is Q_{sup} if the invention is effective, and reciprocally Q_{inf} if the the invention is counter-productive, with $Q_{sup} > Q_{inf} > 0$. Then, for agent $i \in \{A, B\}$, willingness to pay for the invention is $Q_{sup} * \theta_i$ in the good quality scenario, or $Q_{inf} * \theta_i$ in the bad quality scenario. Initial common belief that the invention is counter-productive is X_0 and, thus, belief in the good scenario is $1 - X_0$, with $X_0 \in [0, 1]$. Subsequent belief at $t = 1$ is denoted X_1. We define the expected quality:

$$Q_{exp}(X_t) = X_t * Q_{inf} + (1 - X_t) * Q_{sup} \text{ for } t \in \{0, 1\} \tag{3.4.2}$$

The discount rate used by all agents is fixed at $r \geq 0$.

[2]The model could alternatively be presented as a decision to adopt a process, managerial or marketing invention by two firms. P would then denote the sunk cost of investing in the invention, whereas Q would be the multiplicative impact on gross profit θ_i of the resulting change on total factor productivity of the firm. Accordingly, the net profit in case of adoption would be: $\Pi_i = \theta_i * Q - P + R_i$, where R_i is the unaffected source of profit of firm i.

When an agent decides to invest at the first period, she produces a message which will re-evaluate X_0 into X_1. Reliabilities of messages created are defined as follows: $p^{pos} > 0.5$ is the probability to receive a message compliant with a positive scenario (probability that the message is positive when the invention is effective); $p^{neg} > 0.5$ is the probability to receive a message compliant with a negative scenario (probability that the message is negative when the invention is counter-productive).

As p^{pos} and p^{neg} are common knowledge, from above we can define rational expectations of agents on the receipt of positive messages from $t = 0$ to $t = 1$, and respectively on the receipt of negative messages: $Prob_{pos,0}$ is the probability of receiving a positive message if the other player adopts the invention at $t = 0$, respectively $Prob_{neg,0}$ the probability of receiving a negative message if the other player adopts the invention at $t = 0$.

$$\begin{cases} Prob_{pos,0} = p^{pos} * (1 - X_0) + (1 - p^{neg}) * X_0 \\ Prob_{neg,0} = (1 - p^{pos}) * (1 - X_0) + p^{neg} * X_0 \\ Prob_{pos,0} + Prob_{neg,0} = 1 \end{cases} \tag{3.4.3}$$

As a message will be incorporated in the common belief on the nature of the innovation, Bayesian re-evaluation will give the following $X_{1,+}$ (respectively $X_{1,-}$) if the message is positive (respectively negative). If no message is received between $t = 0$ and $t = 1$, then $X_{1,\emptyset} = X_0$.

$$\begin{cases} X_{1,+} = \dfrac{1 - p^{neg}}{Prob_{pos,0}} * X_0 \\ X_{1,-} = \dfrac{p^{neg}}{Prob_{neg,0}} * X_0 \\ X_{1,\emptyset} = X_0. \end{cases} \tag{3.4.4}$$

As we have $p^{pos} + p^{neg} > 1$, then $X_{1,-} > X_0 > X_{1,+}$ and then $Q_{exp}(X_{1,+}) > Q_{exp}(X_0) > Q_{exp}(X_{1,-})$ where $Q_{exp}(X_t)$ is defined in (0).

With λ the probability each agent gives to the other one to invest at the first period, we analyze agents' strategic choices. As in this first framework only two agents are interacting, the analysis of two periods is sufficient. Indeed, reasoning recursively, there is three possible states of nature at the second period:

- Both agents have adopted the invention at the first period. Then further analysis is not needed.

- None of the agents has adopted the invention during the first period: as information is endogenously produced in this game, it means that beliefs on invention nature (effective or counter-productive) have not been revised, and then option problem is similar to the one of the first period, and rationally, each agent will keep her strategy of postponing. By recurrence, in this case no agent will ever adopt the invention, and the two periods game is sufficient to analyze strategies.

- A third possible state of nature is that only one of the two agents has adopted the invention. Then, for the remaining agent with the option of adopting, belief on invention nature has been revised according to the message produced by the agent who has adopted the invention. Remaining agent can then make her decision to adopt or postpone the adoption, but if she postpones, she is in reality giving up definitely as no more information can be revealed about invention nature. Again, a two periods game captures all possible strategies of the two agents.

Thus there are only two relevant periods of analysis for our game. The option problem in the first period is to decide between adopting immediately the invention or postponing the decision to the second period. If the expected utility derived from immediate adoption is easy to calculate with the initial belief on invention nature, expected utility of postponing is more complex as it embodies both the possibility that the decision to adopt or not will be enlightened by the adoption of the other agent during the first period (with probability λ) and the alternative state of nature where no more information will be disclosed (with probability $1-\lambda$). If she receives a message, agent i can rationally anticipate the evolution of expected utility if this message is positive or negative. Accordingly, the option problem writes as follows:

$$F_i = Max \begin{cases} \text{Utility of immediate exercise of the option:} \\ U_{i,adoption} = \theta_i * Q_{exp}(X_0) + R_i - P + \dfrac{\theta_i * Q_{exp}(X_0) + R_i}{1+r} \\ \\ \text{Utility of postponing:} \\ U_{i,delay} = R_i + (1-\lambda) * \frac{Max\{\theta_i * Q_{exp}(X_0) + R_i - P; R_i\}}{1+r} \\ +\lambda * \frac{Prob_{pos,0} * Max\{\theta_i * Q_{exp}(X_{1,+}) + R_i - P; R_i\} + Prob_{neg,0} * Max\{\theta_i * Q_{exp}(X_{1,-}) + R_i - P; R_i\}}{1+r} \end{cases} \quad (3.4.5)$$

The linearity of u_i implies that R_i has no influence on the exercise rule of the option. Depending on parameters initial values, three cases have to be considered:

- If $0 > U_{i,adoption} \Leftrightarrow P > \theta_i * Q_{exp}(X_0) * \frac{2+r}{1+r}$: agent i systematically delays, no matter how the other agent behaves. Indeed, the value of immediate execution is negative, whereas the value of report is always superior or equal to 0, because the agent is never forced to adopt the invention. The strategic interaction has no influence on the agent's decision in this case.

- If $P < \theta_i * Q_{exp}(X_{1,-})$: agent i always decides to exercise her option immediately and to adopt the invention. Indeed, even with a negative message, expected net gains resulting from the adoption will be positive. Then the information hypothetically earned through waiting will not change agent's decision, whereas waiting has a cost for the agent, through the discount rate. The strategic interaction never influence the agent's decision in this case.

- If $\theta_i * Q_{exp}(X_0) * \frac{2+r}{1+r} > P > \theta_i * Q_{exp}(X_{1,-})$: expected net gains from immediate exercise is positive for the agent, but if a negative message is received between the first and the second period, expected net gains become negative. Then in the second period the agent will not choose to adopt. The optimal decision relies on the probability λ confered to the other agent to invest. Finding λ is a prerequisite to solve the option problem.

3.4.1.2 Solving the 2 agents model with strategic delay

We consider the third case presented above: $\theta_i * Q_{exp}(X_0) * \frac{2+r}{1+r} > P > \theta_i * Q_{exp}(X_{1,-})$. We can rewrite the option problem as follows:

$$F_i = Max \begin{cases} \text{Utility of immediate exercise of the option:} \\ U_{i,adoption} = (\theta_i * Q_{exp}(X_0)) * \frac{2+r}{1+r} - P \\ \\ \text{Utility of postponing:} \\ U_{i,delay} = (1-\lambda) * \frac{\theta_i * Q_{exp}(X_0) + R_i - P}{1+r} \\ +\lambda * \frac{Prob_{pos,0} * (\theta_i * Q_{exp}(X_{1,+}) + R_i - P)}{1+r} + \lambda * \frac{Prob_{neg,0} * R_i}{1+r} \end{cases} \tag{3.4.6}$$

Where λ belongs to the interval $[0, 1]$. By definition, λ is the probability that the value of immediate exercise is superior to the value of postponement for the other player: it is an anticipation made by agents on the probability that others adopt. As agents are rational, share of adopters observed at the end of the period has to be consistent with the adoption probability used by agents in their economic rationale.

$$\lambda = Pr\{U_{i,adoption} > U_{i,delay}\} \tag{3.4.7}$$

Substituting in equation (3.4.7) the expression of $U_{i,adoption}$ and $U_{i,delay}$ given in (3.4.6), this is equivalent to:

$$\lambda = Pr\{\theta_i > P * \frac{r + \lambda * Prob_{neg,0}}{(1 + \lambda + r) * Q_{exp}(X_0) - \lambda * Prob_{pos,0} * Q_{exp}(X_{1,+})}\} \tag{3.4.8}$$

Solving this inequation requires to specifiy the belief agents have on the marginal rate of substitution of others. For computational convenience, we use a uniform distribution of θ on the interval $[\theta_m, \theta_M]$. Equation (3.4.8) then becomes:

$$\lambda = \frac{\theta_M - P * \frac{r+\lambda*Prob_{neg,0}}{(1+\lambda+r)*Q_{exp}(X_0)-\lambda*Prob_{pos,0}*Q_{exp}(X_{1,+})}}{\theta_M - \theta_m} \tag{3.4.9}$$

This equation in λ can be conveyed into the second-order polynomial stated in equation 3.4.10:

$$\begin{aligned} 0 =& \lambda^2 * (\theta_m - \theta_M) * (Q_{exp}(X_0) - Prob_{pos,0} * Q_{exp}(X_{1,+})) + \lambda * (\theta_M * (Q_{exp}(X_0) \\ &- Prob_{pos,0} * Q_{exp}(X_{1,+})) + (\theta_m - \theta_M) * (1 + r) * Q_{exp}(X_0) - Prob_{neg,0}) - P * r \end{aligned} \tag{3.4.10}$$

As shown in Appendix 3.B, we can easily prove that this polynomial admits a unique positive solution in λ, noted λ_{sol}, and that this solution is strictly positive. The solution of the option problem is denoted by λ^* and may depart from λ_{sol}. If $\lambda_{sol} > 1$ then the corner solution $\lambda^* = 1$ is obtained and agents will both adopt the invention at the first period. In this case, the option value of waiting is not high enough in comparison to the expected loss due to discounting. But if $\lambda_{sol} < 1$, then $\lambda^* = \lambda_{sol}$, the adoption at the first period is not systematic anymore. A sufficient condition ensuring $\lambda^* < 1$ is $\theta_m < \frac{P}{Q_{sup}} * \frac{1-p^{pos}}{r+p^{pos}}$. This condition is not limiting for our analysis: it simply means that an agent might have a quality preference low enough to prevent him from ever investing in the invention.

Proposition 1. In a two agents game, the probability that an agent affects to the other exercizing her option to adopt immediately the invention has a unique solution $\lambda^* \in]0; 1]$ which depends on p^{pos}, p^{neg}, θ_m, θ_M, Q_{inf}, Q_{sup}, X_0, P and r.

3.4.2 Generalization: $N+1$ agents and up to $N+1$ periods

3.4.2.1 Framework of the game

We now consider $N+1$ agents, $A_1, A_2, ..., A_{N+1}$ who can adopt the same invention. As in the previous section, their quality preferences are respectively $\{\theta_1, \theta_2, ..., \theta_{N+1}\} \in [\theta_m; \theta_M]^{N+1}$ and are private information of each agent. Willingness to pay for the invention of agent i is $\theta_i * Q_{sup}$ if the invention is effective, or $\theta_i * Q_{inf}$ if the invention is counter-productive. Initial common belief in the bad scenario is X_0, and respectively initial belief in the good scenario is $1 - X_0$, with $X_0 \in [0, 1]$. We define expected quality at period t as $Q_{exp}(X_t) = X_t * Q_{inf} + (1 - X_t) * Q_{sup}$. The discount rate used by all agents is fixed at $r \geq 0$.

The expected utility gain of the agent i when adopting at period t is then written:

$$u_{i,t} = \theta_i * Q_{exp}(X_t) - P + R_i \tag{3.4.11}$$

Agents' rational expectations on positive and negative messages at period t are written following the same lines than in the previous section (two players game):

$$\begin{cases} Prob_{pos,t} = p^{pos} * (1 - X_t) + (1 - p^{neg}) * X_t \\ Prob_{neg,t} = (1 - p^{pos}) * (1 - X_t) + p^{neg} * X_t \\ Prob_{pos,t} + Prob_{neg,t} = 1 \end{cases} \tag{3.4.12}$$

Unlike the previous model, multiple messages can now be incorporated in the revision of common belief from date to date. Indeed we do not limit the number of agents who can choose to adopt the invention at each period - contrary to most informational cascades models. Bayesian re-evaluation will give the following $X_t = Rev_{\alpha,\beta}(X_{t-1})$ common belief [3] on the nature of invention at a given period t, given that α positive messages and β negative messages have been received since the previous date $t-1$. The function $Rev_{\alpha,\beta}(.)$ gives the belief on invention nature revised bayesianly with those α positive and β negative messages.

$$Rev_{\alpha,\beta}(X_{t-1}) = \frac{(\dfrac{1-p^{neg}}{p^{pos}})^{\alpha} * (\dfrac{p^{neg}}{1-p^{pos}})^{\beta} * X_{t-1}}{1 - X_{t-1} * (1 - (\dfrac{1-p^{neg}}{p^{pos}})^{\alpha} * (\dfrac{p^{neg}}{1-p^{pos}})^{\beta})} \tag{3.4.13}$$

Demonstration of equation (3.4.13) is given in Appendix 3.C. We consider an agent A_i facing the decision of investing immediately or postponing for one period to gather information

[3] We operate a change from previous section's notations: here $X_{1,+}$ becomes $Rev_{1,0}(X_t)$.

from other agents on the invention's nature. We generalize the option problem firstly presented in equation (3.4.5) at a period $t \geq 0$, when there are still n other agents who have not adopted the invention yet ($n \leq N+1$). As the information produced about the invention is public, all agents share with A_i the same belief on invention nature. Moreover, as preferences are private information, all agents affect the same probability λ_t of investing at the period t to other agents. For computational convenience, agents are only one-period forward looking. Therefore, the value function of their decision is:

$$F_{A_i,t} = Max \begin{cases} \text{Utility of immediate exercise:} \\ U_{i,t,adoption} = \theta_i * Q_{exp}(X_t) + R_i - P + \dfrac{\theta_i * Q_{exp}(X_t) + R_i}{1+r} \\ \\ \text{Utility of postponing:} \\ U_{i,t,delay} = R_i \\ + \frac{\sum_{k=0}^{n}[\binom{n}{k} * \lambda_t^k * (1-\lambda_t)^{n-k} * \sum_{j=0}^{k}[\binom{k}{j} * Prob_{pos,t}^{j} * Prob_{neg,t}^{k-j} * Max\{\theta_i * Q_{exp}(Rev_{j,k-j}(X_t) - P + R_i; R_i\}]]}{1+r} \end{cases} \tag{3.4.14}$$

With $Rev_{j,k-j}(X_t)$ common belief on the nature of invention when j positive messages and $k-j$ negative messages have altered the belief X_t.

3.4.2.2 Solving the $N+1$ agents game

Like in the two agents-two periods model, we assume that belief each agent has about other agents' preferences for quality can be represented by a uniform distribution of θ_i on the interval $[\theta_m, \theta_M]$. Hence, by the following rationale, we deduce the $(n+1)$-order polynomial representing the option: (P^{n+1}). To obtain this polynomial, we calculate $\theta_{agent,t}$, threshold of θ separating agents who choose to invest at period t and those who choose to postpone at period $t+1$. But, unlike the 2 agents-2 periods model, in this $n+1$ agents framework we have to take into account that, at each period, agents who have already adopted the invention quit the game. Over periods and adoptions, there are fewer and fewer agents in the game, and the remaining rational agents take this demographic effect into account in their expectations of new messages. More precisely, as the first agents to invest are the ones with the highest preferences for quality, θ_M decreases with the number of adopters. We thus switch to the notation $\theta_{M,t}$, with $\theta_{M,0} = \theta_M$ and $\theta_{M,t+1} = \theta_{agent,t}$.

By definition, λ_t is the probability that an agent j invests at the period t:

$$\begin{aligned}\lambda_t &= Pr\{\theta_j > \theta_{agent,t}\}\\ &= \frac{\theta_{M,t} - \theta_{agent,t}}{\theta_{M,t} - \theta_m}\end{aligned}$$

$$\Leftrightarrow \theta_{agent,t} = \theta_{agent,t-1} - \lambda_t * (\theta_{agent,t-1} - \theta_m) \tag{3.4.15}$$

By proceeding along the same method than in section 2, and using jointly the value function (3.4.14) and the equation (3.4.15), we write (P_t^{n+1}):

$$\begin{aligned}(P_t^{n+1}) =&(1+r) * (Q_{exp}(X_t) * (\theta_{M,t} + \lambda_t * (\theta_m - \theta_{M,t})) - P)\\ &+ Q_{exp}(X_t) * (\theta_{M,t} + \lambda_t * (\theta_m - \theta_{M,t}))\\ &- \sum_{k=0}^{n}[\binom{n}{k} * \lambda_t^k * (1-\lambda_t)^{n-k}\\ &* \sum_{j=0}^{k}[\binom{k}{j} * Prob_{pos,t}^{j} * Prob_{neg,t}^{k-j}\\ &* Max\{(\theta_{M,t} + \lambda_t * (\theta_m - \theta_{M,t})) * Q_{exp}(Rev_{j,k-j}(X_t)) - P; 0\}]]\end{aligned} \tag{3.4.16}$$

According to the sign of the polynomial (P_t^{n+1}) for $\lambda_t \in [0;1]$, three cases have to be envisioned:

- If $(P_t^{n+1})(\lambda_t) < 0$ on $[0;1]$: all the $(n+1)$-agents delay the adoption at period t, there is no adoption of the new product. The solution to the option problem is then $\lambda_t^* = 0$ and the diffusion stops.
- If $(P_t^{n+1})(\lambda_t) > 0$ on $[0;1]$: all the $(n+1)$-agents decide to exercise their option at period t and to adopt the invention. The solution to the option problem is then $\lambda_t^* = 1$ and the diffusion over all the population is completed.
- If $(P_t^{n+1})(\lambda_t)$ switches its sign on $[0;1]$: only of fraction of agents will adopt the innovation at period t. This is the most interesting case. The fix point value of λ_t^* associated with the option problem is then the polynomial root between 0 and 1. Proposition 2 states the unicity of the solution.

Proposition 2. In a $N+1$-agents game, the probability that an agent who has not yet adopted the invention at period t optimally decides to adopt immediately is unique.

Proof. ***Proposition 2***

Existence: Immediate from the discussion on the sign of polynomial (P_t^{n+1}) (see equation (3.4.16) above).

Uniqueness: Immediate if $(P_t^{n+1})(\lambda_t)$ does not switch sign on $[0;1]$; if it does, we make proof by contradiction. Assume that there is more than one solution to $(P_t^{n+1})(\lambda_t) = 0$ between 0 and 1. $(P_t^{n+1})(\lambda_t)$ is a $n+1$ degree polynomial, it has a finite number of solutions. Let consider two successive different solutions $(\lambda_a, \lambda_b) \in [0;1]^2$. Being distinct, λ_a and λ_b admit an order relation. We arbitrarily posit that $\lambda_a < \lambda_b$. According to equation (3.4.15), their associated quality preference frontiers admit the opposite order relation $\theta_a > \theta_b$. We can then choose a quality preference verifying $\theta_a > \theta_x > \theta_b$. As θ's distribution is continuous and uniform among agents, we can find the corresponding agent x.
As $\theta_a > \theta_x$, the optimal decision of agent x is to postpone rather than exercising immediately.
As $\theta_x > \theta_b$, the optimal decision of agent x is to exercise immediately rather than postponing.
From the two previous statements we deduce that the option value of agent x is the same if she immediately exercises or if she postpones: then λ_x associated to θ_x is also a solution of $(P^{n+1})(\lambda) = 0$. Yet $\lambda_a < \lambda_x < \lambda_b$, which is impossible as we have taken two successive solutions of the polynomial.

Thus the solution λ_t^* of the equation $(P_t^{n+1})(\lambda_t) = 0$ is unique. □

Proposition 2 is the theoretic foundation of the invention progressive diffusion: λ_t^* is not necessarily equal to 0 or 1, it lies in this interval and diffusion is progressive.

3.5 Bimodal distribution of steady state

If an analytical solution is computationally complex to establish, numerical simulations enable an insightful illustration of the model. Indeed, the objective is to evidence some effects on diffusion paths unprecedented in the economic literature. Especially, numerical simulations highlight that steady states exhibit special characteristics.

3.5.1 Calibration

In order to further analyze the micro-founded model of adoption diffusion, and more specifically its properties, we parametrize the model as follows. There are $N = 101$ agents in strategic interaction. These agents can all either adopt a new brand product with uncertain quality, or postpone their decision at the following period. If the invention is effective, its quality will be $Q_{sup} = 1$.If it is counter-productive, its quality will be $Q_{inf} = 0$. Quality preferences of agents are uniformly distributed between $\theta_m = 10$ and $\theta_M(t = 0) = 110$. The common initial belief on the invention is $X_0 = 0.9$. Noise parameters are fixed at $p^{pos} = 0.6$ and $p^{neg} = 0.65$. The price of the product is constant over time and fixed at $P = 19$; this price is the one maximizing the firm's profit, as further discussed in subsection 5.4. The discount rate of agents is $r = 0.05$. We fix the time limit of the game at 101 periods, since the maximum number of learning periods equals the number of agents.

The model is solved recursively, subtracting to n at period $t+1$ the number of agents having adopted the product at period t. We compute $\lambda^*(t)$ given the current belief X_t obtained with Bayes rule. As agents are rational, they anticipate that those adopting first are the ones with the highest preferences for quality. Then, on the basis of how many agents have adopted the invention, they are able to revise the maximal preference for quality of agents still playing as follows:

$$\theta_{M,t+1} = \theta_{M,t} - \lambda^*(t) * (\theta_{M,t} - \theta_m). \tag{3.5.1}$$

At each period t, once the number of agents $a(t)$ who choose to invest in the invention, whereas they have not already, is determined, we make a random draw from the binomial distribution defined either by p^{pos} or p^{neg} (depending on which scenario we exogenously impose) to determine how many positive and negative messages are emitted. The shared common belief on the nature of the invention among the agents still in the game is revised on the basis of these messages.

3.5.2 S-shape of the diffusion curve and steady state

In this subsection, we present our simulations results in the case of an *effective* invention, with the aim to highlight how an "intrinsically good" invention can be doomed due to informational externalities. Given the calibration of parameters detailed in the previous subsection, if the invention is effective, its optimal diffusion is 99% among our population, which corresponds to 100 agents[4].

Figure 3.51 displays the result of one of our one-shot simulations, when the real nature of the invention is *effective*. We can observe in this case that after 5 periods, the full development of the invention is reached in the population of 100 agents. Besides, the diffusion path follows the S-shaped curve generally observed empirically, as detailed in Section 2.

[4]Indeed, population is made up of 101 agents, but given the quality of invention and their preference quality, only 100 agents would derive a positive utility from invention adoption.

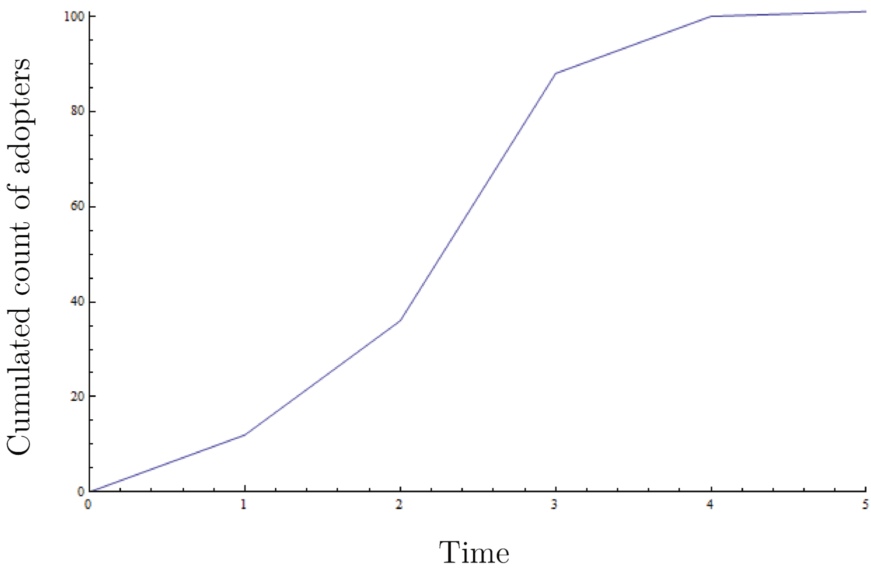


Figure 3.51: S-shaped diffusion ("Good invention" scenario)

However, each simulation yields a different diffusion path of the invention, as shown in Figure 3.52. These graphs deserve two main observations: firstly the steady state is always reached after 5 periods, sometimes quicker. This might come from a peculiarity of our model : agents are short-sighted and only implement in their decision at period t the possibility of postponing the decision at period $t+1$, but do not take into account the possibility of postponing it in further periods. Secondly, the steady state does not always match with the full development of the innovation. Sometimes the adoption process is stopped after a few periods. This result stems from the random nature of messages. Indeed, in the case studied here, the innovation is effective, but its adoption can still generate negative messages. As in the first periods only a few agents adopt the innovation, a limited number of messages on the invention nature is produced. If noise is loud enough and negative messages are received first, the shared belief on the invention's nature leans towards the "bad" scenario. Therefore agents stop adopting the invention, nipping in the bud the invention's diffusion.

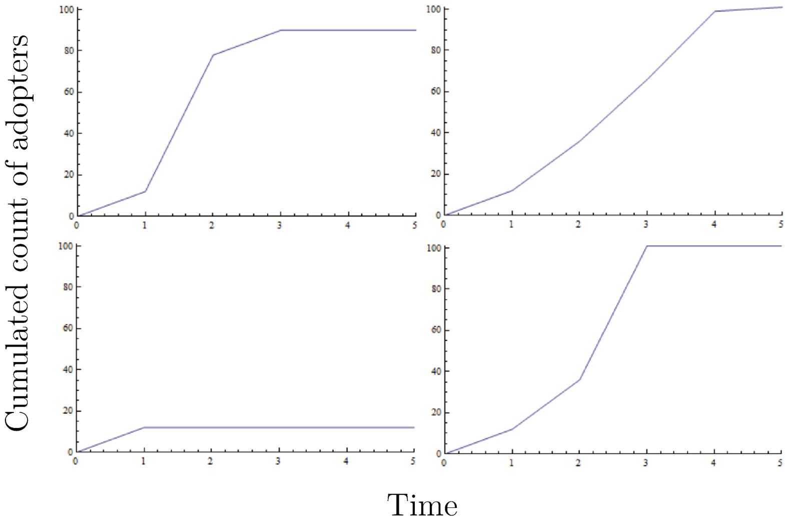


Figure 3.52: Numerical illustrations of varying diffusion paths ("Good invention" scenario)

3.5.3 Bimodal distribution of the steady state

In order to have a look at the distribution of steady states generated with numerical simulations, we have drawn 10, 000 simulations under the "good invention" scenario, and computed the resulting mean diffusion path, with its standard deviation interval. Result is shown in Figure 3.53.

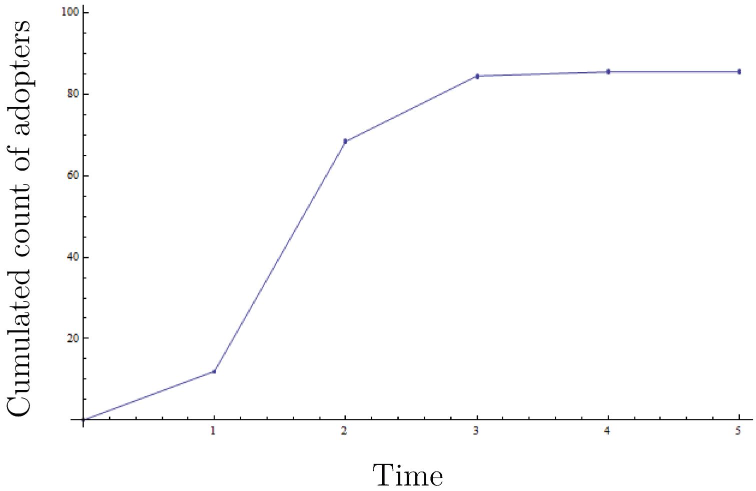


Figure 3.53: Mean diffusion path over 10,000 simulations ("Good invention" scenario)

Figure 3.53 highlights that even if the invention is effective for all agents, the mean steady state does not correspond to full development, but is capped (in this configuration, the mean diffusion is limited to around 85% of the population).

Besides the mean diffusion path, we can observe the distribution of steady states over 10, 000 simulations. Figure 3.54 presents the histogram of the distribution of the maximum number of adopters across steady states. We can observe a bi-modal distribution of these steady states. The first mode is a full diffusion of the invention, with 100 adopters in the steady state. This mode gathers about 80% of simulation results. The second mode is a stillborn diffusion, with less than 15 adopters, gathering about 15% of simulations in this setting.

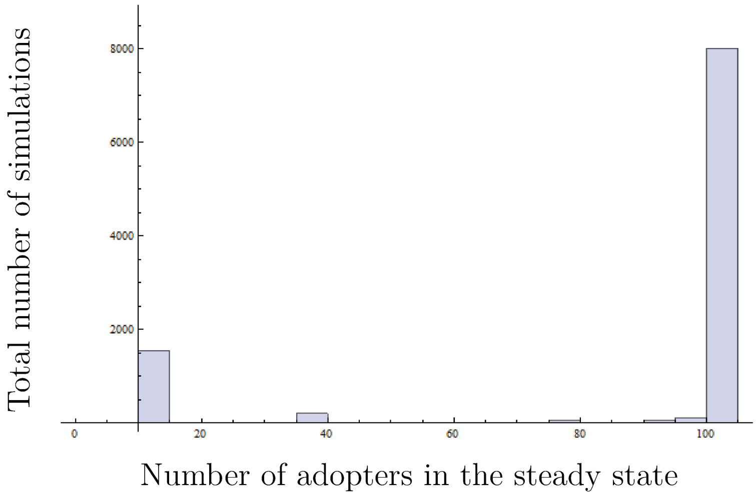


Figure 3.54: Distribution of steady states for 10,000 simulations ("Good invention" scenario)

This bi-modal distribution is explained by the imperfection of information transmission: at early stages, messages are crucial to sustain the dynamics of innovation diffusion. But, notably because of the strategic interactions and because of the heterogeneity of agents' preferences, at this early stage only a few agents adopt the invention. Among this limited number of messages produced, if negative messages are received first, then noise about the real nature of the invention shades its true nature, and the diffusion is capped. When there are enough positive messages among early messages about the invention's quality, the probability of stopping the diffusion process is lower. Figure 3.54 typically illustrates that a "good" invention may have a "bad" fate.

By contrast, under the "bad" scenario, if the invention is counter-productive, we do not have a bi-modal distribution. The rationale for this result is that the more messages you get, the more likely it is agents discover that the invention nature is "bad" and the diffusion process stops. The histogram of steady states distribution in a counter-productive invention scenario is presented in Figure 3.55.

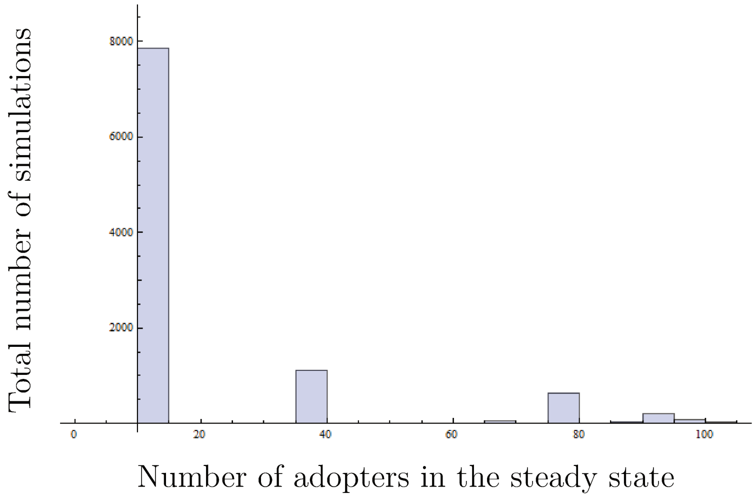


Figure 3.55: Distribution of steady states for 10,000 simulations ("Bad invention" scenario)

3.5.4 Firm's optimal pricing strategy

One could argue that firms producing inventions are aware of the reputational risk, and could cope with the fate of inventions exhibited in the previous numerical simulations by adjusting their pricing of the invention. Indeed, as the price decreases, there are more adopters in the first periods, and messages multiply. With more messages, the probability that noise shades the invention's true nature gets smaller, and the fate phenomena softens.

In a second step of our analysis, we thus consider the possibility for the invention's producer to choose the selling price maximizing its expected profit. A rational producer will choose the price maximizing its expected profit. We determine the associated optimal price by firstly computing the inter-temporal profit for each set of simulations conditional on the price level, as described in the previous section, with a discount rate of 5%. We iterate this calculus with steps of 0.25 for the invention's price. We draw the expected profit curve conditional on the price in Figure 3.56, all others parameters being kept as specified earlier.

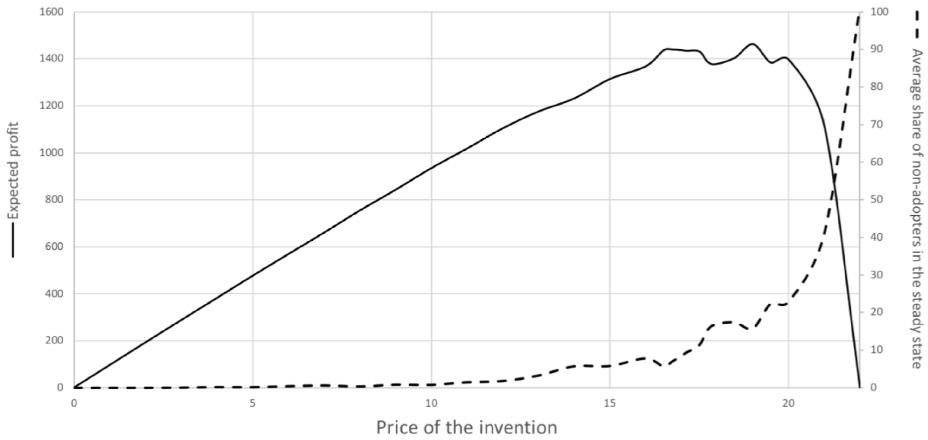


Figure 3.56: Maximization of firm's profits with the fate of inventions ("Good invention" scenario)

The curve brings out that expected profits become strictly superior to 0 only when the price belongs to the range $(0, 22)$. Below $P = 0$ the firm will obviously earn no positive profit. The upper limit, $P = 22$, is due to information imperfection. As invention quality is uncertain, when $P = 22$ no agent will derive a positive expected utility from adoption, then none will adopt and expected profits are zero from that point. For a price level between 0 and 16.5, the discounted sum of expected profits increases quasi linearly with the price, and are almost stable from 16.5 to 20. Then, they fall down to zero when $P = 22$. The maximum expected profit is reached when the price amounts to 19. The two factors influencing this profit pattern are the classical price and volume effects. The volume effect is linked to the expected diffusion of the invention, which depends on the price as the fate of inventions becomes stronger when the invention's price increases. We can observe that the plateau where profits are the highest is tied in with a strong reputational risk. As seen in section 4.3, when the price is optimal, $P = 19$, about 15% of inventions will fail to conquer their market with this price. In annex C, we draw profit maximization when information is perfect: optimal price is then much higher, about 105. Together, Figure 6 and Appendix 3.D underline that information imperfection induces a much lower pricing by the firm compared to the full information case, but the firm's optimal pricing strategy does not obliterate the fate of inventions.

3.6 Conclusion

The research work presented in this chapter contributes to the economic literature interested in invention adoption and innovation diffusion: we model the adoption decision of economic agents as an inter-temporal and strategic choice in a situation of uncertainty, where information on the invention nature becomes a public good produced by private actions. We demonstrate that informational externality is a sufficient condition to induce an endogenous S-shaped diffusion curve. Moreover, we show that noise derived from teething troubles can nip in the bud the diffusion of an effective invention, and curse its fate. We believe that our analytical framework can be useful to explain cases of innovations developing unevenly over various markets, especially when reputational damages are identified. Firms' strategies to overcome this reputational valley of death can also be analyzed through our model. Three different strategies could be envisioned by the firm offering a new product to answer this issue: the first strategy would be to act on the price, for instance by discriminating early adopters and offering them a lower price P in order to produce enough messages on the invention quality in order to trigger the virtuous circle of information: a "launch price" strategy. The second strategy would be to set up larger informational hubs, for instance by introducing a rating website for consumers or by organizing meetings with early adopters. Both of these two first strategies aim at scaling up the number of messages gathered by potential adopters on invention's quality. The third firm's strategy could be to make information production about its invention more reliable, for instance by offering tools to estimate faithfully the benefits derived from the invention, a solution which seems especially relevant for inventions related to energy-efficiency. The "Dieselgate" enlightened recently the risk of unfair assessment of quality, and the response of the European Commission roots in this third strategy: new certifications and quality control standards are set up to provide a better information for the consumer.

Appendices of Chapter 3

3.A Power curves

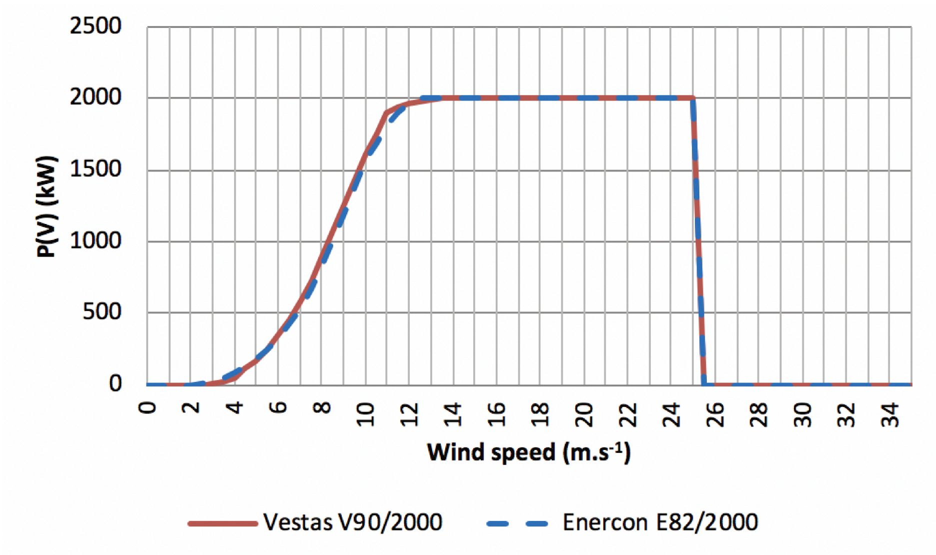


Figure 3.A1: Power curves for the E82 Enercon turbine and the V90 Vestas turbine

3.B Mathematical proof: 2 agents problem

Proof of Proposition 1

$$a * \lambda^2 + b * \lambda + c = 0, \tag{3.B.1}$$

$$with \begin{cases} a = (\theta_M - \theta_m) * (Q_{exp}(X_0) - Q_{exp}(X_{1,+}) * Prob_{pos,0}) \\ b = P * Prob_{neg,0} + \theta_M * Q_{exp}(X_{1,+}) * Prob_{pos,0} \\ \quad + (\theta_M - \theta_m) * (Q_{exp}(X_0) * (1 + r) - \theta_M * Q_{exp}(X_0)) \\ c = -(1 + r) * \theta_M * Q_{exp}(X_0) \end{cases} \tag{3.B.2}$$

a can be rewritten as follows :

$$a = (\theta_M - \theta_m) * (Q_{sup} * (1 - X_0) * (1 - p^{pos} + Q_{inf} * X_0 * p_{neg}) \tag{3.B.3}$$

Our framework hypotheses imply that $a > 0$ and $c < 0$. As we define $\Delta = b^2 - 4 * a * c$, then $\Delta > 0$. There exists then two real roots of equation (3.B.1) of opposite signs.
Let consider the positive root $\lambda^+ = \dfrac{-b + \sqrt{\Delta}}{2 * a}$. We look for a condition ensuring $\lambda^+ \leq 1$
$\Leftrightarrow \frac{-b+\sqrt{\Delta}}{2*a} \leq 1$
$\Leftrightarrow 0 \leq 4 * a * (a + b + c)$
$\Leftrightarrow 0 \leq (a + b + c)$
$\Leftrightarrow P \geq \theta_m * \frac{Q_{sup}*(1-X_0)*((1+r)-(1-p^{pos}))+Q_{inf}*X_0*(1+r-p^{neg})}{(1-p^{pos})*(1-X_0)+p^{neg}*X_0}$

Then a sufficient condition to ensure $\lambda^+ \leq 1$ is $P \geq \theta_m * Q_{sup} * (\frac{r+p^{pos}}{1-p^{pos}})$.

3.C Bayesian re-evaluation in $N + 1$ agents game

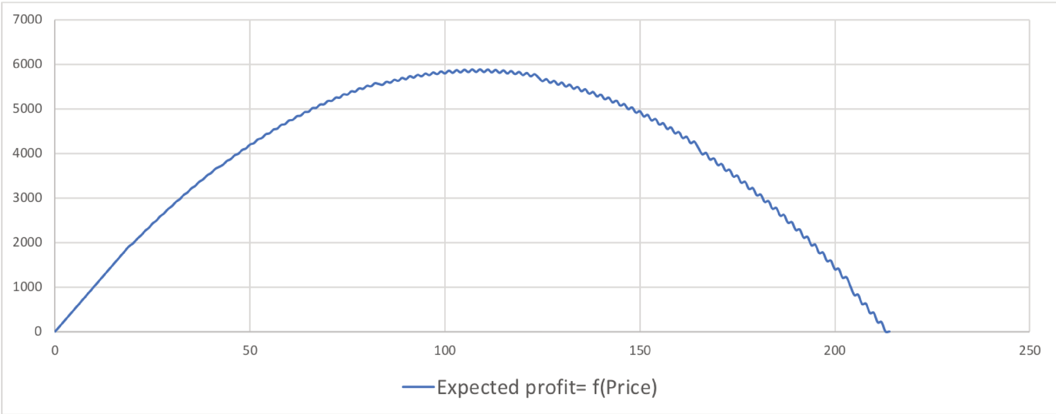
In order to compute the belief evolution after α positive messages and β negative messages, we define the likelihood ratio:

$$Z_t = \ln \frac{X_t}{1 - X_t} \tag{3.C.1}$$

Then we define $\Delta Z_+ = Z_{1+} - Z_0 = \ln \dfrac{X_{1+}}{1 - X_{1+}} * \dfrac{1 - X_0}{X_0}$ and we introduce expressions (3.4.3) and (3.4.4).
By computation, we obtain $\Delta Z_+ = \ln (\dfrac{1 - p^{neg}}{p^{pos}})$.
Similarly, we can compute $\Delta Z_- = Z_{1-} - Z_0 = \ln (\dfrac{p^{neg}}{1 - p^{pos}})$.
Hence, after α positive messages and β negative messages, we have:
$Z_t = Z_0 + \alpha * \ln (\dfrac{1 - p^{neg}}{p^{pos}}) + \beta * \ln (\dfrac{p^{neg}}{1 - p^{pos}})$
Using the exponential function, we finally get the Bayesian revision of belief after α positive messages and β negative messages :

$$X_t = Rev_{\alpha,\beta}(X_0) = \frac{(\dfrac{1 - p^{neg}}{p^{pos}})^{\alpha} * (\dfrac{p^{neg}}{1 - p^{pos}})^{\beta} * X_0}{1 - X_0 * (1 - (\dfrac{1 - p^{neg}}{p^{pos}})^{\alpha} * (\dfrac{p^{neg}}{1 - p^{pos}})^{\beta})} \tag{3.C.2}$$

3.D Firm's optimal pricing strategy when information on product quality is perfect



Discounted sum of expected profit (vertical axis) as a function of Invention's Price (horizontal axis)

* * *

* * *

«De tout temps et dans toute espèce d'avantages, on met plus de passion à obtenir ce qu'on n'a pas qu'à conserver ce qu'on a.»

–Stendhal.

* * *

Chapter 4

Is the Cure Worse than the Disease? Willingness-To-Pay for Information and Winner's Curse in a Common-Value Auction

* * *

We build a laboratory economic experiment where participants play a Common Value Auction (CVA) game obtaining the opportunity to bid for additional information about the intrinsic value of the auctioned good. In our CVA game, groups of 2 bidders obtain free and private information about the true value of a Prize and should bid repeatedly for buying it as additional information may be provided throughout the bidding process. In a *benchmark* treatment, free information occurs and could result in various information structures for bidders. In the other *'Buy'* treatment, after obtaining some free information, participants bid for buying an additional signal before bidding again for the good. This treatment implies in particular that information asymmetry may be endogenously created between bidders, while it is exogenously created in the benchmark. We had 260 participants for which we control for cognitive abilities and risk aversion. We observe the Winner's Curse (WC) phenomenon consistently across the different information structures. Overbidding occurs both for the Prize but also for costly information. We give statistical evidence for explaining overbidding as the consequence of various well-known behavioral biases.

* * *

This Chapter is an adaptation of a collaboration with Laurent Denant-Boemont.

4.1 Introduction

In 2010, a huge fraud was discovered in Germany, as forgers sold to famous buyers, including the Metropolitan Museum in New York, false paintings of Max Ernst or Fernand Léger, for a total value of 34.1 millions of US$. An expert finally discovered that some tickets at the back of fake paintings were not authentic. In the field of public utilities, the public service delegation process for water, energy or transport imply competition among tenders for obtaining the contract for a mid-term duration (from 6 to 10 years, see Saussier and Tirole, 2015). One important criteria, among others, in the company selection stage, may be the lowest price for a level of service that is fixed and publicly announced by public local authorities at the call stage. In this case, the insider firm that compete with outsider has more information about operating costs and revenues for the public service. Long durations can also lead to foreclosure of the market. Asymmetric information, reputational effects and learning-by-doing grant incumbents a relative advantage in the rebidding stage, particularly for highly specialised contracts, discouraging rivals to participate (OECD, 2014). Klemperer (2007) illustrates these dominance effects with the example of tendering for the U.K. National Lottery: while there were eight bidders in the first auction, the winning concessionaire acquired substantial incumbency advantages over the seven-year term and there were only two bidders for the second tender. These examples illustrate the problems raised by auctions procedures when the economic value or the economic benefit may be the same for all bidders but remains uncertain at the time when bidders compete to obtain goods or rights to operate. This problem would be especially relevant when *ex ante* information about the potential value may be different between, let's say, an expert or an incumbent firm compared to less informed bidders or new entrants that compete together.

In a Common Value Auction Game, the unknown value of the auctioned item is the same to all bidders, but bidders have different private information about its actual value. In such situations, it had been extensively shown that bidders are prone to the "winner's curse" (Wilson, 1969, 1977). The Winner's Curse (hereafter, WC) is a situation where the highest bidder tends to be the one with the most optimistic estimate of the item's value and neglects the fact that winning the auction is itself informative (Holt and Sherman, 2014) in the sense that if the bidder wins, other bidders' value estimates were relatively low. As a consequence, the WC may result in very small payoff or oven in negative ones. This is puzzling since the optimal bid in a game theoretic equilibrium solution setting could not result in negative payoff. Therefore, Winner's Curse may derive from overbidding behavior. There had been an extensive experimental literature about Winner's Curse in Common-Value Auction games (see the extensive review by Kagel and Levin, 2002 and Kagel and Roth, 2016)[1].

Most of these economic experiments were based on a simultaneous sealed-bid First-Price Auction (FPA) where each bidder first obtain a signal about the true value of the item that is to be computed as the average (or the sum) of all bidders' signals. Then, sealed bids are compared and the highest bidder wins the true value, pays his bid, and gets a payoff as the difference. Losing bidders get nothing. In most cases, these economic experiments consider (i) *symmetric players*, which does not imply that all bidders have identical information, but rather than each draws his private signal for the the same distribution conditional of the true value of the item (Hausch, 1987), and (ii) *no common uncertainty* (i.e., each bidder knows privately one different component of the value). To our knowledge, the only experimental paper that considers both asymmetric information structures and common uncertainty is Grosskopf et al. (2018). Authors studied a 2-bidders CVA game, the item value being randomly chosen in a uniform distribution and implement in particular a treatment where one bidder gets a signal when the other gets nothing. They observed that, compared to Nash equilibrium bidding, informed bidders tend to overbid when, on the contrary, uninformed bidders tend to underbid. In short, Grosskopf et al. (2018) conclude that having no information is some kind of *blessing for the winner*. Actually, our experimental results give some additional evidence about this result, as our participants tend to overbid when being more informed. What we also observe is that they also tend to overbid for buying additional information about the item value. One strong originality of our experiment is to introduce endogenous information asymmetry, as bidders could buy more information during the auction process. In our design, information asymmetry may be either exogenous, depending on a random process (our benchmark treatment) or endogenous, depending on a bidding process about costly information to be acquired (our "Buy" treatment). Moreover, inspiring upon Brocas et al. (2015), we consider a rich set of information structures that may be possible, as we consider an item for which the value is

[1] In fact, as Kagel and Levin wrote: *"The winner's curse has been such a pervasive phenomenon in the laboratory that most of these initial experiments have focused on its robustness and the features of the environment that might attenuate its effects"*.

made of four signals (components). As a consequence, we have information structures where some private signals may be known by *both* bidders, which is not the case in Grosskopf et al. (2018) or even Brocas et al. (2015). Experimental evidence had shown the relevancy of WC phenomenon in CVA contexts, especially in the case of inexperienced bidders (Kagel and Roth, 2016). For these experiments, participants obtain (or not) a signal, then bid and the outcome of the competition is revealed. It is therefore a question of interest to wonder if a more dynamic information acquisition over the bidding process could magnify or decrease the WC phenomenon. For answering this question, we build a design where bidders could accumulate information about the true value of the good and bid repeatedly for it as private information may grow. Considering also that actual bidders are prone to be exposed to WC in the case of CVA, what may happen under *dynamic* information acquisition? There is a clear trade-off for the bidder: on the one hand, additional signal is reducing the uncertainty about the common value and therefore should reduce the payoff uncertainty associated to a given bid. Moreover, given that WC is partly due to the lack of strategic thinking, making information acquisition costly for the bidder should trigger more sophisticated decision-making process, being constrained to weigh carefully the expected benefit of information in the competition with other bidder, and therefore induces more strategic reasoning. But, on the other hand, if information cost occurs before its revelation, it implies some expectation about the true value of the information for the bidder. We conjecture that, if the value of information is uncertain for the bidder, buying it before observing the signal during the bidding process may trigger some *second-order winner's curse*. Bidders who decide to buy additional information may pay too much for a signal that happens *ex post* to be worthless.

In order to study this problem, we build a laboratory economic experiment where participants propose simultaneously and repeatedly sealed bids for a Common Value good under various information dynamics. More precisely, in our CVA game, groups of 2 bidders obtain free and private signals (information) about the true value of the good and should bid in a First-Price Auction (FPA) repeatedly for the good as additional information is observed during the bidding process. In a benchmark treatment, information is always free and could result in various information structures for bidders. In the other treatment, after obtaining free information, participants could also bid for buying an additional signal before bidding again for the good. This treatment implies in particular that information asymmetry may be endogenously created between bidders, while it is exogenously created in the benchmark. For each treatment, the CVA game is repeated during 24 periods. As it has been shown by Casari et al. (2007), some personality traits may intervene strongly in bidding strategies of participants. In order to provide a control for these traits, we measure cognitive ability for each participant thanks to a simplified Raven's test (Raven, 1941, 1960) and elicit risk preferences at the individual level. To preclude our main experimental results, we observe Winner's Curse (WC) - i.e., a situation where overbidding behavior occurs compared to Nash equilibrium bidding - consistently across the various information structures. We evidence that costly information acquisition through the buying process is associated to more strategic behavior of participants, compared to the benchmark treatment where they behave in a more "naïve" way. However, if the first order WC - that is, bidding too much for the good - is reduced thanks to costly information acquisition, buying information triggers also several cognitive biases which may cancel out its benefits, in some case reducing final payoffs for participants compared to the benchmark. Indeed, we document evidence for three behavioral failures arising from costly information acquisition. First, the second order WC appears in players' bids: subjects' Willingness-To-Pay for information is significantly higher than its theoretic value. Second, participants are exposed to sunk cost fallacy. Participants who actually pay for additional information raise subsequently their bids for the item in order to increase the probability of winning, which finally reduce payoffs. Lastly, a "Price-as-Quality" effect appears for information buyers (that is, paying for information makes it more useful), whom consider the costly information they buy as more relevant for choosing their bids compared to the free information they obtain.

This last chapter is organized as follows. Section 4.2 is dedicated to the theoretical background. Section 4.3 describes our experimental design and procedures, and following section details experimental results. Our last section is for concluding comments.

4.2 Theoretical Background & Predictions

Likewise Brocas et al. (2015), we consider a single good made of four components. Each component $i \in \{1, 2, 3, 4\}$ has a value x_i independently drawn from a uniform and continuous distribution on $[0, 50]$. The total value of the good is the sum of its components values $X_{tot} = x_1 + x_2 + x_3 + x_4$. Two risk neutral players A and B bid for this good in a first price sealed bid auction with no reserve price. Before bidding, the player A observes the first r components of the good $\{x_1, ..., x_r\}$ and the player B observes the last s components of the good $\{x_{4-s+1}, ..., x_4\}$ with $\{r, s\} \in \{1, 2, 3\}^2$. Winner of the auction is the player with the highest bid: winner gets the totality of the four components of the good and pays its bid. The player who loses does not get the good and does not pay its bid. If both players bid the same amount, the winner is randomly drawn between them with a probability 1/2. The information structure of the auction is perfectly known by players: each player knows which components are exclusively known by her and which are exclusively known by the opposite player (the distribution of private information). Each player also knows which components are known by both of them (*i.e.* public information) and which are known by none of them (*i.e.* common uncertainty). We study five different informational structures that can arise in this auction:

1. Symmetric private information of the players with common uncertainty: A observes $\{x_1\}$, B observes $\{x_4\}$, no player observes $\{x_2, x_3\}$.

2. Symmetric private information of the players with no uncertainty: A observes $\{x_1, x_2\}$, B observes $\{x_3, x_4\}$.

3. Symmetric private information of the players with public information: A observes $\{x_1\}$, B observes $\{x_4\}$, both players observe $\{x_2, x_3\}$.

4. Asymmetric private information of the players with common uncertainty: A observes $\{x_1, x_2\}$, B observes $\{x_4\}$, no player observes $\{x_3\}$, or conversely for A and B.

5. Asymmetric private information of the players with public information, A observes $\{x_1, x_2\}$, B observes $\{x_4\}$, both players observe $\{x_3\}$, or conversely for A and B.

While Brocas et al. (2015) concentrated on symmetric information structure, we investigate optimal bidding functions when the volume of private information of each player is unequal. Symmetric structures refer to cases where $r = s$. Asymmetric structures refer to cases where $r = s \pm 1$. For our analysis, we introduce the following notations:

- $X_A^r = \sum_{i=1}^{min(r,4-s)} x_i$: total private information of player A,
- $X_B^s = \sum_{i=max(r+1,4-s+1)}^{4} x_i$: total private information of player B,
- $E[X_\emptyset^{r,s}] = \sum_{i=r+1}^{4-s} E[x_i]$: expected common uncertainty when $r + s < 4$,
- $X_{Pub}^{r,s} = \sum_{i=4-s+1}^{r} x_i$: public information when $r + s > 4$,
- $b_A^{r,s}(X_A^r)$: bidding function of A when the information structure is (r, s),
- $b_B^{r,s}(X_B^s)$: bidding function of B when the information structure is (r, s),
- $F^r(X_A^r)$ the cumulative distribution and $f^r(X_A^r)$ the density function for total private information of player A,
- $F^s(X_B^s)$ the cumulative distribution and $f^s(X_B^s)$ the density function for total private information of player B.

Symmetric equilibrium bidding functions are detailed and demonstrated in section 4.2.1, along the same method used by Brocas et al. (2015). For asymmetric cases, equilibrium bidding functions are demonstrated in section 4.2.2.

4.2.1 Symmetric information structure

Proposition 1 states the bidding functions when information structure is symmetric.

Proposition 1. When information structure is symmetric (i.e. $r = s$), the unique equilibrium bidding function of player j is:

- $b_j^r = E[X_\emptyset^{r,s}] + X_j^r$ when r=1
- $b_j^r = X_j^r$ when r=2
- $b_j^r = X_{Pub}^{r,s} + X_j^r$ when r=3

(The proof of propositions are given in Appendix 4.A).

4.2.2 Asymmetric information structure

Proposition 2 states the bidding functions when information structure is asymmetric.

Proposition 2. When information structure is asymmetric (i.e. $r \neq s$), the unique equilibrium bidding functions of players A and B are:

1. When $r = 2$ and $s = 1$
   - $b_A^{r,s} = E[X_\emptyset^{r,s}] + \begin{cases} \frac{2}{3} * X_A^r & \text{if } X_A^r \leq 50 \\ \frac{2}{3} * \frac{125000+(X_A^r-150)(X_A^r)^2}{5000+(X_A^r-200)(X_A^r)} & \text{if } X_A^r \geq 50 \end{cases}$
   - $b_B^{r,s} = E[X_\emptyset^{r,s}] + \frac{X_B^s}{2} + 5\sqrt{\frac{X_B^s}{2}}$
2. When r=3 and s=2
   - $b_A^{r,s} = X_{Pub}^{r,s} + \begin{cases} \frac{2}{3} * X_A^r & \text{if } X_A^r \leq 50 \\ \frac{2}{3} * \frac{125000+(X_A^r-150)(X_A^r)^2}{5000+(X_A^r-200)(X_A^r)} & \text{if } X_A^r \geq 50 \end{cases}$
   - $b_B^{r,s} = X_{Pub}^{r,s} + \frac{X_B^s}{2} + 5\sqrt{\frac{X_B^s}{2}}$

See Proof in Appendix 4.A.

4.2.3 Optimal bidding functions

On figure 4.21 we represent optimal bids corresponding to the Nash equilibrium for the auction in which A and B interact, in function of the signals they observe. The optimal bids evidence that in an asymmetric informational structure, players optimally should strongly shade their bids. For instance, if we consider the player B who only observes one signal in the cases $\{r = 1, s = 1\}$ and $\{r = 2, s = 1\}$ (respectively purple and blue curves), we note that the addition of a component to the private information of the opposite player decreases the bid of player B for a given signal $X_B^{s=1}$. But one should note that the intercept of the curves in $X_j = 0$ are driven by the public information or common uncertainty remaining in the information structure. Then, rather than the absolute level of bids, study of their slopes is more insightful. When the informational structure is unfavorable to him, the player with only one signal (blue and purple curves) has a tendency to increase its bids more aggressively for low signals. On the contrary, the player with 2 signals will grow slower her bids when she benefits from an informational advantage (case of the orange versus green curves).

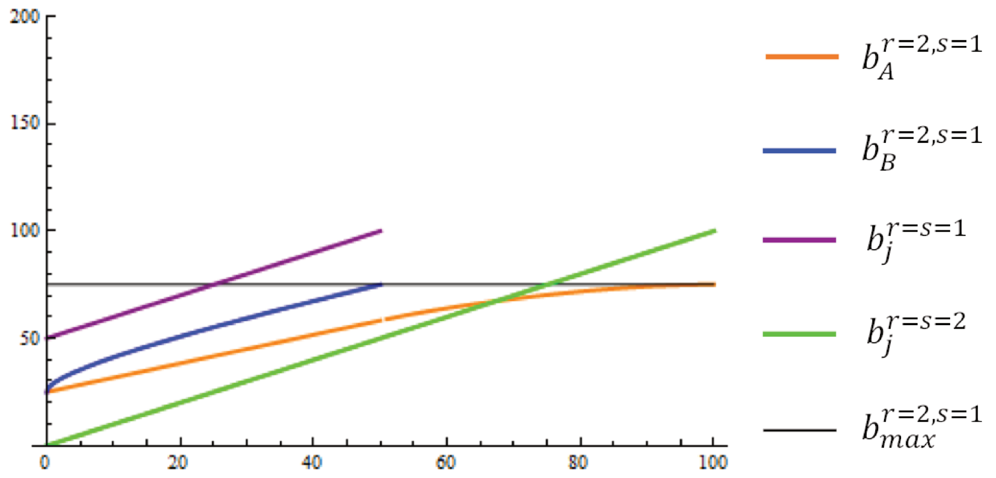


Figure 4.21: Optimal bidding functions

4.2.4 Information value

In the 'Buy Information' treatment of our experiment, we create the possibility of buying another component of information before bidding for the good. Both players were allowed to bid in order to observe another component of the good. For player A, who initially observes the first r components, the information bid aimed at observing the component $\{x_{r+1}\}$, and respectively for player B, who initially observes the last s components, the information bid aimed at observing the $\{x_{4-(s+1)+1}\}$ component. Two initial informational structures are considered, both symmetric. Firstly the situation of private information with common uncertainty: A observes $\{x_1\}$ and bids to observe $\{x_2\}$, while B observes $\{x_4\}$ and bids to observe $\{x_3\}$. In this information structure, both players want to acquire a component which is common uncertainty and can become a private information. The second informational structure considered is private information with no uncertainty: A observes $\{x_1, x_2\}$ and bids to observe $\{x_3\}$, while B observes $\{x_3, x_4\}$ and bids to observe $\{x_2\}$. Both players bid to acquire a component which is already observed by the opponent, and which can become then public information. In both cases, the theoretic value of information will be equal to the increase of expected utility of the player and will then vary according to the components she already observes. Theoretic value of information is then computed using optimal bidding functions previously demonstrated. Section 4.2.4.1 explicits information value when players can acquire common uncertainty components, and section 4.2.4.2 explicits information value when players bid to observe an information component of their opponent.

4.2.4.1 Theoretic value of common uncertainty

We consider the first initial information structure, where $r = s = 1$. For player A, the value of information is the gain of expected utility if she can bid while observing two components of the good (*i.e.* x_1 and x_2) rather than only one (x_1). As when player A bids for observing the second component she obviously does not observe it yet, information value will be the integration of this difference over the possible values of x_2. However, two cases can occur: indeed as player B can also bid for information, player A has to incorporate the possibility that player B will also observe a second component of the good when making her bid in the second step. The probability that player B acquires the observation of another component of the good, and then observes not one but two components of the good, will be written $P_{1\to 2}(B)$. Then the theoretic information value for player A (*i.e.* the gain in expected utility from observing the second component x_2 of the good, written $I_A^{x_2}$) is:

$$\begin{aligned} I_A^{x_2}(x_1) = &\int_0^{50} f^r(x_2) * (P_{1\to 2}(B) * (U_A^{r+1,s+1}(x_1, x_2) - U_A^{r,s+1}(x_1, x_2)))\,\mathrm{d}x_2 \\ &+ \int_0^{50} f^r(x_2) * ((1 - P_{1\to 2}(B)) * (U_A^{r+1,s}(x_1, x_2) - U_A^{r,s}(x_1, x_2)))\,\mathrm{d}x_2 \end{aligned}$$

A Becker-De Groot-Marschak (BDM) procedure, with $y_{min} = 0$ and $y_{max} = 50$ as bounds for the picked number y_i, is applied to each player after in order to determine if their bids for information will enable them to buy another information component (see section 4.3.2.2). Then the probability that player B acquires the observation of another component is:

$$\begin{aligned} P_{1\to 2}(B) &= \frac{E[I_B^{x_3}(x_4)] - y_{min}}{y_{max} - y_{min}} \\ &= \frac{1}{50}\int_0^{50} f^r(t) * I_B^{x_3}(t)\,\mathrm{d}t \end{aligned}$$

As player A and B are symmetric, we have $I_B^{x_3} \equiv I_A^{x_2}$. In order to ease the reading of following equations, we introduce the following notations:

- $\gamma(x_1) = \int_0^{50}(U_A^{r+1,s}(x_1,x_2) - U_A^{r,s}(x_1,x_2))f^r(x_2)\,\mathrm{d}x_2$
- $\delta(x_1) = \frac{1}{50}\int_0^{50}(U_A^{r+1,s+1}(x_1,x_2) - U_A^{r,s+1}(x_1,x_2) - U_A^{r+1,s}(x_1,x_2) + U_A^{r,s}(x_1,x_2))f^r(x_2)\,\mathrm{d}x_2$

We can then rewrite information value for player A as follows:

$$I_A^{x_2}(x_1) = \gamma(x_1) + \delta(x_1) * \int_0^{50} f^r(t) * I_A^{x_2}(t)\,\mathrm{d}t$$

By deriving the previous equation we can get the differential equation in $I_A^{x_2}$, which general solution is:

$$I_A^{x_2}(x_1) = \delta(x_1) * (K + \int_0^{x_1}(\gamma(t)\delta'(t) - \gamma'(t)\delta(t))\,\mathrm{d}t)$$

The constant K is determined by reinjecting the general solution in the initial equation, leading to the solution for the theoretic value of information, which depends on the first component observed by the player A:

$$I_A^{x_2}(x_1) = \frac{\gamma(x_1) + \delta(x_1) * \int_0^{50}\delta(u)f^r(u) * (\int_{x_1}^{u}(\gamma(t)\delta'(t) - \gamma'(t)\delta(t))\,\mathrm{d}t)\,\mathrm{d}u}{1 - \int_0^{50}\delta(u)f^r(u)\,\mathrm{d}u}$$

The theoretic value of purchasing an information belonging to common uncertainty is then fully determined: indeed $\gamma(x_i)$ and $\delta(x_i)$ are known using analytical solutions of Nash equilibrium bids (both in symmetric and asymmetric information structures) demonstrated in the previous section. Figure 4.22 represents the evolution of this information value for a player according to the component she observes. It evidences that information value grows from 0 to 14 when the first component value increases from 0 to 50. This expansion of information with the first component is consistent: when a player observes a larger value, her optimal bid will be greater, raising the probability of winning the auction but also the probability that the bid is superior to the good value. Then probability of important losses will grow. On the contrary, a smaller signal in the first component will lower player's bid, reducing both the probability of winning the auction and the potential excess of the bid regarding the actual value of the good.

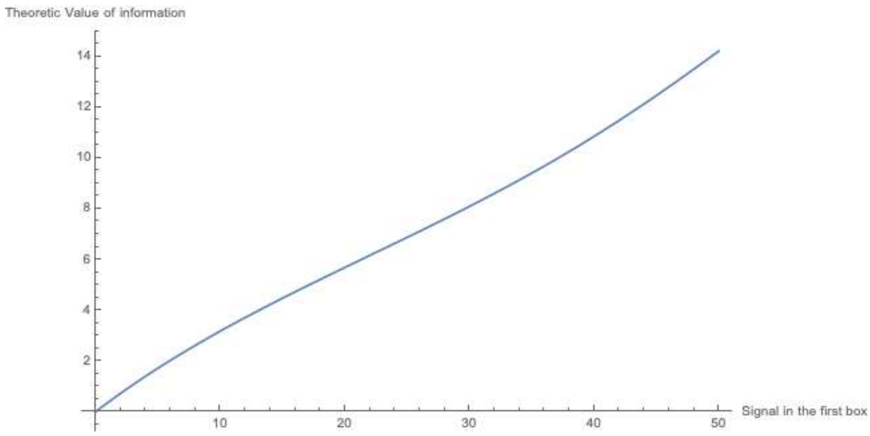


Figure 4.22: Information value over common uncertainty

4.2.4.2 Theoretic value of adverse private information

The same method is used to find the theoretic value of information in the case where both agents initially observe two components of the good ($r = s = 2$). However, in this setting, the two components observed have to be considered separately as they have different strategic implications. Indeed, let's take for instance player A: if initially her two observed components are private information, x_2 might become public information as player B might observe a supplementary component, while x_1 will remain private information. The probability density function of one component of the good, either initially observed or potentially added is then $f^{r-1}(x_i)$, as $r = s = 2$ and only one component can be discovered by bidding for information. The theoretic value of information acquisition for player A, (*i.e.* observing the component x_3) is then written $I_A^{x_3}$:

$$
\begin{aligned}
I_A^{x_3}(x_1, x_2) = &\int_0^{50} f^{r-1}(x_3) * (P_{2\to3}(B) * (U_A^{r+1,s+1}(x_1, x_2, x_3) - U_A^{r,s+1}(x_1, x_2, x_3)))\,\mathrm{d}x_2 \\
&+ \int_0^{50} f^{r-1}(x_3) * ((1 - P_{2\to3}(B)) * (U_A^{r+1,s}(x_1, x_2, x_3) - U_A^{r,s}(x_1, x_2, x_3)))\,\mathrm{d}x_3
\end{aligned}
$$

In this case, the probability that player B acquires the observation of a third component (for this player, x_2) is:

$$
\begin{aligned}
P_{2\to3}(B) &= \frac{E[I_B^{x_2}(x_3, x_4)] - y_{min}}{y_{max} - y_{min}} \\
&= \frac{1}{50} \iint_0^{50} I_B^{x_2}(t, u) * f^{r-1}(t) * f^{r-1}(u)\,\mathrm{d}t\,\mathrm{d}u
\end{aligned}
$$

Previous easing notations are extended to this case where players observe initially two components of the good:

- $\Gamma(x_1,x_2) = \int_0^{50}(U_A^{r+1,s}(x_1,x_2,x_3) - U_A^{r,s}(x_1,x_2,x_3))f^{r-1}(x_3)\,\mathrm{d}x_3$
- $\Delta(x_1,x_2) = \frac{\int_0^{50}(U_A^{r+1,s+1}(x_1,x_2,x_3) - U_A^{r,s+1}(x_1,x_2,x_3) - U_A^{r+1,s}(x_1,x_2,x_3) + U_A^{r,s}(x_1,x_2,x_3))f^{r-1}(x_3)\,\mathrm{d}x_3}{50}$

Hence the writing of theoretic information value for a third component, which is similar to the one of section 4.2.4.1:

$$I_A^{x_3}(x_1,x_2) = \Gamma(x_1,x_2) + \Delta(x_1,x_2) * \iint_0^{50} I_A^{x_3}(t,u) * f^{r-1}(t) * f^{r-1}(u)\,\mathrm{d}t\,\mathrm{d}u$$

Likewise the previous section, the general solution is obtained through the resolution of a differential equation, obtained by deriving according to x_1.

$$I_A^{x_3}(x_1,x_2) = \Delta(x_1,x_2) * (K + \int_0^{x_1} (\Gamma(t,x_2) * \frac{\partial\Delta}{\partial x_1}(t,x_2) - \frac{\partial\Gamma}{\partial x_1}(t,x_2) * \Delta(t,x_2))\,\mathrm{d}t)$$

We introduce another notation for this partial derivation:

- $\omega(x_1,x_2) = \Gamma(x_1,x_2) * \frac{\partial\Delta}{\partial x_1}(x_1,x_2) - \frac{\partial\Gamma}{\partial x_1}(x_1,x_2) * \Delta(x_1,x_2)$

Reinjection of the general solution in the initial equation allows the determination of the constant K, and yields the result:

$$I_A^{x_3}(x_1,x_2) = \frac{\Gamma(x_1,x_2) + \Delta(x_1,x_2) * (\iint_0^{50} \Delta(u,t) f^{r-1}(u) f^{r-1}(t) * (\int_0^u \omega(v,t)\,\mathrm{d}v - \int_0^{x_1} \omega(v,x_2)\,\mathrm{d}v)\,\mathrm{d}t\,\mathrm{d}u)}{1 - \iint_0^{50} \Delta(u,t) f^{r-1}(u) f^{r-1}(t)\,\mathrm{d}u\,\mathrm{d}t}$$

Likewise for section 4.2.4.1, the theoretic value of purchasing an information belonging to the opponent is then fully determined, as $\Gamma(x_i,x_j)$ and $\Delta(x_i,x_j)$ rely on the Nash equilibrium bids previously demonstrated.

4.3 Experimental Design and procedures

From October to November, 2018, we ran 14 experimental sessions, each session being made of 20 participants, at the Laboratory for Economic Experiments of the University of Rennes, Department of Economics (LABEX-EM), Rennes, France. Our 260 subjects were recruited via ORSEE (Greiner, 2015) and all the experiment was computerized using the z-Tree software (Fischbacher, 2007). In a given session composed of 20 participants, subjects are engaged in three experimental phases. The first one consists in an individual setting effort task where participants complete a Raven's test. The second phase is the auction game where pairs of participants interact repeatedly to purchase a good. The third phase consists in a lottery-choice experiment. All phases are incentivized. The experiment ends with the usual post-questionnaire phase and, when the payments are made, the experimental session is completed.

Our main experimental auction game inspires upon Brocas et al. (2015, 2017) where pairs of bidders compete for purchasing a common value good and receive signals that give them additional information about the true value for the good. Compared to Brocas et al. (2015), the main difference is that we introduce the possibility for participants to purchase additional information regarding the true value of the good. Purchasing information consists in an auction procedure, that is information price is endogenous.

Our experimental design aims at assessing how individual willingness-to-pay for the common value might be affected by information levels a bidder could obtain within a purchasing sequence. As a consequence, within a purchasing period, each bidder obtain 2 opportunities to make bids, depending on his information level.

4.3.1 The Situation Game

4.3.1.1 Observing signals and bidding for the good

Participants are randomly matched into pairs for a given period and participate to 24 periods (or matches). At each period, each bidder obtain a role (*Yellow Bidder* or *Blue Bidder*). The game closely followed the setting described in Section 2. Subjects within a pair had to bid in a first-price sealed bid auction for a good made of $N = 4$ components. Each component $i \in \{1, ..., 4\}$ contained x_i tokens drawn from a uniform distribution in [0, 50] (to simplify computations, we restricted x_i to integer values). The total value of the good, V, was common to both bidders and equal to the sum of the four components, $V = \sum_{i=1}^{4} x_i$. Visually, each component was represented by a box on the computer screen (see Figure 1). The number of tokens inside each of the four boxes was drawn at the beginning of the match and did not change during the match.

It was clearly and repeatedly explained to all participants that the colors for boxes were to be considered carefully, i.e., that yellow boxes were known by the yellow bidder, that blue

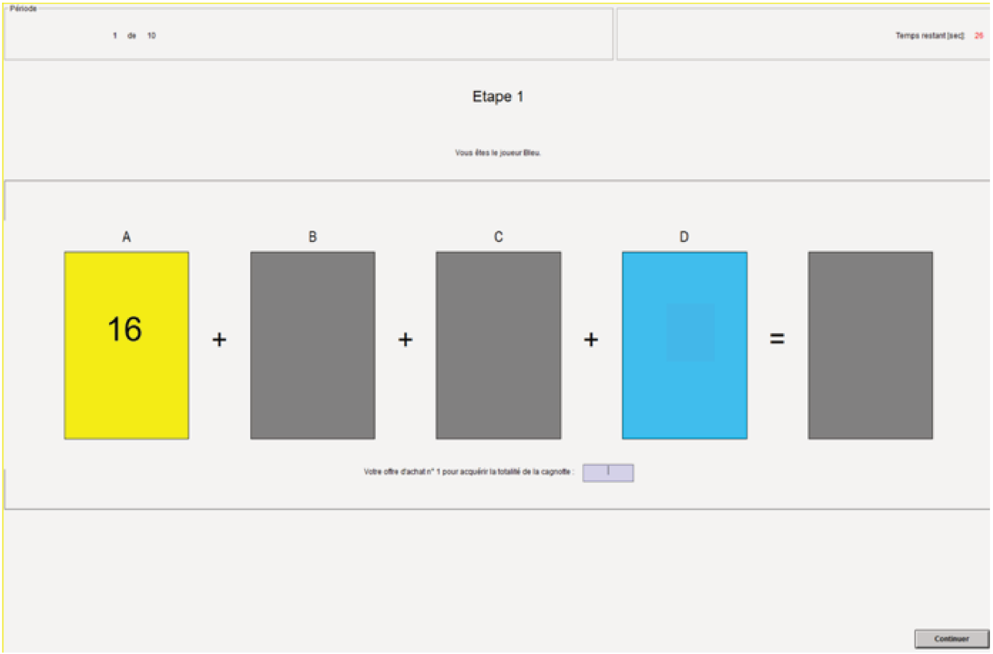


Figure 4.31: Screen Capture of ZTREE's computer interface for boxes: Step 1, yellow bidder

boxes were known by the blue bidder, that grey boxes were unknown for both bidders and that green boxes were known for both bidders.

Each match consists in 2 successive sequences where for each sequence participants bid to purchase the good. The first sequence begins after each bidder observed one or two signals that gives him information about the common value for the good. Then, subjects make their bids. In a second sequence, they have the opportunity to obtain additional signals — for free or not, depending on the treatment — and after observing (or not observing) additional signals, they make bids another time. After all bids being submitted, the computer randomly chooses the sequence to apply and compares bids to announce to each subject which step was considered for payoffs, if he succeeds to purchase the good, the final value for the good and final payoffs for the match depending on prices to be paid.

4.3.1.2 Information structures

Each match consists in changing partners but also the value for the good, V, as well as the information structure regarding signals. In order to have a balanced design, we implement all possible variations about the information structure for each match enabling us to observe behavioral responses to information change over the match (see Figure 2).

For instance, going from information structure 1 to information structure 2 means that each player starts the first bidding sequence with one signal and starts the second bidding

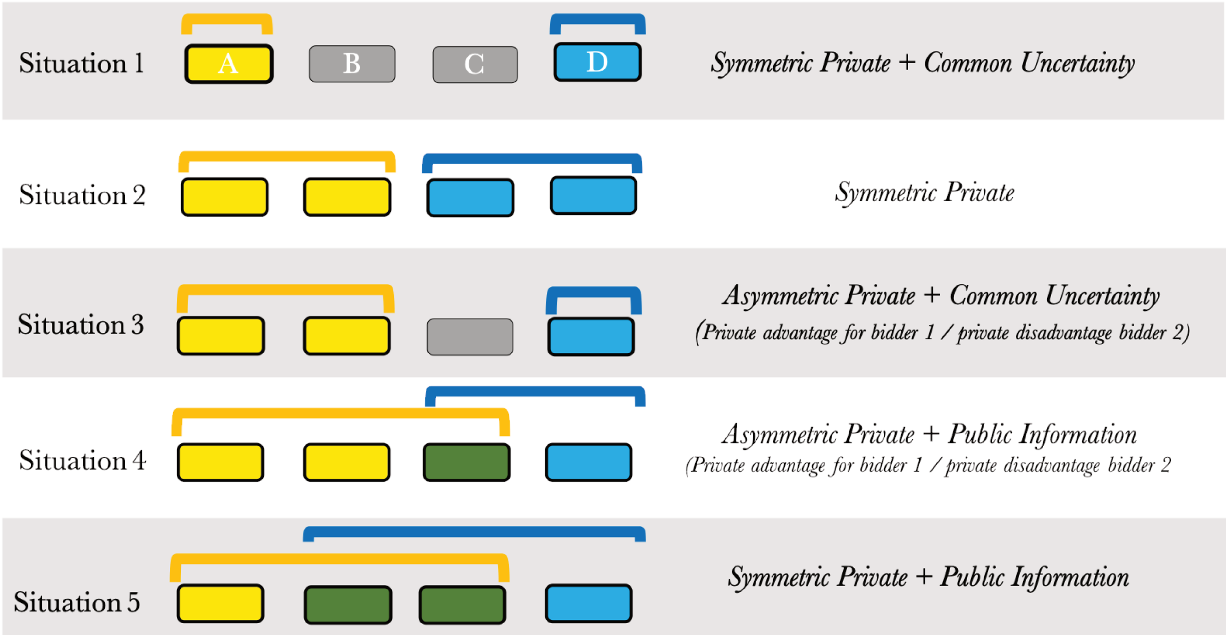


Figure 4.32: Information Structures for a given match

sequence with 2 signals. This imply perfect symmetrical players each of them obtaining one additional signal about the value. This is a possible match to be implemented among the 24. Another one would be to have no additional signal in sequence 2, staying in situation 1. A third possible match would be for instance to start at situation 2, where each bidder knows 2 different signals about the value (that is, altogether they would be perfectly informed about the true value), and to go to situation 4, where the yellow bidder obtains an additional signal, but the blue bidder does not get any additional signal. In this match, bidders became asymmetrically informed, and there is one common signal that is known by both bidders. The 24 matches that bidders participate in correspond to all possibilities of information acquisition, given the initial information bidders may have, consisting of one or two signals (no more, no less) and where *no piece of information could be public* (i.e., known by both bidders, see Brocas et al. 2015). More precisely, participants experience 12 matches under Situation 1 (one signal observed in sequence 1) and 12 matches under Situation 2 (both bidders observe 2 signals). Under each starting situation, they experience 4 matches where no additional signal is observed for both bidders (remaining either in situation 1 or in situation 2) and 4 matches where each bidder obtains 1 signal more, which means bidders to be in symmetric information. We implement therefore the 4 remaining matches where only a single bidder obtains extra-information (asymmetric information).

4.3.2 Experimental Treatments

4.3.2.1 The benchmark treatment

In the benchmark treatment, participants made 24 successive matches where signals are obtained without any cost all along the match in two successive sequences where purchasing bids for the good are to be made for each sequence. Participants are initially endowed with 300 tokens in the Benchmark treatment and accumulate gains or losses during the entire auction game. A certain order for information structures have been initially randomly determined for the 24 matches and is implemented in the same order for all our sessions, for all treatments.

4.3.2.2 The 'Buy Information' treatment

In this treatment, participants also made 24 successive matches and are confronted to the same procedure as in the benchmark. The only change is that before the second sequence of auctioning, participants are asked to make a bid for buying an additional signal (i.e., obtaining the value of an additional single box). The possible bid for buying signal, p_i, is to be between [0,...,50] and this bid is to be compared to a randomly picked number y_i in the same interval. If $p_i > y_i$, then the participant obtain the additional signal information and pays it y_i. In the contrary case, he does not obtain additional signal information and pays nothing. This setting corresponds to a Becker-De Groot-Marschak (BDM) procedure. In order to cope with the additional cost of information purchasing and obtaining similar average payoffs between treatments, we slightly increase the endowment of participants in this treatment: 400 tokens (compared to 300).

4.3.3 Behavioral Conjectures

Clear theoretical predictions assuming risk-neutrality had been given in the theory section about Nash equilibrium bids and information value. We develop now behavioral conjectures given the specificities of our experimental design based on previous experimental evidence. Several behavioral conjectures could be made about information impact on bidding behavior.

- The first one is that Winner's Curse is a frequent result in Common Value Auction (see Holt and Sherman 2014; Brocas et al. 2015). Bidders tend to pay too high prices compared to intrinsic ex post value for the common value good that could result in monetary losses for them. Does information acquisition over the bidding process an increasing or a decreasing factor of winner's curse? Does costly information acquisition magnifies or lessens winner's curse?

Conjecture 1. Costly information acquisition modifies subjects' bidding behavior for the common value good.

- The second one is a possible sunk cost fallacy due to information pricing. As information is to be paid whatever the bidding process outcome about the common value good, not winning the bidding process for the good might entail a direct loss, as the loosing bidder gains 0 and should pay the price for information. As a consequence, a successful information buyer might increase his bid for the good in order to increase the probability of winning, which might, in fact, reduce potential payoff and could even provoke some looses.

  Conjecture 2. Subjects suffer from the sunk cost fallacy, increasing their bids proportionally to information cost.

- The third conjoncture is that participants could grant a value to the signal just because it is costly compared to a situation where it is free. If participants consider that paying for information is a signal for its quality, then we should observe that they are ready to bid higher all things being equal for the good in the costly information treatment compared to the free-information treatment. They would hence reveal their beliefs about the positive association between pricey information and its quality (called "Placebo effect" by Shiv et al. 2005, or "non-Budgetary Constraint" price effect by Heffetz and Shayo 2009).

  Conjecture 3. Subjects are ready to bid higher for the good when information is costly compared to when it is free.

- The last one is that if information is costly and price being endogenously determined by bidders, we could have a second-order winner's curse, that consists in paying too much for a signal that is not very useful. As a consequence, if information value is less than information price, the bidder might regret to have this additional signal over the good value.

  Conjecture 4. Subjects willingness-to-pay for information is higher than information theoretic value.

4.3.4 Additional Controls

It has been noticed in the experimental literature that both risk-aversion and cognitive abilities may influence bidding strategies as well as possibility to experience a winner's curse (see Holt and Sherman 2014, and Costa-Gomes et al. 2001). As a consequence, in order to measure cognitive ability, we ask participants to complete a short version of the Raven's Test (as used in Gill and Prowse 2016 for instance) at the beginning of the experiment. Moreover, before completing the final ex post experimental questionnaire, we elicit risk-aversion level by using the Holt–Laury procedure (Holt and Laury, 2002). This questionnaire was incentivized.

4.3.4.1 The Raven's Test

At the beginning of the session, participants were asked to complete a computerised version of the nonverbal Raven's test consisting in 16 multiple-choice questions (Raven, 2000) during 10' (see Figure 4.33 below). For each question, the participant has to identify the missing element that completes a visual pattern. Within each question, participants could mode move back and forth between the 16 question by clinking on a button on the computer screen. The Raven's test had been recognized as a leading measure of analytic intelligence (Carpenter et al., 1990; Carroll et al., 1993; Jensen, 1998) and had been often used in experimental economics (Burks et al., 2009; Charness et al., 2012; Gill and Prowse, 2016). At the end of the questionnaire, a test score is computed. The mean test score was 9.95, with individual scores ranging from 1 to 15. Distribution of test scores in our sample is shown in Figure 4.35.

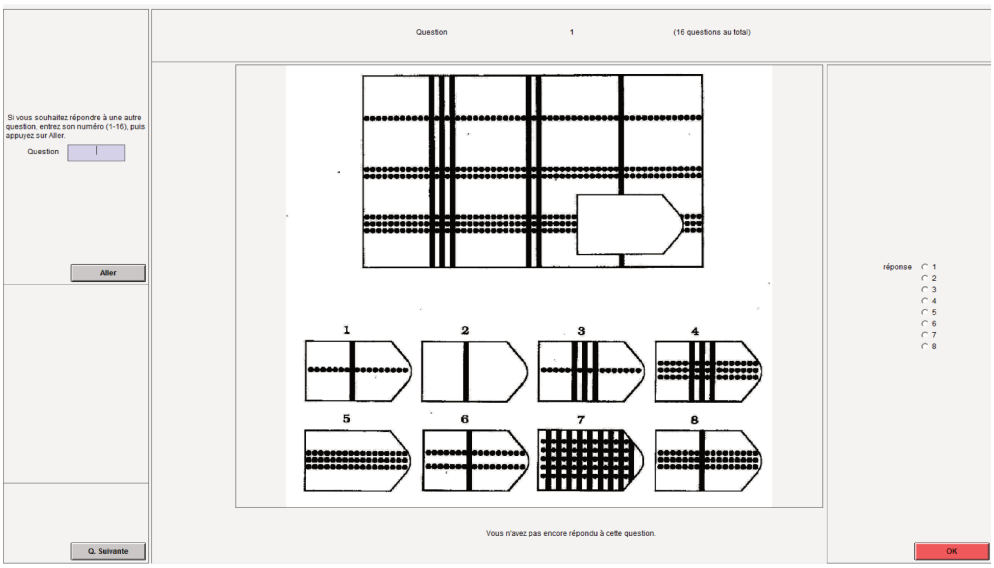
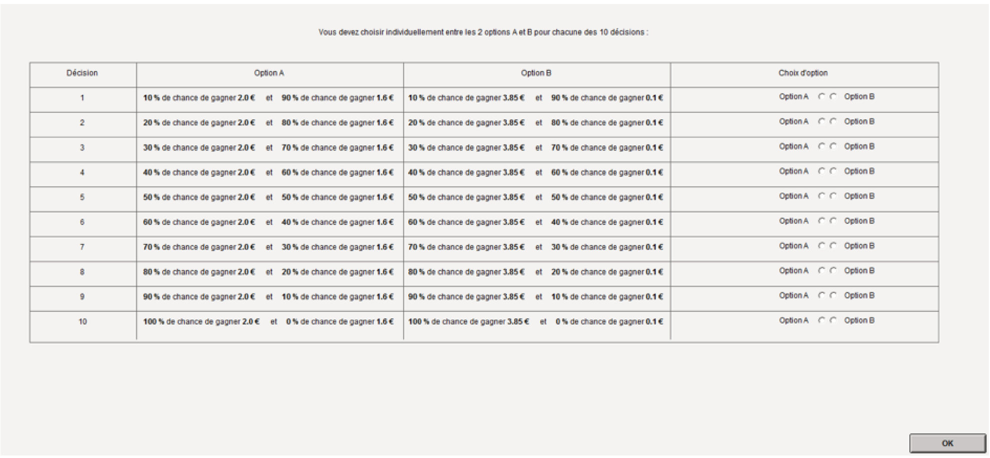


Figure 4.33: Screen Capture of ZTREE's computer interface for Raven's test

4.3.4.2 Elicitation of Risk Preferences

After playing the CVA game for 24 periods, participants completed the Holt–Laury procedure. In this task, participants were given a set of paired lottery choices. These pairs are structured so that the lesser payoff in choice "A" is constant and worths more than the lesser payoff in choice "B", also constant (e.g., the high payoff in "A" is 2.00 and the low payoff is 1.60, whereas the high payoff in "B" is 3.85 and the low payoff is 0.10). The gap between the high payoff and the low payoff is then almost ten times more important in the "B" choice compared to the "A" choice. In the first row, the probability to get the high payoff is 1/10 and the low payoff 9/10. Line after line, the probability of the high payoff steadily increases by 1/10 (e.g., the second pair has a 2/10 probability for the high payoff and 8/10 for the low payoff, the third one a 3/10 chance for the high and 7/10 for the low, etc.). Presentation of the lottery can be seen on Figure 4.34. For each line, the participant has to choose one lottery between the "A" and the "B" one. When the probability of the high payoff is low, choosing the "B" lottery can be seen as a risky decision: indeed, expected gains are lower in the "B" lottery. As the probabilities change, the expected value of "B" over "A" increases. From line 5, expected gains from the "B" lottery are higher than those of the "A" lottery. Then, the later the participant starts choosing the "B" lottery rather than the "A" one, the more we consider her as "risk-averse". In the following sections, we use the line number at which participant changes its choice from "A" to "B" as an indicator of her risk aversion. The mean value for this risk aversion over our sample was 6.14, with individual scores ranging from 2 to 9. Distribution of risk aversion levels is shown in Figure 4.35. Pearson test does not find a significant correlation between risk aversion level and Raven score; this is consistent with the experimental literature, which does not evidence a clear-cut relationship between those two variables (Andersson et al., 2016).


Vous devez choisir individuellement entre les 2 options A et B pour chacune des 10 décisions :

Décision	Option A	Option B	Choix d'option
1	**10 %** de chance de gagner **2.0 €** et **90 %** de chance de gagner **1.6 €**	**10 %** de chance de gagner **3.85 €** et **90 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
2	**20 %** de chance de gagner **2.0 €** et **80 %** de chance de gagner **1.6 €**	**20 %** de chance de gagner **3.85 €** et **80 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
3	**30 %** de chance de gagner **2.0 €** et **70 %** de chance de gagner **1.6 €**	**30 %** de chance de gagner **3.85 €** et **70 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
4	**40 %** de chance de gagner **2.0 €** et **60 %** de chance de gagner **1.6 €**	**40 %** de chance de gagner **3.85 €** et **60 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
5	**50 %** de chance de gagner **2.0 €** et **50 %** de chance de gagner **1.6 €**	**50 %** de chance de gagner **3.85 €** et **50 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
6	**60 %** de chance de gagner **2.0 €** et **40 %** de chance de gagner **1.6 €**	**60 %** de chance de gagner **3.85 €** et **40 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
7	**70 %** de chance de gagner **2.0 €** et **30 %** de chance de gagner **1.6 €**	**70 %** de chance de gagner **3.85 €** et **30 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
8	**80 %** de chance de gagner **2.0 €** et **20 %** de chance de gagner **1.6 €**	**80 %** de chance de gagner **3.85 €** et **20 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
9	**90 %** de chance de gagner **2.0 €** et **10 %** de chance de gagner **1.6 €**	**90 %** de chance de gagner **3.85 €** et **10 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B
10	**100 %** de chance de gagner **2.0 €** et **0 %** de chance de gagner **1.6 €**	**100 %** de chance de gagner **3.85 €** et **0 %** de chance de gagner **0.1 €**	Option A ○ ○ Option B

OK

Figure 4.34: Screen Capture of ZTREE's computer interface for the Holt–Laury lotteries

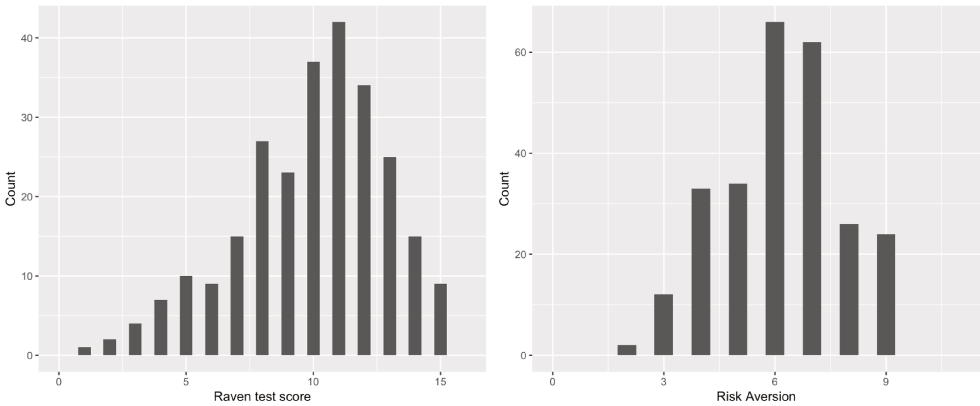


Figure 4.35: Histograms of Raven test score and Risk Aversrion

4.4 Results

In this section, we investigate on the one hand subjects bids, both for the common value good and for acquiring information. On the other hand, we study the gap between empirical bids and the corresponding Nash Equilibrium bids which were predicted in section 4.2. Section 4.4.1 describes data collected in this experiment. We present subjects' global net gains in both treatment, but also bids and their gaps to the Nash Equilibrium ones within each information structure, evidencing the winner's curse phenomena across most of them. Section 4.4.2 evidences the "costly information" treatment effect: subjects bidding behavior for the common value good varies when information is acquired through a bidding procedure rather than obtained for free. In section 4.4.3, we disentangle the multiple behavioral channels altering the WC phenomena from the "free information" to the "costly information" treatment. Finally, in section 4.4.4, we spot a second-order WC, by comparing subjects willingness-to-pay for information and theoretic value of information.

4.4.1 Data visualization

We give a first glance at data by looking at subjects gains at the end of the CVA game. Figure 4.41 represents boxplots of final net gains after the 24 periods. Final net gains are the difference between the final stock of tokens and the initial endowment, which was of 300 tokens in the benchmark and of 400 tokens in the 'Buy information' treatment. On Figure 4.41 we also display the boxplot of final net gains in the 'Buy information' treatment corrected by the prices paid for information. Uncorrected final net gains of the treatment are lower than those of the benchmark (mean of 94.6 against 142), but treatment final net gains corrected by information prices are similar to those of the benchmark (respective means of 138 and 142). These results show that, even when correcting for the information prices paid in the treatment, the 'Buy information' treatment does not raise or loosen significantly subjects' gains.

Nevertheless, in the free information treatment (benchmark), 16 out of 128 subjects ended with negative net final gains (*i.e.* final stock of tokens was below the initial endowment). In the 'Buy information' treatment, this number raises to 30 out of 132 subjects (or to 21 out of 132 when you correct for information price). We can then suspect that a Winner's Curse phenomena is occurring.

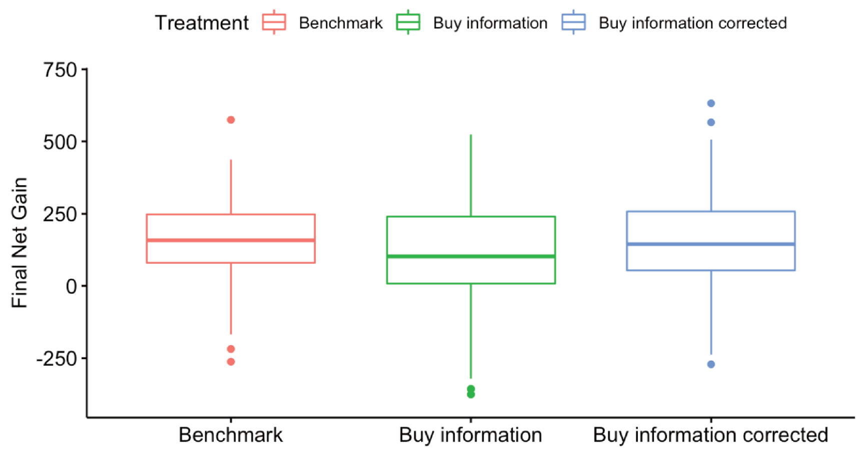


Figure 4.41: Subjects' net final gains in both treatments

We refine our analysis by looking at subjects' bids for the common value good and the gap between those bids and the Nash equilibrium bids predicted. Figure 4.42 display those data for each information structure in the second round[2]. For ease of understanding, we have systematically set the bidder as the "yellow" one. We fit a linear curve of empirical bids for each information structure, evidencing that bids grow with the global amount of tokens observed by the bidder. But public and private information have different strategic implications, then we draw in the second column of Figure 4.42 the histograms of overbids in each information structure. We define overbids as the difference between subjects bids and the Nash Equilibrium bids predicted. Those predicted bids depend on the information structure but also on the various amounts of tokens the player observes in public and private boxes.

[2]We chose to present the analysis of the second round bids. First round bids are less interesting as they cover only two informational structures, namely the symmetric private information either with or without common uncertainty, which are also covered by the second round bids.

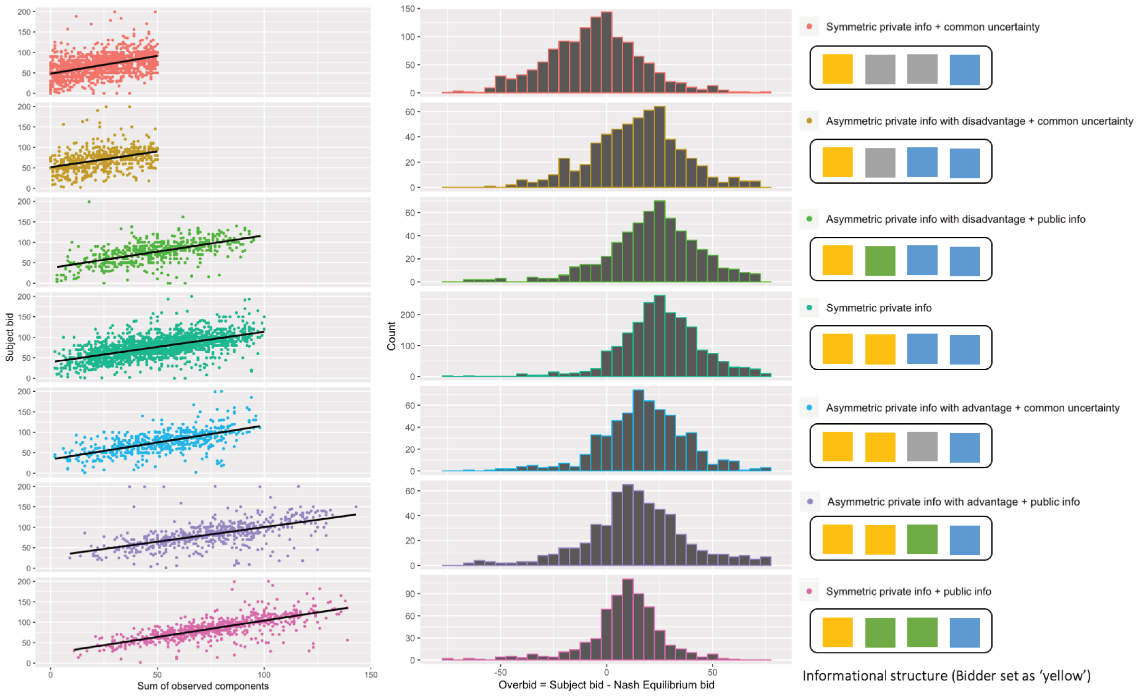


Figure 4.42: Subjects' bids in the various information structures

We can note that overbids distributions are centered on positive values for all but one information structures. Except in the case where each bidder observes only one box and two boxes remain in common uncertainty, histograms evidence that a large majority of subjects' bids are too high. Overall, 75% of empirical bids are superior to the Nash equilibrium ones (this proportion rises to 85% when withdrawing the first information structure). On average, the amount of overbid is 15.0 tokens, while mean bid is 75.9 tokens and mean value of the auctioned goods is 100 tokens. We observe a massive overbid, namely a Winner's Curse consistent with the literature on common value auctions.

4.4.2 Treatment impact on subjects' bids

Our experiment involved two treatments: in both of them, players could initially observe one or two boxes for free in the first round. In the second round, the observation of a supplementary box was possible. But if this observation was free and random in the benchmark, in the 'Buy information' treatment players had to bid for the supplementary signal, making information revelation endogenous. This treatment could stimulate the strategic thinking of players by emphasizing the value of information, and then modify subjects' bidding behavior. Table 4.41 presents how individual bids are affected by the treatment and by other variables, either specific to the game architecture or to individual characteristics. We process a linear regression on the second round bid for the common value good for subjects who have observed a supplementary box between the two rounds.

Table 4.41: Bids made post-acquisition of information

	Dependent variable: Second round bid for the CV good		
	All subjects	Free information	Costly information
'Costly information' treatment	$\mathbf{-5.348^{***}}$	*N.A.*	*N.A.*
	(1.280)		
Information structure:			
Symmetric private	*Reference*	*Reference*	*Reference*
Private advantage + common uncertainty	−1.150	−0.156	−3.723
	(1.296)	(1.400)	(2.539
Private advantage + public information	$\mathbf{-13.045^{***}}$	$\mathbf{-12.199^{***}}$	$\mathbf{-13.738^{***}}$
	(1.455)	(1.572)	(2.827)
Symmetric private + public information	$\mathbf{-12.233^{***}}$	$\mathbf{-12.462^{***}}$	$\mathbf{-13.538^{***}}$
	(1.391)	(1.338)	(3.339)
Value of private box(es)	$\mathbf{0.746^{***}}$	$\mathbf{0.815^{***}}$	$\mathbf{0.625^{***}}$
	(0.026)	(0.029)	(0.049)
Value of public box(es)	$\mathbf{0.857^{***}}$	$\mathbf{0.856^{***}}$	$\mathbf{0.841^{***}}$
	(0.045)	(0.043)	(0.102)
Value of the supplementary box	−0.011	−0.013	0.021
	(0.043)	(0.044)	(0.087)
Raven score	−0.205	$\mathbf{-0.899^{***}}$	0.484
	(0.159)	(0.172)	(0.296)
Risk Aversion	0.392	−0.469	$\mathbf{1.650^{***}}$
	(0.274)	(0.296)	(0.508)
Period	0.016	0.047	−0.075
	(0.064)	(0.067)	(0.122)
Gender: Man	$\mathbf{-3.193^{***}}$	$\mathbf{-1.983^{**}}$	$\mathbf{-3.640^{**}}$
	(0.917)	(0.953)	(1.800)
Age	−0.115	$\mathbf{0.399^{***}}$	$\mathbf{-1.022^{***}}$
	(0.076)	(0.080)	(0.149)
Price paid for the supplementary box	$\mathbf{0.300^{***}}$	*N.A.*	$\mathbf{0.373^{***}}$
	(0.072)		(0.087)
Constant	$\mathbf{42.035^{***}}$	$\mathbf{38.666^{***}}$	$\mathbf{49.499^{***}}$
	(3.127)	(3.402)	(5.895)
Observations	2,478	1,536	942
R^2	0.408	0.535	0.337
Adjusted R^2	0.406	0.531	0.329
Residual Std. Error	22.041 (df = 2464)	18.234 (df = 1524)	25.845 (df = 929)
F Statistic	131.5^{***}	159.1^{***}	39.37^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

First insight from Table 4.41 is the treatment effect: the 'costly information' treatment lowers subjects bids, which is a positive effect on subjects behavior as they bid too much for the good. Indeed, when gathering all control and treated subjects together, the dummy variable for the 'Costly information treatment' is highly significant, evidencing lower bids for subjects who paid information. When estimating the two groups separately, we can observe that the influence of private and public boxes, which are treated as equivalent in the free information treatment, are treated differently in the costly information treatment, with a lower coefficient for private boxes. This means that in the 'Buy' treatment, subjects have a better understanding of the strategic value of information. In the theory section, the predictions indicated that when players have an informational advantage, they should increase their bids proportionally to public information, but that bids' increase should be less than proportional to their private information. This difference in the reaction to public vs. private information is only observed in the 'Costly information' treatment (coefficient of private boxes is significantly lower than the one of public boxes, whereas it is not in the 'Free information' treatment). This treatment effect confirms our first conjecture, as stated in result 1.

Result 1. Conjecture 1 is supported by our experiment: costly information acquisition modifies bidding behavior of subjects by inducing a more strategic rationale.

When running the regression on the two treated groups separately, we observe that the treatment plays through multiple channels on subjects' behavior. We can identify especially four variables which effects vary from the benchmark to the treatment, namely Raven score, risk aversion level, gender, and age. The Raven score, which lowered bids in the benchmark, doesn't exhibit a significant effect on bidding behavior in the treatment. The risk aversion level raised bids in the treatment while it had no effect in the benchmark. Gender effect is reinforced: men bid less than women in the benchmark, and bids gap is widened in the treatment. Finally, while older subjects bided more than younger ones in the benchmark, this effect reverses in the treatment as older subjects tend to bid less. Those different effects of the treatment are not self-evident and will be detailed in the next section.

Nevertheless, the last variable in Table 4.41 deserves attention. Indeed, the price paid for the supplementary box between the two rounds has an impact on subjects bids in the treatment, as about 37% of this price is conveyed in the bid for the common value good. This is a sunk cost fallacy: subjects increase their bids when they have paid for information, while this information is already paid and should not be involved in the bidding decision for the good. This confirms conjecture 2:

Result 2. Conjecture 2 is confirmed by experimental results: a sunk cost fallacy appears in the 'Costly information' treatment, subjects increasing their bids of about a third of information cost.

4.4.3 Pricing information plays both ways on winner's curse

In the previous section, we evidenced that the costly information treatment lowered bids but that it also changed subjects bidding behaviors through other multiple channels. In order to have a better understanding of these effects, we analyze the determinants of overbidding (*i.e.* winner's curse) in the second round both for the control subjects and for the treated ones. Results are shown in Table 4.42.

Besides controlling for the informational structure effect on the winner's curse, we gather changing effects of the variables between the 'Free information' and the 'Costly information' treatment in three groups. First, variables that evidence a reduction of the winner's curse thanks to the treatment (informational structure of the auction, values of private box(es) and public boxes seen by the player, period of the game). Secondly, variables evidencing that the treatment triggers also various cognitive biases (value of the supplementary box seen by the player and price paid for the this box). Thirdly, individual characteristics influence is altered by the treatment, either reinforcing, cancelling or reversing their effects on the WC (namely Raven score, risk aversion level, gender and age of the subject).

Table 4.42: Winner's curse in both treatments

	Dependent variable: Overbid = Subject bid - Nash equilibrium bid	
	Benchmark: Free information	Treatment: Costly information
Information structure:		
Symmetric private	*Reference*	*Reference*
Symmetric private + common uncertainty	**−34.359*****	**−32.425*****
	(1.277)	(1.348)
Private disadvantage + common uncertainty	**−11.501*****	**−12.550*****
	(1.566)	(1.692)
Private disadvantage + public info	**−4.770****	**−9.286*****
	(1.868)	(2.254)
Private advantage + common uncertainty	**−6.511*****	**−12.799*****
	(1.489)	(1.942)
Private advantage + public info	**−8.494*****	**−19.538*****
	(1.657)	(2.199)
Symmetric private + public information	**−20.443*****	**−35.431*****
	(2.177)	(3.926)
Period	0.015	**−0.159****
	(0.054)	(0.063)
Value of private box(es)	−0.031	**−0.119*****
	(0.022)	(0.025)
Value of public box(es)	0.053	0.103
	(0.039)	(0.063)
Value of the supplementary box	0.011	**0.111****
	(0.034)	(0.054)
Price paid for the supplementary box	*NA*	**0.313*****
		(0.077)
Raven score	**−1.067*****	0.357
	(0.135)	(0.152)
Risk Aversion	**−0.747*****	**0.607****
	(0.235)	(0.259)
Gender: Man	**−1.579****	**−3.158*****
	(0.758)	(0.902)
Age	**0.350*****	**−0.759*****
	(0.063)	(0.096)
Constant	**35.795*****	**43.472*****
	(2.806)	(3.308)
Observations	3,072	3,168
R^2	0.272	0.216
Adjusted R^2	0.269	0.212
Residual Std. Error	20.486 (df = 3057)	24.451 (df = 3152)
F Statistic	81.751*** (df = 14; 3057)	57.732*** (df = 15; 3152)
Note:		*p<0.1; **p<0.05; ***p<0.01

The first group of variables evidence a better understanding of the strategic value of information in the auction in the 'Costly information' treatment. Indeed, while in the benchmark private information and public information were treated as similar by players, in the treatment they use private information more strategically (the value of private box(es) has a negative effect on overbids). Moreover, for several information structures, the level of winner's curse is more decreased in the treatment than in the benchmark: in a symmetric private information structure, levels of winners' curse are globally equivalent in both treatments (on average 26.2 for the benchmark and 26.5 for the 'Buy information' treatment). The WC level is reduced in all other information structures compared to this first one. Overbid reductions are similar for benchmark and treatment for two information structures (symmetric private information with common uncertainty, and private information disadvantage with common uncertainty). But for the four other information structures, winner's curse is significantly lower in the 'Buy information' treatment. Lastly, while the game was repeated for 24 periods, in the benchmark the period did not have an effect on overbidding level. On the contrary, in the treatment, the winner's curse diminish gradually as the game is repeated: this is a *learning effect*, which occurs only in the 'Buy information' treatment. In our understanding, those three effects are consistent: the treatment makes subjects more attentive to information structures and more strategic. Through these variables, we evidence that making subjects pay for information is an efficient way to signal that information has a 'value'.

But the second group of variables evidences a backfire effect of making subjects pay for information. Indeed, we trigger two new cognitive biases by trying to cancel out one, the winner's curse. First, the sunk cost fallacy which was already identified in the previous section in subjects' bids, is also present in the overbid: the more subjects have paid for information, the more they suffer from the winner's curse. But another bias appears: the value of the supplementary box, which does not have an effect in the benchmark, increases winner's curse in the 'Buy information' treatment. This "over-reaction" to the supplementary signal is then only present when this signal had a price. While bought information should be treated either as private information or public information according to its nature, subjects give additional weight to this costly information on this information, weighting it too much compared to information initially known for free. A possible explanation is the 'Placebo effect' (Shiv et al., 2005), where a pricey item is associated to a bigger economic value than the same but free item, as price may be incorrectly perceived as a quality signal. Shiv et al documented this effect thanks to a marketing experiment, where consumers informed about the price of an energy drink should report their perceived efficacy regarding its ability to increase participant's performance to real-effort tasks. Discounts in price were associated to lower efficacy by consumers (see also Plassmann et al. 2008, for neuroeconomic evidence of this effect on wine consumption). Using both laboratory and field experiment, Heffetz and Shayo (2009) also report evidence for what they called 'Non- Budgetary Constraint' effect on price elasticity of demand (price variation being associated to a same sign variation for individual demand), even if this effect was marginally significant and smaller compared to the more usual 'Budgetary Constraint' effect (price variations being associated to opposite variations in individual demand). This effect is stated in result 3

Result 3. Conjecture 3 is supported by our experiment: subjects 'overreact' to costly information compared to free information.

The treatment effect on the third group of variables (individual characteristics) is more ambiguous. First, the Raven test score, indicator of subject cognitive ability, reduces the WC in the benchmark but does not have a significant effect in the treatment. We interpret this changing effect as a co-result of the first group of variables: treatment makes all subjects more attentive and strategic towards information. Subjects with more cognitive capacities may have already partially integrated the strategic value of information in the benchmark, but the treatment put subjects on a level playing field and then cancel out the advantage of subjects with important Raven scores. Secondly, the risk aversion level, which lowers the winner's curse in the benchmark, significantly increases it in the 'Buy information' treatment. This effect can be interpreted as a co-result of the second group of variables, linked with the sunk cost fallacy. Indeed, this bias results from the fact that a successful information buyer increases his bid for the good to increase the probability of winning: risk averse subjects being more averse to potential losses due to the cost of information, they increase even more their bids to increase the probability of winning, which in fact reduces potential payoff. Thirdly, the gender effect is reinforced in the treated subjects: consistently with results from Table 4.41, which shows that men bid less than women in both treatments, and that is bidding gap is wider in the 'Buy information' treatment, Table 4.42 evidences that WC is smaller for men, and even smaller in the treatment. This result is consistent with Casari et al. (2007), who found that women are more susceptible to the winner's curse than men. Lastly, the age variable changes its sign between the two treatments: while older subjects were more susceptible to the winner's curse in the benchmark, they are less affected by the WC in the 'Buy information' treatment.

To say it in a nutshell, pricing information enables to make subjects understand information value and to act more strategically with it, reducing the winner's curse. However this effect comes along with two new cognitive failures, a sunk cost fallacy and a placebo effect, which overshadow subjects' behavioral improvements.

4.4.4 Willingness-to-pay for information: a second curse?

In this section, we investigate subjects willingness-to-pay for information and compare it to the theoretic value of information. Subjects' willingness-to-pay for information are elicited through a Becker-De Groot-Marschack procedure. We represent those bids for information on Figure 4.43. We observe that, besides being strongly scattered, they poorly vary with the amount of tokens observed in the private box(es) of the player.

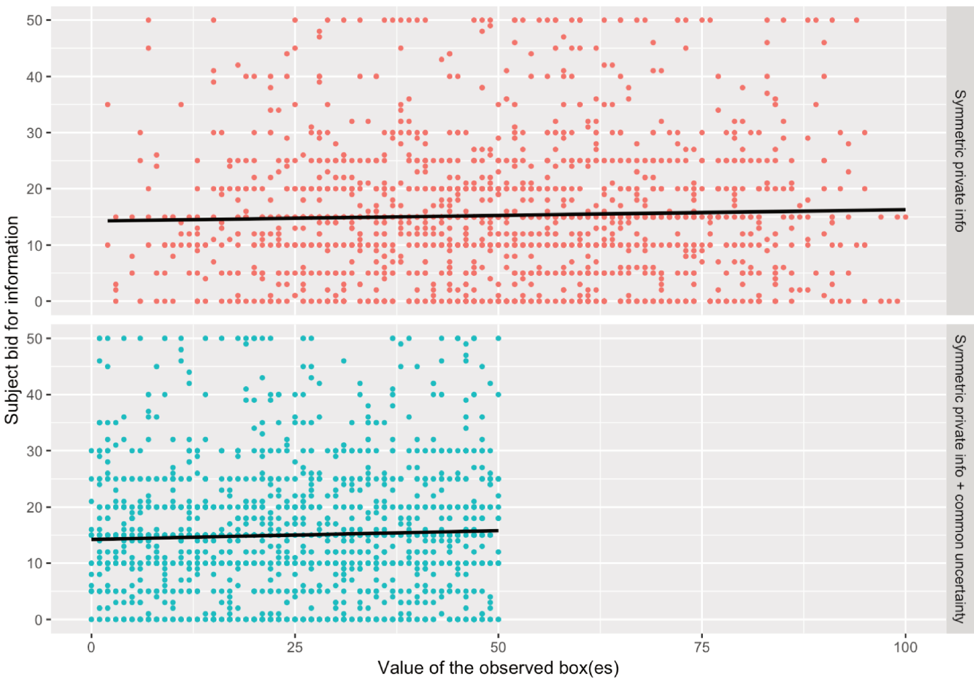


Figure 4.43: Subjects' willingness-to-pay for information

We focus on the case where subjects can bid to observe an informative box which belongs to common uncertainty, turning it into their private information. Predicted value of information was presented in Figure 4.22. On Figure ??, we represent the histogram of subjects' overbids for information. Overall, 73% of bids are superior to theoretic value of information. On average, the amount of overbid for information is 8.04 tokens, while mean bid for information is 15.0. Overbid is then massive, representing more than half of subjects' bids for information. This is a second order "winner's curse": subjects pay too much to observe a supplementary box, more than the strategic value of observing this box. This confirms conjecture 4:

Result 4. Conjecture 4 is supported by our experiment: subjects suffer from a second level Winner's Curse as they bid too much to acquire information.

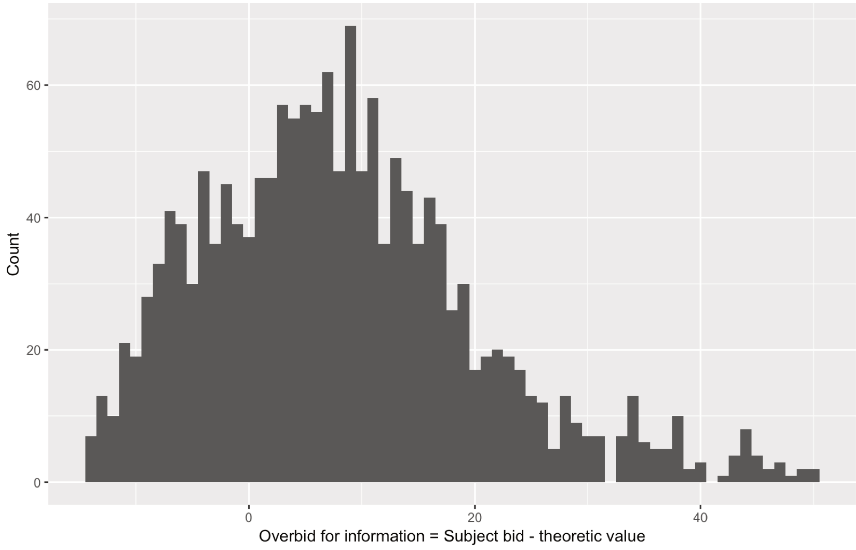


Figure 4.44: Winner's curse on information - Buying "common uncertainty"

In Table 4.43, we investigate the determinants of this "winner's curse" on information. Individual characteristics effects are consistent with previous regressions. First, as the value of the box observed by the player increases, the overbid tends to decrease. This result was expected, as mean bid for information varies poorly with the value of the observed box and is close to the maximum theoretic value of information. Secondly, effect from the Raven test score is also consistent: subjects with higher cognitive abilities are less susceptible to this second order curse. Moreover, as the period number increases, the information curse diminishes, consistently with the learning effect already identified in the previous section. Risk aversion level does not exhibit a significant effect on subjects bids for information. Like bids for the common value good, the gender variable evidences a smaller curse for male subjects. Older subjects are also less susceptible to the information winner's curse.

Table 4.43: Drivers of information's winner's curse

	Dependent variable: Overbid for information
	Subject bid - Nash equilibrium bid
Value of the observed box	$\mathbf{-0.240^{***}}$
	(0.020)
Raven score	$\mathbf{-0.527^{***}}$
	(0.097)
Risk Aversion	-0.267
	(0.167)
Period	$\mathbf{-0.250^{***}}$
	(0.039)
Gender: Man	$\mathbf{-2.238^{***}}$
	(0.580)
Age	$\mathbf{0.430^{***}}$
	(0.061)
Constant	$\mathbf{16.081^{***}}$
	(1.985)
Observations	1,584
R^2	0.156
Adjusted R^2	0.152
Residual Std. Error	11.161 (df = 1577)
F Statistic	48.439^{***} (df = 6; 1577)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.5 Concluding comments

In this laboratory experiment, we give additional evidence that Winner's Curse is a strong empirical stylized fact in Common Value Auctions under various settings. In our novel situation, where costly information enables participants to refine endogenously their expectation about the true value of the good, participants fall prey to WC.

One important debate about auctions mechanisms is the ability that prices may correctly aggregate information in a competitive environment (Kremer, 2002). Wilson (1977) was the first to show an important result regarding information aggregation in CVA: under appropriate conditions on the structure relating value to signals, price converges in probability to the true value of the object as the number of bidders goes to infinity. Pesendorfer and Swinkels (1997) generalize this result of *full-information aggregation* to the case where the number of objects goes to infinity. In a subsequent paper, Pesendorfer and Swinkels (2000) also show that this full-information aggregation conveyed by equilibrium also ensures allocative efficiency.

To say the least, even in a dynamic setting where information grows over the competitive auction, this convergence of bids to the true value of the good is seldom observed. This experimental result could be related to the small number of bidders or to this single-item auction setting, and, consequently, an interesting follow-up of our experiment would be to assess the impact on WC occurrence when group size is to be increased. Indeed, there is actually a *positive* effect of costly information that limits exposure to WC. On the one hand, participants being more aware of the item's value tend to decrease their bids for it, as information helps them to limit overbidding behavior that causes WC. In a sense, additional costly information implies more strategic players in that they tend to reduce their bids for the item, and are therefore less prone to overbidding behavior that causes subsequent WC. This is a result already observed by Goeree and Offerman (2002): efficiency of a first-price auction procedure is higher and WC less pronounced when uncertainty about the common value object is reduced. This result is consistent with theoretical models of auctions. Persico (2000), considering costly information acquisition in a Interdependent-Value model (for which our pure CVA is a special case), showed that under a FPA, learning with higher accuracy has two effects: first, the information about the own valuation becomes more precise and second, bidders obtain a better estimate of the signals of other bidders. The latter effect does not longer exist in a Second-Price Auction (SPA). As a consequence, there is a stronger incentive to acquire information in FPA compared to SPA.

But, on the other hand, paying for information acquisition conveys other individual biases that raise the probability participants fall prey to WC. The first one is a sunk cost fallacy effect, participants having actually paid for information increasing their bids to increase the probability of winning the auction. The second one is the incorrect belief that paying for information might make it more useful compared to free information, price being perceived as a signal of information quality. The last and more important effect is what we called a 'second-order WC' on information. Participants were ready to pay too much for information compared to its intrinsic economic value. In fact, combined with the former biases, this informational WC makes the usual WC (paying too much for the auction item) even stronger. These results are in line with the ones obtained by Charness et al. (2019), who showed that WC exists even in the case where information is public and identical to all players. At the end, they concluded that WC comes both from inadvisable bidding behavior and from considerable variation in the estimates for the auction item value.

This gives way to additional explanations for cognitive processes at play in economic decision-making. As underlined by Gabaix et al. (2006), dealing with experimental results involving costly information acquisition in complex problems could be better explained by using boundedly rational models.

Appendices of Chapter 4

4.A Proofs for propositions of the theory section

Proof. ***Proposition 1***

As in Brocas et al. (2015), we can treat players as symmetric. We prove the result in the case when $r = s = 1$, the second and third part of the proposition is demonstrated along the same lines. We restrict the attention to monotonic bidding strategies that are differentiable. The expected utility of player A is $U_A^{r,s} = Pr(b_A^{r,s} \geq b_B^{r,s}(X_B^s)) * (X_A^r + E[X_\emptyset^{r,s}] + E[X_B^s | b_A^{r,s} \geq b_B^{r,s}(X_B^s)] - b_A^{r,s})$ which can be rewritten:

$$U_A^{r,s} = F^s((b_B^{r,s})^{-1}(b_A^{r,s})) * (X_A^r + E[X_\emptyset^{r,s}] - b_A^{r,s}) + \int_0^{(b_B^{r,s})^{-1}(b_A^{r,s})} X_B^s f^s(X_B^s)\, \mathrm{d}X_B^s$$

The first order condition is given maximizing the expected utility of A and using the symmetry property $b_A^{r,s} = b_B^{r,s} = b_j^r$. Hence:

$$(2X_A^r + E[X_\emptyset^{r,s}])f^r(X_A^r) = F^r(X_A^r)(b_j^r)'(X_A^r) + b_j^r(X_A^r)f^r(X_A^r)$$

By integrating both sides and using the cumulative distribution $F^r(X_A^r) = \frac{X_A^r}{50}$ and the density function $f^r(X_A^r) = \frac{1}{50}$, we get $b_j^r = E[X_\emptyset^{r,s}] + X_j^r$.

□

Proof. ***Proposition 2***

We prove the result in the case when r=2 and s=1, the second part of the proposition is demonstrated along the same lines. We restrict the attention to monotonic bidding strategies that are twice differentiable. Expected utility of the players A and B are respectively $U_A^{r,s} = Pr(b_A^{r,s} \geq b_B^{r,s}(X_B^s)) * (X_A^r + E[X_\emptyset^{r,s}] + E[X_B^s | b_A^{r,s} \geq b_B^{r,s}(X_B^s)] - b_A^{r,s})$ and $U_B^{r,s} = Pr(b_B^{r,s} \geq b_A^{r,s}(X_A^r)) * (X_B^s + E[X_\emptyset^{r,s}] + E[X_A^r | b_B^{r,s} \geq b_A^{r,s}(X_A^r)] - b_B^{r,s})$. Using the cumulative distribution and the density functions enables the rewriting of the expected utility of each player as a function depending only on its bid.

$$\begin{cases} U_A^{r,s} = F^s((b_B^{r,s})^{-1}(b_A^{r,s})) * (X_A^r + E[X_\emptyset^{r,s}] - b_A^{r,s}) + \int_0^{(b_B^{r,s})^{-1}(b_A^{r,s})} X_B^s f^s(X_B^s)\, \mathrm{d}X_B^s \\ U_B^{r,s} = F^r((b_A^{r,s})^{-1}(b_B^{r,s})) * (X_B^s + E[X_\emptyset^{r,s}] - b_B^{r,s}) + \int_0^{(b_A^{r,s})^{-1}(b_B^{r,s})} X_A^r f^r(X_A^r)\, \mathrm{d}X_A^r \end{cases}$$

We get the first-order condition by maximizing expected utilities of each player with respect to their respective bids. In order to ease the reading of following equations, we introduce these notations:

- $\alpha = (b_B^{r,s})^{-1}(b_A^{r,s}(X_A^r))$ which can be interpreted as the value of the signal B needs to observe in order to bid as much as A when A observes X_A^r. Then $\alpha \in [0, 50]$.
- $\beta = (b_A^{r,s})^{-1}(b_B^{r,s}(X_B^s))$, which can be symmetrically interpreted as the value of the signal A needs to observe in order to bid as much as B when B observes X_B^s. Then $\beta \in [0, 100]$.
- $\phi(.) \equiv b_B^{r,s}(.)$, the function which associates to a signal in $[0, 50]$ the optimal equilibrium bid that player B would make.
- $\chi(.) \equiv b_A^{r,s}(.)$, the function which associates to a signal in $[0, 100]$ the optimal equilibrium bid that player A would make.

Rewriting the first-order conditions using the previous notations gives us:

$$\begin{cases} (\chi^{-1}(\phi(\alpha)) + \alpha + E[X_\emptyset^{r,s}]).f^s(\alpha) = F^s(\alpha).\phi'(\alpha) + \phi(\alpha).f^s(\alpha) \\ (\phi^{-1}(\chi(\beta)) + \beta + E[X_\emptyset^{r,s}]).f^r(\beta) = F^r(\beta).\chi'(\beta) + \chi(\beta).f^r(\beta) \end{cases}$$

$$\Leftrightarrow \begin{cases} \phi(\alpha) = \chi(\frac{F^s(\alpha)}{f^s(\alpha)}\phi'(\alpha) + \phi(\alpha) - \alpha - E[X_\emptyset^{r,s}]) \\ \chi(\beta) = \phi(\frac{F^r(\beta)}{f^r(\beta)}\chi'(\beta) + \chi(\beta) - \beta - E[X_\emptyset^{r,s}]) \end{cases}$$

Cumulative distributions and density functions of signals are different for each player as their information volumes are not symmetric:

- Player B observes only one signal, then, when $\alpha \in [0, 50]$, we have $f^s(\alpha) = \frac{1}{50}$ and $F^s(\alpha) = \frac{\alpha}{50}$.
- Player A observes two signals; using the Irvin-Hall distribution we calculate cumulative distribution and density when the sum of the two signals, *i.e.* β, belongs to $[0, 50]$ and $[50, 100]$:

$$\rightarrow \text{ When } \beta \in [0, 50] \begin{cases} f^r(\beta) = \frac{\beta}{50^2} \\ F^r(\beta) = \frac{\beta^2}{2*50^2} \end{cases}$$

$$\rightarrow \text{ When } \beta \in [50, 100] \begin{cases} f^r(\beta) = \frac{100-\beta}{50^2} \\ F^r(\beta) = 1 - \frac{(100-\beta)^2}{2*50^2} \end{cases}$$

Hence we find second-order differential equations for $\phi(.)$ and $\chi(.)$:

$$\begin{cases} \chi''(\beta).(\frac{F^r(\beta)}{f^r(\beta)})^2 + \chi'(\beta).(\frac{F^r(\beta)}{f^r(\beta)})'.(\frac{F^r(\beta)}{f^r(\beta)}) - \chi(\beta) - \frac{F^r(\beta)}{f^r(\beta)} + \beta + E[X_\emptyset^{r,s}]) = 0 \\ \phi''(\alpha).\alpha^2 + \phi'(\alpha).2\alpha - \alpha = \dfrac{F^r(\frac{F^s(\alpha)}{f^s(\alpha)}\phi'(\alpha) + \phi(\alpha) - \alpha - E[X_\emptyset^{r,s}])}{f^r(\frac{F^s(\alpha)}{f^s(\alpha)}\phi'(\alpha) + \phi(\alpha) - \alpha - E[X_\emptyset^{r,s}])} \end{cases}$$

In order to explicit the analytical solutions to these equations, we need to evidence the border solutions of A and B bidding functions. A rationale on the Nash equilibrium when both players face their respective maximal signals (*i.e.* $Max(X_A^r) = 100$ and $Max(X_B^s) = 50$) imply that $b_A^{r,s}(Max(X_A^r)) = b_B^{r,s}(Max(X_B^s)) = b_{max}$.

Lemma 1. The Nash equilibrium bid b_{max} for player A, resp. player B, when she faces its maximal signal $Max(X_A^r)$, resp. $Max(X_B^s)$, is $b_{max} = Max(X_B^s) + E[X_\emptyset^{r,s}]$.

Proof. We can cap b_{max} by looking at the expected utility of player B when $X_B^s = Max(X_B^s)$. By writing P_A^{Max} for $Prob(X_A^r = Max(X_A^r))$, expected utility of player B is her probability of winning the auction multiplied by expected profit diminished of the bid b_{max}:

$$U_B^{r,s}(Max(X_B^s), b_{max}) = (1 - \frac{P_A^{Max}}{2}) * (Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r] - b_{max})$$

As $U_B^{r,s}(Max(X_B^s), b_{max}) > 0$, we get $b_{max} < Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r]$.

We prove the equality $b_{max} = Max(X_B^s) + E[X_\emptyset^{r,s}]$ by contradiction. Let's suppose that the Nash equilibrium bid $b_{max} < E[X_\emptyset^{r,s}] + Max(X_B^s)$. Then, for any $\epsilon > 0$, expected utility of player B bidding b_{max} must be strictly superior to expected utility of the same player bidding $b_{max} + \epsilon$.

$$U_B^{r,s}(Max(X_B), b_{max}) > U_B^{r,s}(Max(X_B), b_{max} + \epsilon)$$

$$\Leftrightarrow (1 - \frac{P_A^{Max}}{2}) * (Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r] - b_{max}) > Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r] - b_{max} - \epsilon)$$

$$\Leftrightarrow \epsilon > \frac{P_A^{Max}}{2} * (Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r] - b_{max})$$

As $Max(X_B^s) + E[X_\emptyset^{r,s}] + E[X_A^r] - b_{max} > 0$, there exists an $\epsilon > 0$ which yields $U_B^{r,s}(Max(X_B), b_{max} + \epsilon) > U_B^{r,s}(Max(X_B), b_{max})$, which is a contradiction. Indeed player

B benefits from deviating unilaterally its own strategy by bidding above b_{max} as it strictly increases its expected utility. Then $b_{max} < E[X_{\emptyset}^{r,s}] + Max(X_B^s)$ cannot be a Nash equilibrium.

Let's now suppose that the Nash equilibrium bid b_{max} is strictly superior to $E[X_{\emptyset}^{r,s}] + Max(X_B^s)$. For any $\epsilon > 0$, expected utility of player B bidding b_{max} must be strictly superior to expected utility of the same player bidding $b_{max} - \epsilon$. We get:

$$\forall \epsilon > 0, U_B^{r,s}(Max(X_B), b_{max}) > U_B^{r,s}(Max(X_B), b_{max} - \epsilon)$$

With:

$$\begin{cases} U_B^{r,s}(Max(X_B), b_{max}) = (1 - \frac{P_A^{Max}}{2}) * (Max(X_B^s) + E[X_{\emptyset}^{r,s}] + E[X_A^r] - b_{max}) \\ U_B^{r,s}(Max(X_B), b_{max} - \epsilon) = (1 - P_A^{Max}) * (Max(X_B^s) + E[X_{\emptyset}^{r,s}] \\ \qquad + E[X_A^r \mid X_A^r < Max(X_A^r)] - b_{max} - \epsilon) \end{cases}$$

As $E[X_A^r \mid X_A^r < Max(X_A^r)] < E[X_A^r]$, we get the following inequality:

$$\epsilon > \frac{P_A^{Max}}{2(1-P_A^{Max})} * (Max(X_B^s) + E[X_{\emptyset}^{r,s}] + E[X_A^r] - b_{max})$$

As $Max(X_B^s) + E[X_{\emptyset}^{r,s}] + E[X_A^r] > b_{max}$, there exists an $\epsilon > 0$ which yields $U_B^{r,s}(Max(X_B), b_{max} - \epsilon) > U_B^{r,s}(Max(X_B), b_{max})$, which is a contradiction. Indeed player B benefits from deviating unilaterally her strategy by bidding below b_{max} as it strictly increases its expected utility. Then $b_{max} > E[X_{\emptyset}^{r,s}] + Max(X_B^s)$ cannot be a Nash equilibrium. □

Thus $b_{max} = E[X_{\emptyset}^{r,s}] + Max(X_B^s)$. Given our parameters, $b_{max} = 75$. This initial condition, together with the continuity of $\chi(\beta)$ and $\chi'(\beta)$ in $\beta = 50$, yields the results of the proposition 2:

$$\begin{cases} \phi(\alpha) = E[X_{\emptyset}^{r,s}] + \frac{\alpha}{2} + 5\sqrt{\frac{\alpha}{2}} \\ \\ \chi(\beta) = E[X_{\emptyset}^{r,s}] + \begin{cases} \frac{2}{3} * \beta & \text{if } \beta \leq 50 \\ \frac{2}{3} * \frac{125000+(\beta-150)(\beta)^2}{5000+(\beta-200)(\beta)} & \text{if } \beta \geq 50 \end{cases} \end{cases}$$

□

4.B Instructions for the "BUY" sessions

A

Instructions

Bonjour à tous et bienvenue dans cette session.

Les décisions que vous allez prendre se feront par l'intermédiaire de l'ordinateur qui est devant vous, et toutes les interactions avec les autres participants se feront par cet intermédiaire.

Merci de ne pas communiquer oralement ni d'aucune manière que ce soit avec les autres participants, sous peine d'être exclu de la session (et donc des gains).

La session comportera 3 phases. Dans une première phase, vous répondrez à 16 questions. Dans la seconde phase, celle du jeu 1, vous interagirez avec d'autres participants de la session. Lors de la troisième phase, celle du jeu 2, vous prendrez des décisions individuelles.

Vos gains à l'issue de cette session dépendront de vos décisions, des décisions des autres concurrents et du hasard. Les gains peuvent différer d'un participant à l'autre.

Le montant que vous gagnerez à la fin de la session sera la somme de vos gains lors du jeu 1 et du jeu 2, à quoi s'ajoutera un forfait de participation de 4 euros. Chacun d'entre vous sera payé par chèque à la fin de l'expérience.

Questionnaire

Votre écran va faire apparaître une série de questions auquel vous devez répondre. Tous les participants de cette session devront répondre aux mêmes questions.
Merci de bien vouloir répondre à ce questionnaire, en suivant les instructions décrites ci-dessous :

(1) Pour chacune des questions, choisissez, parmi les 8 options affichées en bas de l'écran, l'image la plus adaptée pour remplir l'espace blanc dans le dessin du dessus. Afin d'enregistrer votre choix, veuillez cocher le nombre y correspondant dans la partie droite de l'écran, puis appuyez sur le bouton « OK ».

(2) Il y a 16 questions au total. Essayez de répondre correctement au plus grand nombre de questions possible dans le délai imparti de 10 minutes.

(3) Si vous souhaitez accéder directement à une question, vous pouvez entrer son numéro (1-16) et appuyer sur le bouton « Aller » dans la partie gauche de l'écran.

(4) Vous pouvez également passer à la question précédente (suivante) en appuyant sur les boutons « Précédente » (« Suivante ») figurant dans le coin inférieur gauche de l'écran.

1

A

Jeu 1

Nous allons commencer par vous expliquer les règles du premier jeu. A l'issue des instructions, il y aura un questionnaire de compréhension très bref. Il faut donc que vous soyez très attentif durant la lecture des instructions, et si vous avez la moindre question durant cette lecture, svp levez la main et un des instructeurs viendra vous répondre.

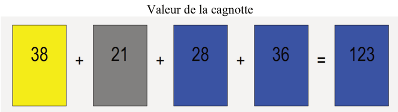
Vos gains durant ce jeu sont donnés en points. Vous commencez le jeu avec une dotation de 300 points. En fonction de vos décisions, vous pourrez gagner ou perdre des points. A la fin du jeu, l'ordinateur comptera le nombre total de points accumulés et les convertira en euros selon la règle suivante : 1 euro pour 25 points gagnés.

Le jeu 1 consiste en 24 périodes. A chaque période, vous formerez une paire d'acheteurs potentiels avec un participant tiré au sort dans la session. Comme il y a 20 participants dans la session, il y aura à chaque période 10 paires d'acheteurs. L'identité de l'autre participant avec lequel vous allez interagir ne vous sera pas donnée, tout comme votre identité ne sera pas communiquée à l'autre acheteur. Votre gain dépendra uniquement de vos décisions, des décisions de l'autre acheteur, et aussi du hasard, mais en aucun cas des décisions prises par les autres paires de participants. Vos décisions ne seront pas connues des autres participants, tout comme vous ne connaitrez pas les leurs.

Au début de chaque période, l'ordinateur formera des paires d'acheteurs en tirant au sort parmi les participants de la session, et au sein de chaque paire, un des acheteurs sera l'acheteur « Jaune » et l'autre l'acheteur « Bleu ». Chaque participant au sein d'une paire a les mêmes chances d'être l'acheteur « Jaune » ou « Bleu ». A l'issue de chaque période, l'ordinateur tirera à nouveau au sort les paires et les rôles pour chaque participant. Dès lors, si vous êtes en interaction avec un participant lors d'une période donnée, il y a de fortes chances que vous soyez en interaction avec un autre participant lors de la période suivante.

Une fois les paires constituées au début de chaque période, chaque acheteur devra faire une proposition pour acheter une cagnotte. L'écran ci-dessous illustre comment la valeur de la cagnotte (en points) sera déterminée par l'ordinateur.

Valeur de la cagnotte



La cagnotte a une valeur qui sera la somme des valeurs de 4 boites. Dans la capture d'écran ci-dessus, les valeurs de chaque boite de gauche à droite sont « 38 », « 21 », « 28 » et « 36 ». Par conséquent, la valeur de la cagnotte est

Valeur de la cagnotte = 31 + 21 +28 + 36 = 123

Les chiffres donnés ici sont uniquement à titre illustratif et l'écran ci-dessus ne correspond pas nécessairement à ce qui s'affichera sur votre écran, il permet juste ici d'expliquer comment la

2

A

valeur de la cagnotte sera déterminée par l'ordinateur. Notez que, compte tenu des nombres possibles pour chaque boite, la cagnotte peut valoir un minimum de 0 points (0 point dans les quatre boites) et un maximum de 200 points (50 points dans les quatre boites).

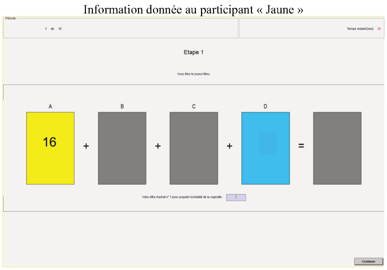
La valeur des boites sera tirée au sort par l'ordinateur en début de période entre 0 et 50 points, chaque valeur entre 0 et 50 ayant exactement les mêmes chances d'être tirées au sort (seules les valeurs entières sont possibles, soit 0, 1, ..., 49, 50).
Chaque tirage au sort est réalisé par l'ordinateur pour chaque boîte de manière indépendante. Le fait d'avoir une valeur élevée pour la première boite de gauche ne signifie pas qu'il y a moins de chances d'avoir une valeur élevée pour la seconde boite en partant de la gauche.

Durant une même période, la valeur de la cagnotte sera déterminée au début de la période par l'ordinateur et ne changera pas. Toutefois, l'information concernant les valeurs de boites vous sera communiquée graduellement, et pas en une seule fois.
Plus précisément, chaque période sera divisée en *deux étapes*. Les participants gardent les mêmes rôles au sein d'une même paire. A chaque étape, vous pourrez faire des propositions d'achat. La *première étape* vous donnera la possibilité d'observer de l'information sur la valeur des boites et de faire une première proposition d'achat de la cagnotte, tandis que la *seconde étape* vous donnera la possibilité d'acheter éventuellement plus d'information et de faire une seconde proposition d'achat de la cagnotte. L'autre acheteur de votre paire aura également les mêmes possibilités (observer de l'information et faire des propositions d'achat).

a) Etape 1

Lors de l'étape 1, au début de cette étape, chaque participant verra un écran similaire à l'écran ci-dessous.
Le participant « Jaune » verra soit la valeur de la boite « A » située à l'extrême gauche, soit les valeurs des 2 boites « A » et « B » les plus à gauche (ces boites sont de couleur jaune), comme dans l'écran ci-dessous.

Information donnée au participant « Jaune »

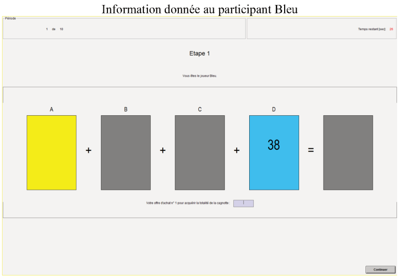


3

A

Le participant « Bleu » verra soit la valeur de la boite située à l'extrême droite (boite « D »), soit les valeurs des 2 boites les plus à droite (ces boites sont de couleur bleue et appelées « C » et « D »), comme dans l'écran ci-après :

Information donnée au participant Bleu



Le participant « Jaune » connaît la valeur de la boite jaune (la boite « A », c'est son « information »), mais pas la valeur de la boite « D » (bleue). Au contraire, le participant « Bleu » connaît la valeur de la boite bleue « D » mais pas de la boite jaune « A ».

Dans le cas où chaque participant observe la valeur d'une seule boite, les deux participants voient aussi les deux boites centrales, mais ne connaissent pas leurs valeurs (*les boites dont les valeurs ne sont connues d'aucun participant seront de couleur grise*). Dans le cas où chaque participant observe les valeurs de deux boites, le participant « Jaune » n'observe pas la valeur des deux boites de droite (dont la valeur est par contre connue par le participant « Bleu ») et le participant « Bleu » n'observe pas la valeur des deux boites de gauche (connues par le participant « Jaune »).
Notez bien que le participant « Jaune » peut observer la valeur d'une (la boite « A ») ou de deux boites (les boites « A » et « B »), et que le participant « Bleu » peut observer la valeur d'une (la boite « C ») ou de deux boites (« C » et « D »).

Une fois que les deux participants « Jaune » et « Bleu » obtiennent de l'information sur la valeur de certaines boites, ils devront faire une proposition d'achat pour la cagnotte. Dans l'exemple ci-dessus, le participant « Jaune » sait que la valeur de la cagnotte est au moins de 16 (c'est ce qu'il observe) mais ne sait pas ce que sont les valeurs des autres boites à droite. Au contraire, le participant « Bleu » sait que la valeur de la cagnotte est au moins de 38 (c'est ce qu'il observe), mais ne sait pas quels sont les valeurs des autres boites à gauche. *La valeur des boites de couleur jaune ne sera connue que par le participant jaune, tandis que la valeur des boites de couleur bleue ne sera connue que par le participant bleu.*
Dans cette étape compte tenu des informations dont vous disposez, vous devrez faire **une proposition d'achat** pour la cagnotte par l'intermédiaire de votre ordinateur. Le participant avec lequel vous formez une paire fera de même. Vous ne connaitrez pas sa proposition, et il

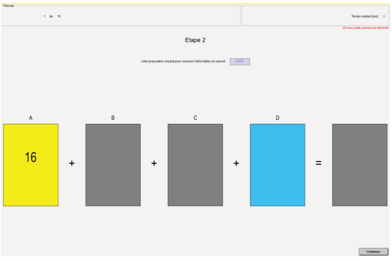
4

A

ne connaitra pas la vôtre, comme tous les autres participants. Cette proposition doit être comprise entre 0 et 200, tous les entiers étant possibles, et ne peut être (strictement) supérieure à 200 points (il s'agit de la valeur maximale de la cagnotte).

a) Etape 2

Au début de l'étape 2, l'ordinateur vous donnera la possibilité d'acheter une information supplémentaire sur la valeur d'une boite.
La procédure d'achat d'information sera la suivante. Si vous êtes le participant « jaune », vous pourrez acheter une information sur la valeur de la boite à droite des boites jaunes dont vous connaissez déjà la valeur (révélées lors de l'étape 1). Si vous êtes le participant « bleu », vous pourrez acheter une information sur la valeur de la boite à gauche des boites bleues dont vous connaissez déjà la valeur. Un exemple d'écran pour le participant jaune est donné ci-dessous :



Ici, le participant jaune connaît la valeur de la boite jaune, qui est de 16, information qu'il a obtenue lors de l'étape 1, information qui n'est pas connue par le participant bleu. Il peut proposer d'acheter l'information concernant la valeur de la boite B.
Le participant bleu connaitra la valeur de la boite bleue D lors de l'étape 1, cette information n'étant pas connue par le participant jaune. Il peut aussi proposer d'acheter de l'information sur la valeur de la boite C. Chaque participant ne peut acheter de l'information que sur la valeur d'une seule boite.

Pour acheter l'information, vous avez la possibilité de proposer un prix compris entre 0 et 50 points (seuls les entiers sont possibles) et vous jouerez contre l'ordinateur. L'ordinateur tirera au sort un chiffre compris entre 0 et 50, chaque nombre entier ayant les mêmes chances d'être tiré au sort. Si le chiffre tiré au sort par l'ordinateur est plus petit que votre proposition, alors vous pourrez acheter l'information et le prix que vous paierez correspondra au chiffre tiré au sort par l'ordinateur. Si le chiffre tiré au sort par l'ordinateur est plus grand que votre proposition, alors vous ne pourrez pas acheter l'information. Tous les participants désirant acheter de l'information et proposant des prix pour obtenir l'information seront soumis à la

5

A

même règle. Il y aura autant de tirages au sorts indépendants et potentiellement différents qu'il y a de participants. Surtout, la possibilité d'acheter de l'information sera proposée à tous les participants, quel que soit leur rôle.
Si vous avez gagné le droit d'acheter de l'information (conformément à la procédure décrite à l'instant), alors l'ordinateur vous communiquera la valeur d'une boite supplémentaire. Le prix d'achat de l'information sera déduit de votre gain à la fin de la période. Si vous n'avez pas acheté d'information, aucun montant ne sera déduit de votre gain à la fin de la période.

Par conséquent, le participant jaune pourra connaître la valeur d'une, deux ou trois boites. Il en est de même pour le participant « Bleu ». De plus, il est possible que la valeur d'une ou de deux boites communes soit connue par les deux participants.
Un exemple d'écran pour le participant jaune est donné ci-dessous :

Ici, le participant « Jaune » connait les valeurs des boites jaunes, 14 et 3, informations obtenues lors de l'étape 1, et inconnues du participant bleu. Il obtient de plus à l'étape 2 la valeur de la boite verte qui est de 30. Cette information est également connue par le participant « Bleu » (*la couleur verte de la boite signifie que l'information est connue des deux participants*).
Au début de l'étape 2, un écran récapitulera les informations dont vous disposez concernant la valeur de la cagnotte.
Dans cette étape, compte tenu des informations dont vous disposez, vous devrez à nouveau faire une proposition d'achat pour la cagnotte par l'intermédiaire de votre ordinateur, tout comme l'autre participant.
Puis, au sein de chaque paire, l'ordinateur tirera au sort quelle étape comptera pour la détermination du gain final, soit la 1ère, soit la seconde. Pour l'étape sélectionnée, il comparera les deux propositions et le participant ayant fait la proposition la plus élevée remportera la valeur de la cagnotte. Il paiera le prix qu'il a proposé lors de l'étape sélectionnée. Le participant qui n'a pas emporté la cagnotte gagnera 0 points. Par exemple, supposons que le participant jaune a fait une proposition de 10 dans l'étape 1 et de 18 dans l'étape 2, alors que le participant bleu a fait une proposition de 20 dans l'étape 1 et de 15 dans l'étape 2. Si l'ordinateur tire au sort l'étape 1, alors le participant bleu gagne et il paiera la cagnotte 20 points. Si l'ordinateur tire au sort l'étape 2, alors c'est le participant jaune qui gagne et il paiera la cagnotte 18 points. Le participant qui n'a pas emporté la cagnotte gagnera 0 points.

6

A

A l'issue de l'étape 2, la période sera terminée, et l'ordinateur vous donnera un certain nombre d'informations : si vous avez gagné, la valeur de la cagnotte (c'est-à-dire la somme des valeurs des 4 boites), le prix que vous payez si vous l'avez emporté, le prix d'achat de l'information éventuel et votre gain net pour la période. Le gain net sera égal à :

Gain net pour la période = valeur de la cagnotte – prix payé pour le bien – prix payé pour l'information

Si vous n'avez pas emporté la cagnotte, votre gain net sera égal à :

Gain net pour la période = 0

L'ordinateur affichera aussi votre gain cumulé pour la période en cours. Ce gain cumulé est calculé comme suit :

Gain cumulé à la période (t) = 300 + gain période 1 + gain période 2 + …+ gain période t

Récapitulatif

Votre objectif dans cette partie est d'acheter une cagnotte, sachant que vous êtes 2 acheteurs à pouvoir faire des propositions. La valeur de ce bien n'est pas totalement connue par vous ou par l'autre acheteur. Vous aurez la possibilité d'obtenir de l'information (gratuitement ou moyennant un prix) avant de faire une proposition d'achat de la cagnotte.
Pour l'information sur la valeur des boites, n'oubliez pas que :
- La valeur des boites de couleur jaune ne sont connues que du participant jaune,
- La valeur des boites de couleur bleue ne sont connues que du participant bleu,
- La valeur des boites de couleur grise est inconnue des deux participants,
- La valeur des boites de couleur verte est connue par les deux participants.

Votre gain dépendra de la valeur de la cagnotte (qui dépend du tirage au sort par l'ordinateur des valeurs des boites), du prix d'achat éventuel de cette cagnotte et du prix d'achat éventuel de l'information.

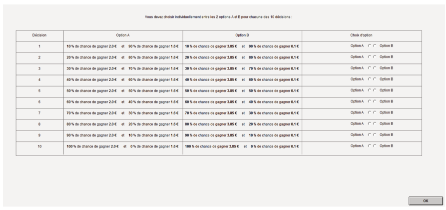
Bonne chance !

7

A

Jeu 2

Vous avez 10 décisions à prendre, chacune consiste à choisir une option parmi deux options : l'option A et l'option B. Chaque option vous permet d'obtenir un gain en euros avec un certain niveau de chances. Par exemple, pour la décision 3 (voir tableau ci-dessous), l'option A vous donne 30% de chances de gagner 2 euros et 70% de chance de gagner 1,6 euros, tandis que l'option B vous donne 30% de chances de gagner 3,85 euros et 70% de chances de gagner 0,1 euros.
Vous devez indiquer votre choix d'option pour chaque décision en cliquant sur l'option correspondante (dans la colonne à droite du tableau intitulée "choix d'option").



Vous devez choisir individuellement entre les 2 options A et B pour chacune des 10 décisions :

Décision	Option A	Option B	Choix d'option
1	10 % de chance de gagner 2.0 € et 90 % de chance de gagner 1.6 €	10 % de chance de gagner 3.85 € et 90 % de chance de gagner 0.1 €	Option A Option B
2	20 % de chance de gagner 2.0 € et 80 % de chance de gagner 1.6 €	20 % de chance de gagner 3.85 € et 80 % de chance de gagner 0.1 €	Option A Option B
3	30 % de chance de gagner 2.0 € et 70 % de chance de gagner 1.6 €	30 % de chance de gagner 3.85 € et 70 % de chance de gagner 0.1 €	Option A Option B
4	40 % de chance de gagner 2.0 € et 60 % de chance de gagner 1.6 €	40 % de chance de gagner 3.85 € et 60 % de chance de gagner 0.1 €	Option A Option B
5	50 % de chance de gagner 2.0 € et 50 % de chance de gagner 1.6 €	50 % de chance de gagner 3.85 € et 50 % de chance de gagner 0.1 €	Option A Option B
6	60 % de chance de gagner 2.0 € et 40 % de chance de gagner 1.6 €	60 % de chance de gagner 3.85 € et 40 % de chance de gagner 0.1 €	Option A Option B
7	70 % de chance de gagner 2.0 € et 30 % de chance de gagner 1.6 €	70 % de chance de gagner 3.85 € et 30 % de chance de gagner 0.1 €	Option A Option B
8	80 % de chance de gagner 2.0 € et 20 % de chance de gagner 1.6 €	80 % de chance de gagner 3.85 € et 20 % de chance de gagner 0.1 €	Option A Option B
9	90 % de chance de gagner 2.0 € et 10 % de chance de gagner 1.6 €	90 % de chance de gagner 3.85 € et 10 % de chance de gagner 0.1 €	Option A Option B
10	100 % de chance de gagner 2.0 € et 0 % de chance de gagner 1.6 €	100 % de chance de gagner 3.85 € et 0 % de chance de gagner 0.1 €	Option A Option B

OK

8

* * *

* * *

«Je tremble toujours de n'avoir écrit qu'un soupir, quand je crois avoir noté une vérité.»

–Stendhal.

* * *

General Conclusion

This dissertation has investigated the role of information on energy efficiency in the development of the sustainable habitat market. The two first chapters study the effects of the main informational tool set up by policy makers in the European Union, namely the Energy Performance Certificate. Both its perception by households and its capitalization by the real estate market are examined, using an artefactual field experiment for the first and a hedonic estimation for the latter. In the following chapters, we extend the analysis of information value to its strategic dimensions. The third chapter proposes a theoretic analysis of behaviors when information is both public and noisy, while the fourth chapter explores the Willingness-To-Pay for information through a laboratory experiment.

The approach adopted in the first chapter to evaluate the efficiency of energy labels is new as it proposes to assess the performance of this informational tool towards its primary goal, namely *informing* people, and not towards its expected second-generation consequences on the real estate market. Three main lessons can be drawn from this experiment. First, attention to the label is not constant across the population, and some socio-demographic variables appear to have an important impact on this changing attention. Second, the reliability of the EPC could be enhanced, as it appears that people who have in the past dealt with the label have a lower confidence in it. Third, and more interestingly, subjects seem to draw information on energy efficiency from the design of the EPC rather than from its intrinsic information. Nonetheless, this information is not used directly but combined with prior beliefs to shape posterior beliefs of subjects regarding energy efficiency. We draw two main recommendations from these results, which could both be used to improve labelling of energy efficiency and to enlighten the development of others informational tools to drive consumers' choices. On the one hand, the visual design matters, potentially more than the intrinsic information on which it is based. It affects both the cognitive salience of a label, and the heuristic that will be used by people to treat this information. On the other hand, reliability of an informational tool is key to induce a significant shift in people's perception.

The second chapter provides estimates of the green premium of the different energy classes in two French real estate markets. The contribution to the literature lies in the demonstration that the green value should be considered in absolute terms rather than relative ones. The gradual green premiums identified for the various energy classes match with a capitalization of the corresponding renovation costs. Nonetheless, on the buyer side, the estimates of discounted energy savings are too low to explain fully those green premiums. A first explanation could be that households choosing efficient houses differ from the whole set of buyers due to strongly future-oriented time preferences, such as a time horizon beyond 20 years and discount rates below 4%. A second and complementary explanation roots in the ancillary benefits of energy renovations, such as improved thermal comfort and protection against regulatory uncertainty. These encouraging findings show that the energy labels are able to reduce adverse selection regarding efficiency of housing. A challenge of the renovation market then lies in the energy renovations dynamics. To speed the uptake rate, targeted behavioral interventions that pull time preferences towards the future and emphasize co-benefits of energy renovations could be more efficient than uniform and costly subsidies.

The third chapter deepens this analysis of the renovation dynamics by spotlighting another informational failure that could hinder renovation decision. Uncertainty on warmth insulation outcomes can create a free rider problem: households postpone their renovation decision to benefit from other's experience. Teething troubles of energy efficiency devices could then lead to important delays in housing energy performance improvement. While Chapter 1 and 2 underlined the importance of information reliability to foster a green differentiation of low consumption houses in the real estate market, Chapter 3 highlights the key role of reliable information to prevent the freezing of renovations at a low uptake rate. Two main lessons can be drawn for policy-makers. First, consistently with the recent literature recommendations on energy efficiency, targeted policies might be more efficient than uniform ones (see Gillingham and Palmer, 2014). Second, as information production is suboptimal in this framework, the development of reliable information regarding outcomes of renovation should be favored. This information production could be provided by third parties, as some recent technological inventions could soon offer a measure of energy efficiency, much more reliable than today's estimation method of Energy Performance Certificates.

The fourth and last chapter of this dissertation investigates people's Willingness-To-Pay for information on quality, and the effect of this information on behaviors. The laboratory experiment tested subjects' behaviors in a common-value auction game. A well-known cognitive failure associated to CVA games is the Winner's Curse, which could, in the specific context of energy efficiency for housing, cap the green differentiation of low consumption houses. Comparing a free information arrival to a costly one, we find that pricing information can efficiently signal information value to subjects and make them use it more strategically. However, pricing information through a bidding process also leaves room to several cognitive biases, which lead subjects to largely overpay information. The magnitude of this "informational winner's curse" is of such importance that it annihilates the strategic gains of information pricing, at least in our framework. It is complex for subjects to understand the true value of information, and as production of reliable information is important to foster the development of greener buildings, this justifies public intervention. In order to prevent some welfare loss among households, who could pay too much for energy efficiency expertise, policy makers might consider the introduction of a flat rate pricing for energy audits. This subject deserves particular attention from the public authorities as Energy Performance Certificates, which were until now purely informative, will become enforceable by the buyer (or tenant) against the seller (or landlord) in 2021 in France[1]. This new regulation together with technologies enabling the measurement of energy performance will probably have important effects on the sustainable habitat market. Further research on this topic could be useful to understand and propose innovative ways to contractualize energy performance.

More broadly, the present dissertation demonstrates that informational interventions are required to enable the development of sustainable habitat. While information disclosure is powerful, the related instruments must be carefully designed and implemented to be fully effective given the limits of human mind in treating complex and miscellaneous information. As environmental externalities related to energy production are increasingly well documented and go beyond climate change, we know that pricing carbon will not be enough to engage the ecological transition. But the important social opportunity costs of public funds advocate for the development of smart and targeted policies rather than scattering subsidies to energy efficiency.

[1] https://www.legifrance.gouv.fr/eli/loi/2018/11/23/2018-1021/jo/article_179

* * *

Bibliography

ADEME (2013). Chiffres clés du bâtiment. *French National Agency for Environment and Energy Management.*

ADEME (2018). Enquête TREMI, Travaux de Rénovation Energétiques des Maisons Individuelles. *French National Agency for Environment and Energy Management.*

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics 84*(3), 488–500.

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics 95*(9-10), 1082–1095.

Allcott, H. and M. Greenstone (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives 26*(1), 3–28.

Allibe, B. (2012). *Modélisation des consommations d'énergie du secteur résidentiel français à long terme-Amélioration du réalisme comportemental et scénarios volontaristes.* Ph. D. thesis, Ecole des Hautes Etudes en Sciences Sociales (EHESS).

Alzetto, F., G. Pandraud, R. Fitton, I. Heusler, and H. Sinnesbichler (2018). QUB: A fast dynamic method for in-situ measurement of the whole building heat loss. *Energy and Buildings 174*, 124–133.

Andersson, O., H. J. Holm, J.-R. Tyran, and E. Wengström (2016). Risk aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association 14*(5), 1129–1154.

Andor, M., A. Gerster, and S. Sommer (2016). Consumer inattention, heuristic thinking and the role of energy labels. *USAEE Working Paper No. 16-287*.

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American Economic Review 53*(5), 941–973.

Arrow, K. J. and A. C. Fisher (1974). Environmental preservation, uncertainty, and irreversibility. *The Quarterly Journal of Economics 88*(2), 312–319.

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

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics 107*(3), 797–817.

Banque de France (2017). Crédits aux particuliers, france, décembre 2016. *Stat Info, Webpage.*

Bartiaux, F. (2003). A socio-anthropological approach to energy related behaviours and innovations at the household level. *ECEEE (European Council for Energy-Efficient Economy): ECEEE 2003 summer study proceedings–Time to turn down energy demand*, 1239–1250.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management science 15*(5), 215–227.

Bâtiprix (2015). *http://www.batiprix.com/.*

Baudry, M. (2008). Un modèle canonique d'option réelle bayesienne et son application au principe de précaution. *Annales d'Economie et de Statistique*, 91–119.

Baudry, M. and C. Bonnet (2019). Demand-pull instruments and the development of wind power in europe: a counterfactual analysis. *Environmental and Resource Economics 73*(2), 385–429.

Beck, M., N. Rivers, and R. Wigle (2018). How do learning externalities influence the evaluation of Ontario's renewables support policies? *Energy Policy 117*, 86–99.

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

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy 100*(5), 992–1026.

Bollinger, B. and K. Gillingham (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science 31*(6), 900–912.

Bonsall, T. E. (2002). *Disaster in Dearborn: The story of the Edsel.* Stanford University Press.

Bowes, D. R. and K. R. Ihlanfeldt (2001). Identifying the impacts of rail transit stations on residential property values. *Journal of Urban Economics 50*(1), 1–25.

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

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

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

Brocas, I., J. D. Carrillo, and M. Castro (2015). The nature of information and its effect on bidding behavior: Laboratory evidence in a first price common value auction. *Journal of Economic Behavior & Organization 109*, 26–40.

Brocas, I., J. D. Carrillo, and M. Castro (2017). Second-price common value auctions with uncertainty, private and public information: experimental evidence. *Journal of Behavioral and Experimental Economics 67*, 28–40.

Brooks, J. (1963). *The Fate of the Esdel & Other Business Adventures.* Harper & Row.

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

Burks, S. V., J. P. Carpenter, L. Goette, and A. Rustichini (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences 106*(19), 7745–7750.

Cabral, L. M. (1990). On the adoption of innovations with 'network' externalities. *Mathematical Social Sciences 19*(3), 299–308.

Cajias, M. and D. Piazolo (2013). Green performs better: energy efficiency and financial return on buildings. *Journal of Corporate Real Estate 15*(1), 53–72.

Capen, E. C., R. V. Clapp, W. M. Campbell, et al. (1971). Competitive bidding in high-risk situations. *Journal of Petroleum Technology 23*(06), 641–653.

Carpenter, P. A., M. A. Just, and P. Shell (1990). What one intelligence test measures: a theoretical account of the processing in the raven progressive matrices test. *Psychological Review 97*(3), 404.

Carroll, J. B. et al. (1993). *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge University Press.

Casari, M., J. C. Ham, and J. H. Kagel (2007). Selection bias, demographic effects, and ability effects in common value auction experiments. *The American Economic Review 97*(4), 1278–1304.

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

CEREN (2018). *https://www.ceren.fr/publications.*

CGDD (2015). La rénovation thermique des logements: quels enjeux, quelles solutions ? *French Ministry of Energy, Environment and Sustainable Development.*

Chamley, C. and D. Gale (1994). Information revelation and strategic delay in a model of investment. *Econometrica: Journal of the Econometric Society*, 1065–1085.

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

Charness, G., U. Gneezy, and M. A. Kuhn (2012). Experimental methods: Between-subject and within-subject design. *Journal of Economic Behavior & Organization 81*(1), 1–8.

Charness, G., D. Levin, and D. Schmeidler (2019). An experimental study of estimation and bidding in common-value auctions with public information. *Journal of Economic Theory 179*, 73–98.

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

Coller, M. and M. B. Williams (1999). Eliciting individual discount rates. *Experimental Economics 2*(2), 107–127.

Costa-Gomes, M., V. P. Crawford, and B. Broseta (2001). Cognition and behavior in normal-form games: An experimental study. *Econometrica 69*(5), 1193–1235.

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

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

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

De Groote, O., F. Verboven, et al. (2018). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *The American Economic Review.*

Dharshing, S. and S. L. Hille (2017). The energy paradox revisited: Analyzing the role of individual differences and framing effects in information perception. *Journal of Consumer Policy 40*(4), 485–508.

Dixit, A. K., R. K. Dixit, and R. S. Pindyck (1994). *Investment under uncertainty.* Princeton University Press.

Eichholtz, P., N. Kok, and J. M. Quigley (2010). Doing well by doing good? green office buildings. *The American Economic Review 100*(5), 2492–2509.

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

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

European Commission (2017, November). European union energy in figures, statistical pocketbook 2017.

Ferrara, M., J. Virgone, E. Fabrizio, F. Kuznik, and M. Filippi (2013). Modeling zero energy building: technical and economical optimization. In *CLIMAMED 2013*, pp. 8–pages.

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

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*(2), 171–178.

Fowlie, M., M. Greenstone, and C. Wolfram (2015). Are the non-monetary costs of energy efficiency investments large? Understanding low take-up of a free energy efficiency program. *The American Economic Review 105*(5), 201–04.

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

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

Gabaix, X., D. Laibson, G. Moloche, and S. Weinberg (2006). Costly information acquisition: Experimental analysis of a boundedly rational model. *The American Economic Review 96*(4), 1043–1068.

Gale, D. (1996). What have we learned from social learning? *European Economic Review 40*(3), 617–628.

Gerarden, T. D., R. G. Newell, and R. N. Stavins (2017). Assessing the energy-efficiency gap. *Journal of Economic Literature 55*(4), 1486–1525.

Gibbons, S. (2015). Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *Journal of Environmental Economics and Management 72*, 177–196.

Gill, D. and V. Prowse (2016). Cognitive ability, character skills, and learning to play equilibrium: A level-k analysis. *Journal of Political Economy 124*(6), 1619–1676.

Gillingham, K., M. Harding, D. Rapson, et al. (2012). Split incentives in residential energy consumption. *Energy Journal 33*(2), 37–62.

Gillingham, K., M. J. Kotchen, D. S. Rapson, and G. Wagner (2013). Energy policy: The rebound effect is overplayed. *Nature 493*(7433), 475.

Gillingham, K., R. G. Newell, and K. Palmer (2009). Energy efficiency economics and policy. *Annu. Rev. Resour. Econ. 1*(1), 597–620.

Gillingham, K. and K. Palmer (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy 8*(1), 18–38.

Gillingham, K. and T. Tsvetanov (2018). Nudging energy efficiency audits: Evidence from a field experiment. *Journal of Environmental Economics and Management 90*, 303–316.

Giraudet, L.-G., S. Houde, and J. Maher (2018). Moral hazard and the energy efficiency gap: Theory and evidence. *Journal of the Association of Environmental and Resource Economists 5*(4), 755–790.

Goeree, K. and T. Offerman (2002). Efficiency in auctions with private and common values: An experimental study. *The American Economic Review 92*(3), 625–643.

Gollier, C., B. Jullien, and N. Treich (2000). Scientific progress and irreversibility: an economic interpretation of the 'precautionary principle'. *Journal of Public Economics 75*(2), 229–253.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association 1*(1), 114–125.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica, Journal of the Econometric Society*, 501–522.

Grosskopf, B., L. Rentschler, and R. Sarin (2018). An experiment on first-price common-value auctions with asymmetric information structures: The blessed winner. *Games and Economic Behavior 109*, 40–64.

Grossman, S. J. and J. E. Stiglitz (1980). On the impossibility of informationally efficient markets. *The American Economic Review 70*(3), 393–408.

Hall, B. H. (2004). Innovation and diffusion. *National Bureau of Economic Research, Working Paper 10212.*

Hansen, A. D., F. Iov, F. Blaabjerg, and L. H. Hansen (2004). Review of contemporary wind turbine concepts and their market penetration. *Wind Engineering 28*(3), 247–263.

Hardy, A. and D. Glew (2019). An analysis of errors in the energy performance certificate database. *Energy Policy 129*, 1168–1178.

Harrison, G. W., M. I. Lau, and M. B. Williams (2002). Estimating individual discount rates in denmark: A field experiment. *The American Economic Review 92*(5), 1606–1617.

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

Hartman, R. S., M. J. Doane, and C.-K. Woo (1991). Consumer rationality and the status quo. *The Quarterly Journal of Economics 106*(1), 141–162.

Hau, E. and H. von Renouard (2003). *Wind turbines: fundamentals, technologies, application, economics*. Springer.

Hausch, D. B. (1987). An asymmetric common-value auction model. *The RAND Journal of Economics*, 611–621.

Hausman, J. A. et al. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics 10*(1), 33–54.

Hayek, F. A. (1945). The use of knowledge in society. *The American Economic Review 35*(4), 519–530.

Heffetz, O. and M. Shayo (2009). How large are non-budget-constraint effects of prices on demand? *American Economic Journal: Applied Economics 1*(4), 170–99.

Henry, C. (1974). Investment decisions under uncertainty: the" irreversibility effect". *The American Economic Review 64*(6), 1006–1012.

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

Holt, C. A. and S. K. Laury (2002). Risk aversion and incentive effects. *The American Economic Review 92*(5), 1644–1655.

Holt, C. A. and R. Sherman (2014). Risk aversion and the winner's curse. *Southern Economic Journal 81*(1), 7–22.

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

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

Insee (2015, August). Les conditions de logement fin 2013. *French National Institute for Statistics and Economic Studies, Webpage.*

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

Jacobsen, G. D. (2015). Do energy prices influence investment in energy efficiency? Evidence from energy star appliances. *Journal of Environmental Economics and Management 74*, 94–106.

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

Jakob, M. (2006). Marginal costs and co-benefits of energy efficiency investments: The case of the Swiss residential sector. *Energy policy 34*(2), 172–187.

Jenner, S., F. Groba, and J. Indvik (2013). Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. *Energy Policy 52*, 385–401.

Jensen, A. R. (1998). *The factor.* Westport CT. Praeger.

Jensen, R. (1982). Adoption and diffusion of an innovation of uncertain profitability. *Journal of Economic Theory 27*(1), 182–193.

Kagel, J. H. and D. Levin (2002). Bidding in common-value auctions: A survey of experimental research. *Common value auctions and the winner's curse 1*, 1–84.

Kagel, J. H. and A. E. Roth (2016). *The handbook of experimental economics*, Volume 2. Princeton University Press.

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

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

Kahneman, D. (2011). *Thinking, Fast and Slow.* Farrar, Straus and Giroux.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–292.

Kelly, D. L. and C. D. Kolstad (1999). Bayesian learning, growth, and pollution. *Journal of Economic Dynamics and Control 23*(4), 491–518.

Kempton, W., D. Feuermann, and A. E. McGarity (1992). "I always turn it on super": user decisions about when and how to operate room air conditioners. *Energy and Buildings 18*(3-4), 177–191.

Kempton, W. and L. Montgomery (1982). Folk quantification of energy. *Energy 7*(10), 817–827.

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

Science 23, 11–25.

Klemperer, P. (2007). Bidding markets. *Journal of Competition Law and Economics 3*(1), 1–47.

Kremer, I. (2002). Information aggregation in common value auctions. *Econometrica 70*(4), 1675–1682.

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

Lacal-Arántegui, R. (2014). Wind status report. *JRC Scientific and Policy Reports.*

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

Lambrecht, B. and W. Perraudin (2003). Real options and preemption under incomplete information. *Journal of Economic Dynamics and Control 27*(4), 619–643.

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

Leboullenger, D., F. Lantz, C. Baumont, et al. (2018). Is there a market value for energy performance in a local private housing market? an efficiency analysis approach. Technical report, University of Paris Nanterre, EconomiX.

Lechtenböhmer, S. and A. Schüring (2011). The potential for large-scale savings from insulating residential buildings in the eu. *Energy Efficiency 4*(2), 257–270.

Loewenstein, G. and R. H. Thaler (1989). Anomalies: intertemporal choice. *Journal of Economic Perspectives 3*(4), 181–193.

Mason, R. and H. Weeds (2010). Investment, uncertainty and pre-emption. *International Journal of Industrial Organization 28*(3), 278–287.

Mata, É., A. S. Kalagasidis, and F. Johnsson (2014). Building-stock aggregation through archetype buildings: France, germany, spain and the uk. *Building and Environment 81*, 270–282.

MEDDE (2009). Guide recommandations : Diagnostic de performance énergétique. *French Ministry of Housing.*

MEDDE (Arrêté du 17 octobre 2012). Méthode 3cl-dpe. *Journal Officiel de la République Française, French Ministry of Housing.*

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

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

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

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

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

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

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

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

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy 78*(2), 311–329.

Newell, R. G. and J. Siikamäki (2014). Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Resource Economists 1*(4), 555–598.

Newell, R. G. and J. Siikamäki (2015). Individual time preferences and energy efficiency. *The American Economic Review 105*(5), 196–200.

OCRE (2015). Analyse de dossiers de financement de travaux de rénovation énergétique. *French Observatory of Energy Renovation Costs.*

OECD (2014, December). Hearing on the use of tenders and auctions, issues note by the secretariat.

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

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

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

Papon, F., D. Nguyen-Luong, and E. Boucq (2015). Should any new light rail line provide real estate gains, or not? the case of the t3 line in paris. *Research in Transportation Economics 49*, 43–54.

Peres, R., E. Muller, and V. Mahajan (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing 27*(2), 91–106.

Persico, N. (2000). Information acquisition in auctions. *Econometrica 68*(1), 135–148.

Pesendorfer, W. and J. M. Swinkels (1997). The loser's curse and information aggregation in common value auctions. *Econometrica: Journal of the Econometric Society*, 1247–1281.

Pesendorfer, W. and J. M. Swinkels (2000). Efficiency and information aggregation in auctions. *The American Economic Review 90*(3), 499–525.

Plassmann, H., J. O'Doherty, B. Shiv, and A. Rangel (2008). Marketing actions can modulate neural representations of experienced pleasantness. *Proceedings of the National Academy of Sciences 105*(3), 1050–1054.

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

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

RAGE (2012). Analyse détaillée du parc résidentiel existant. *Règles de l'Art - Grenelle de l'Environnement*.

Railton, A. R. (1958, March). What owners say aabout the edsel. *Popular Mechanics 103*(3), 90–95.

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

Rao, K. U. and V. Kishore (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews 14*(3), 1070–1078.

Raven, J. (2000). The raven's progressive matrices: change and stability over culture and time. *Cognitive Psychology 41*(1), 1–48.

Raven, J. C. (1941). Standardization of progressive matrices, 1938. *British Journal of Medical Psychology 19*(1), 137–150.

Raven, J. C. (1960). *Guide to the standard progressive matrices: Sets A, B, C, D and E.* HK Lewis.

Renauld-Giard, V. (2014). *Fabrication et usage des écoquartiers, essai critique sur la généralisation de l'aménagement durable en France.* Presses Polytechniques et Universitaires Romandes.

Renauld-Giard, V. (2015). Les risques de contre-productivité des innovations vertes dans le bâtiment. le cas français des chauffe-eau solaire dans l'habitat collectif. *Information & Débats* (38).

Ribas Portella, J. M. (2012). Bottom-up description of the french building stock, including archetype buildings and energy demand. Master's thesis, Chalmers University of technology, Göteborg, Sweden.

Rode, J. and A. Weber (2016). Does localized imitation drive technology adoption? a case study on rooftop photovoltaic systems in germany. *Journal of Environmental Economics and Management 78*, 38–48.

Rogers, E. M. (1962). *Diffusion of Innovations.* The Free Press.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Rothschild, M. and J. E. Stiglitz (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics 90*(4), 629–649.

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

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

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

Sarja, J. and V. Halonen (2013). Wind turbine selection criteria: A customer perspective. *Journal of Energy and Power Engineering 7*(9), 1795.

Saussier, S. and J. Tirole (2015). Strengthening the efficiency of public procurement. *Notes du conseil d'analyse économique* (3), 1–12.

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

Schumpeter, J. A. (1911). *Theorie der wirtschaftlichen Entwicklung.* Duncker & Humblot - Berlin.

Shaked, A. and J. Sutton (1982). Relaxing price competition through product differentiation. *The Review of Economic Studies*, 3–13.

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

Shiller, R. J. (1995). Conversation, information, and herd behavior. *The American Economic Review 85*(2), 181–185.

Shiv, B., Z. Carmon, and D. Ariely (2005). Placebo effects of marketing actions: Consumers may get what they pay for. *Journal of Marketing Research 42*(4), 383–393.

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

Sirmans, S., D. Macpherson, and E. Zietz (2005). The composition of hedonic pricing models. *Journal of Real Estate Literature 13*(1), 1–44.

Smit, H. T. and L. Trigeorgis (2006). Real options and games: Competition, alliances and other applications of valuation and strategy. *Review of Financial Economics 15*(2), 95–112.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics 87*(3), 355–374.

Spence, M. (1976). Informational aspects of market structure: An introduction. *The Quarterly Journal of Economics* (4), 591–597.

Stadelmann, M. and R. Schubert (2018). How Do Different Designs of Energy Labels Influence Purchases of Household Appliances? A Field Study in Switzerland. *Ecological Economics 144*, 112–123.

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

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

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy 69*(3), 213–225.

Stiglitz, J. E. (1975). The theory of "screening", education, and the distribution of income. *The American Economic Review 65*(3), 283–300.

Stiglitz, J. E. (1985). Information and economic analysis: a perspective. *The Economic Journal 95*(Supplement), 21–41.

Stiglitz, J. E. (2000). The contributions of the economics of information to twentieth century economics. *The Quarterly Journal of Economics 115*(4), 1441–1478.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American Economic Review 71*(3), 393–410.

Sutherland, R. J. (1991). Market barriers to energy-efficiency investments. *The Energy Journal*, 15–34.

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

Thaler, R. H. (1992). *The winner's curse: Paradoxes and anomalies of economic life.* New York: Free Press.

Thaler, R. H. and C. R. Sunstein (2008). *Nudge: Improving decisions about health, wealth, and happiness.* Yale University Press.

Thébault, S. and R. Bouchié (2018). Refinement of the ISABELE method regarding uncertainty quantification and thermal dynamics modelling. *Energy and Buildings 178*, 182–205.

Thijssen, J. J. (2010). Preemption in a real option game with a first mover advantage and player-specific uncertainty. *Journal of Economic Theory 145*(6), 2448–2462.

Thijssen, J. J., K. J. Huisman, and P. M. Kort (2012). Symmetric equilibrium strategies in game theoretic real option models. *Journal of Mathematical Economics 48*(4), 219–225.

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

Tversky, A. and D. Kahneman (1974). Judgment under uncertainty: Heuristics and biases. *Science 185*(4157), 1124–1131.

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

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

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

Wilson, R. B. (1969). Competitive bidding with disparate information. *Management Science 15*(7), 446–448.

Wilson, R. B. (1977). A bidding model of perfect competition. *The Review of Economic Studies 44*(3), 511–518.

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

Xiong, H., D. Payne, and S. Kinsella (2016). Peer effects in the diffusion of innovations: Theory and simulation. *Journal of Behavioral and Experimental Economics 63*, 1–13.

Young, H. P. (2009). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *The American Economic Review 99*(5), 1899–1924.

* * *

Abstract

A decade ago, Energy Performance Certificates have been introduced by the European Union to bridge the energy-efficiency gap. As informational failures are blamed for plaguing the development of greener buildings, energy labels could fix these failures by reducing both uncertainty on energy quality and information asymmetry between sellers and buyers. However, economic research has shown that information is a complex economic good, often imperfectly used or valued by real economic agents. This dissertation investigates the value of information in the context of the economics of green buildings, by combining theoretic, empirical and experimental approaches.

First, the perception of Energy Performance Certificate is studied through an artefactual field experiment on a representative sample of the French population. We point up a mixed cognitive efficiency for the label. A significant part of the population ignores it, however attentive subjects do use the label to revise their prior beliefs on energy quality. Second, we provide evidence of the capitalization of this information into real estate prices over two French regions. Low-consumption houses exhibit, *ceteris paribus*, a significant green premium that matches with techno-economic estimations of associated renovation costs.

However, despite this `green value', the pace of energy renovations remains slow in the French market: the energy label information does not reduce uncertainty on the outcomes of the renovation process. In a third time, we show through a strategic option model that the lack of reliable information about renovation quality can delay investment decisions, and even inhibit their diffusion. Recently, several innovations have opened the possibility of producing reliable information on quality in the building industry. Then, fourthly, we explore with a laboratory experiment people's Willingness-To-Pay for information. Its magnitude is evidenced as significantly higher than information theoretic value. Nonetheless, pricing information has overall mixed effects on behaviors, inducing more strategic thinking but also some cognitive biases. A careful design of information markets is thus required.