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WORKING PAPER

Certification, manipulation and competition: evidence from Energy Performance Certificates

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In this paper, we investigate the relationship between competition and certification quality in the Energy Performance Certificates (EPCs) market, which provides mandatory information on the energy performance of dwellings in European countries. Using French administrative data, we present evidence that the distribution of EPCs exhibits bunching at the cut-off points between energy performance classes, suggesting that some certificates are manipulated to secure a more favorable label. Our empirical analysis shows that the likelihood of manipulation increases when certifiers face heightened competition. This effect can be explained by the fact that certifiers, who are paid by potential sellers, are incentivized to issue more lenient certifications to attract clients. Additionally, we demonstrate that labels indicating higher energy efficiency are associated with significant house price premiums. As a result, manipulation has distributional effects, increasing sellers' gains at buyers' expense.

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Executive summary

Energy Performance Certificates (EPCs) are a cornerstone of policies promoting energy efficiency in the residential sector. These labels are intended to provide households with standardized, reliable information about a home's energy efficiency, helping to bridge the energy efficiency gap and guiding investment in retrofits. However, the effectiveness of EPCs depends on their credibility. This study provides compelling evidence that the EPC market in France exhibits systematic manipulation, with energy efficiency ratings strategically misreported to secure more favorable classifications. It further demonstrates that increased competition among certifiers exacerbates this behavior.

Key Findings

- **Bunching at EPC Thresholds:** A significant number of homes are just below key cut-off points, suggesting certifiers intentionally manipulate ratings to improve classifications.
- **Competition Increases Manipulation:** Certifiers in more competitive markets are more likely to manipulate scores, as they are incentivized to provide lenient ratings to gain market shares.
- **Housing Price Distortions:** A one-class better EPC leads to price premiums of about 6%, suggesting buyers rely heavily on labels, even when manipulated. Manipulation has thus welfare implications.

Policy Implications

1. **Stronger Oversight and Enforcement of EPC Assessments**
The findings highlight the need for stricter regulatory oversight of EPC certifiers. France's 2021 reform, which made EPCs legally enforceable, is a step in the right direction but may not go far enough in addressing market incentives for manipulation. More rigorous auditing of EPC assessments and penalties for fraudulent reporting could deter manipulation.

2. **Decoupling Certifier Payments from Homeowners**
A fundamental issue in the EPC market is the misaligned incentive structure: certifiers are paid directly by homeowners, who benefit from favorable ratings. A reform that shifts the payment structure—such as government or independent third-party funding for EPC assessments—could reduce certifiers' conflicts of interest.

3. **Harmonization of EPC Standards Across the EU**
The study underscores the need for more standardized and manipulation-resistant EPC methodologies at the European level. Different national practices create varying degrees of manipulation risk, and more uniform rules—such as stricter guidelines for certifier independence and threshold effects—could improve the integrity of the system.

4. **Enhancing Consumer Awareness to Reduce the Price Premium at cutoffs**
A key reason why EPC manipulation persists is that buyers place disproportionate weight on EPC ratings without fully understanding their calculation methods. Public awareness campaigns and disclosure reforms that emphasize underlying energy efficiency metrics rather than simplistic class labels could mitigate this problem.

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1 Introduction

In most markets, information imperfections arise because the product or service quality is not easily observable ex-ante and sometimes even challenging to ascertain ex-post. Mandatory disclosure of information has become a popular policy tool to reveal product quality in such markets and help consumers optimize their choices. Examples range from credit rating in financial markets to certification of a product's safety, nutritional content, energy efficiency, or environmental impact. In many settings, third-party certifiers carry out product certification. A key question is whether they report unbiased and accurate information. Indeed, when firms that certify the quality of goods are paid by the agents who benefit from more favorable certification, they may be tempted to provide lenient assessments to attract more clients. Moreover, in such markets, increased competition may exacerbate incentives to manipulate certification quality to attract consumers. Assessing the prevalence of such behavior is important from a policy perspective, as it may limit the benefits of mandatory information provision.

In this paper, we focus on the mandatory disclosure of energy performance certificates (hereafter EPC) in housing markets, which have become a prominent policy to foster the renovation of buildings and lower carbon emissions. This disclosure policy aims to address the energy efficiency gap in home renovation (Allcott and Greenstone (2012)) by providing households with certificates that contain reliable and standardized information about the energy efficiency of their homes. Many governments, including several U.S. local authorities and the European Union, have adopted mandatory disclosure of home energy labels. The effectiveness of this policy is, however, still debated: Myers et al. (2022) finds that compulsory disclosure of EPCs in Austin increases the premium for energy-efficient homes, while Aydin et al. (2020) do not detect any effect of the provision of EPCs on the housing market in the Netherlands. The impact of such programs depends on households' initial level of information about energy efficiency but also the accuracy and reliability of the certificates (Lanz and Reins (2021)). The quality of the energy rating provided by certifiers has been the subject of heated debate, with EPCs often accused of providing inaccurate information[1]. Indeed, it has been shown that the predicted energy efficiency of homes and its improvements can be inaccurate if the technical projections used to calculate them are not well calibrated (Fowlie et al. (2018), Davis et al. (2020)), or if EPC assessors disagree on the quality of the observed characteristics of buildings (Hardy and Glew (2019)). The inaccuracy of labels might also come from misaligned incentives between different agents, which could lead to misreporting. However, the incentives for third-party certifiers to manipulate reports have been little studied in the context of home energy performance labeling.

In this paper, we present evidence of manipulation in the EPCs market and analyze the relationship between competition and such manipulation. The EPC label creates incentives for manipulation at specific energy consumption levels. As the label is a discontinuous step function of a house's predicted energy consumption, it generates significant and evident differences in how houses are classified into energy efficiency classes at certain thresholds. Suppose prospective buyers have limited attention or technical knowledge. In that case, they may be willing to pay a premium for houses with a better label than those with similar energy consumption but classified in a less efficient energy class. This dynamic creates strong incentives to manipulate the EPC label at energy consumption thresholds, splitting two energy efficiency classes.

Using the EPC labels issued in France between 2013 and 2021, we provide empirical evidence that the EPC rating is often manipulated. We show clear breaks in the EPC distribution at the thresholds between two categories, with a bunching of houses on the side of the threshold corresponding to a more efficient class. In the market for EPCs, a few papers have shown evidence of bunching at the threshold for more favorable energy classes (Collins and Curtis (2018), Atasoy (2020)). Still, they attribute this to strategic investment in energy-efficient equipment when building or renovating a home. We argue that in the case of France, this bunching reveals manipulation rather than strategic responses. It is present regardless of the method used to assess the EPC, and it adjusts

[1] In France, consumer associations regularly show large variations in EPC established by different certifiers for the same home, see "Nouveau DPE : des erreurs en pagaille !", 60 millions de consommateurs, May 24, 2022)

quickly to regulatory changes in the value of the thresholds. In addition, we uncover one channel for adjusting the EPC score, which is misreporting of dwelling size, and find significant discontinuities in reported size at the threshold, consistent with manipulative behavior. We then analyze how this bunching varies with the degree of competition between certifiers and show that more competition is associated with more manipulation. Since certifiers are paid by homeowners, their behaviour is consistent with the incentives of profit-seeking firms, which could gain market share by offering more lenient ratings to their customers (Dranove and Jin (2010)).

Next, we examine whether this manipulation is profitable for homeowners. We can measure the willingness to pay for a better energy grade by comparing the house price premium attached to houses with similar theoretical energy consumption but which fall on opposite sides of the energy label thresholds and receive different labels. We use a donut Regression Discontunity Design (RDD) estimation strategy to account that houses very close to the threshold may have different characteristics due to manipulation. Crossing an energy class threshold triggers a significant house price premium in France. This effect suggests that some households have a limited attention bias and are willing to pay more for houses with a better EPC rating, even after controlling for the overall level of electricity consumption. Several robustness checks confirm that such effects are only present at the official cut-off points and not at the placebo values, where we find no deformation in the EPC distribution and no price premium. These results suggest that manipulating EPC ratings has welfare consequences, increasing the profits of informed sellers to the detriment of uninformed buyers.

Our study contributes to the economic literature on quality disclosure and certification. Following the seminal work of Tirole (1986) on enforceable capture, Lizzeri (1999), Strausz (2005), Lerner and Tirole (2006) and Mahenc (2017), have modelled certifiers behaviours. These contributions tend to demonstrate that profit-seeking certifiers have incentives to manipulate the information displayed on labels to gain market shares.

The theoretical literature presents a mixed view on how competition affects quality certification. For instance, Bolton et al. (2012) argue that in financial markets, where issuers can shop for the most favourable rating, competition between credit rating agencies can lead to artificially better ratings. On the other hand, in environments as in Lizzeri (1999) where sellers (issuers) have a single chance to be certified or sellers' applications are public, competition between certifiers drive them to fully disclose quality information.

In empirical applications, this relationship has been investigated in a limited number of settings. A few papers have studied the behaviour of credit rating agencies in financial markets (Becker and Milbourn (2011) and Flynn and Ghent (2018)), finding that the arrival of a new competitor on the market leads to an increase in ratings. Other applications include food certification (Zheng and Bar (2021)) and vehicle emission testing (Hubbard (1998), Bennett et al. (2013)), where it has been shown that the pass rate increases when inspectors have a nearby competitor. Our study is the first to investigate the link between competition and manipulation in the market for energy performance certificates. Indeed, while some papers have analysed the strategic response of manufacturers to energy labels for domestic appliances (Houde (2018b)), there is minimal evidence of the strategic behaviour of third-party certifiers for energy efficiency in the residential sector. Our results highlight the usefulness of studying the behavior of third-party certifiers to evaluate the overall effects of mandatory disclosure programs for energy efficiency.

Our study is also directly related to a strand of the environmental literature investigating how labels may encourage households to consider energy efficiency in their residential decisions. Most of the literature has measured the capitalization of energy efficiency in house prices, using hedonic analysis, often finding a sales premium for energy-efficient houses.[2]. In standard OLS regressions, the premium estimation may be biased if unobserved dwelling characteristics correlate with energy efficiency measures. We adopt an RDD approach to identify how households value a house with a better energy class, controlling for the level of energy consumption. In contrast to the null effect of labeling found in RDD by Aydin et al. (2020) in the Netherlands, we find that salient differences

[2]Studies include Eichholtz et al. (2010) and Kahn and Kok (2014) in the US, Brounen and Kok (2011) in the Netherlands ,Hyland et al. (2013) and Fuerst et al. (2015) in Ireland and England. In France, Civel (2019) also finds a significant green premium across several local markets.

in energy ratings trigger significant house premiums, in line with recent results from the UK (Sejas-Portillo et al. (2025)). However, in contrast to these papers, we find evidence of threshold manipulation in France, as the large housing bonuses may increase incentives to exploit information asymmetries.[3]

By investigating how the salience of the class of EPCs affects household decisions, our study also contributes to the behavioral economic literature on salience and limited attention. Theoretical models, reviewed in Bordalo et al. (2022), emphasize that salient information about a product's characteristics can distort consumer choices. In the case of energy-efficiency attributes, several papers have shown, using either hypothetical choices surveys (Newell and Siikamäki (2014), Davis and Metcalf (2016), Civel and Cruz (2018)) or actual purchases (Houde (2018a)) that providing information has an impact on choices. However, many consumers tend to rely primarily on the salient information presented in the label, not exerting effort to understand how they are calculated. In particular, Andor et al. (2020) show that consumers' willingness to pay for refrigerators with a better energy class goes beyond the expected energy savings associated with the certification. Our findings echo this result. In our model, households are willing to pay significant premiums for houses on the better side of an EPC class threshold. Such behavioral effects can lead to substantial welfare losses, especially when exploited by informed third-party certifiers.

Finally, our study also relates to a strand of the public economics literature that exploits bunching to estimate behavioral responses by households (Kleven (2016)), and in particular, to detect fraudulent reporting (Kleven et al. (2011), Fack and Landais (2016))). In the case of energy efficiency labels, Goeschl (2019) and Blonz (2023) uncovered misreporting for refrigerators. Still, there has been, to our knowledge, little research on misreporting in home energy-efficiency labels despite their widespread use. Our study contributes to extending the bunching approach to detect manipulation in such a setting. Moreover, we can relate this manipulation to the competition structure in the certifica-

[3] In the UK, both Comerford et al. (2018) and Sejas-Portillo et al. (2025) find evidence that households are willing to make strategic investments in response to labels to increase home energy ratings, but they argue that the possibilities for manipulation are limited in the english context.

tion market. Our results, therefore, yield specific policy implications, as they emphasize the need to impose clearer rules in the market for third-party assessors.

This paper is structured as follows: Section 2 describes the market for EPC certification, its regulatory framework, and the incentives for manipulation that it may create. Section 3 presents the data and the first evidence of manipulation. Section 4 presents the econometric analysis of the relationship between competition and manipulation, and Section 5 examines the welfare effects by measuring the associated house price premium.

2 The Market for energy performance certificates

2.1 The regulatory framework

The development of a regulated framework to assess the energy performance of buildings in France follows the energy policy objectives defined at the European level to reduce the energy consumption of buildings and limit greenhouse gas emissions.[4] In France, it is mandatory for sellers and landlords to provide an EPC in any sale or rental agreement since 2007, and to include it in property advertisements since 2011. The initial purpose of the policy was to provide households with clear information on the energy performance of their homes. Over the years, the EPC has also become an essential tool for policies to promote the development of energy-efficient buildings.

The French authorities regulate the method for establishing home energy certificates. A certified trained expert must issue the EPC after a visit to the dwelling to record its physical characteristics such as size, structure, quality of insulation, heating installation, ventilation, and energy systems. The information collected is then used to predict the home's total energy consumption using a standardized procedure. For EPCs established before July 2021, the energy consumption of older homes is calculated based on past bills, while it is based on a predictive model for more recent buildings, called "DPE-3CL" and whose calculation and parameters are defined by the French Ministry of Ecololgy

[4]Since 2002, the directive on the energy performance of buildings has established a general calculation framework for energy diagnostics and minimum requirements. Since 2010, all EU countries have been required to operate a certification scheme to provide prospective buyers or tenants with information on the energy performance of a building (Directive 2010/31/EU on the energy performance of buildings).

and Housing. The home is then assigned an energy label based on theoretical consumption thresholds ranging from category A (low energy consumption) to category G (high energy consumption), as well as a greenhouse gas (GHG) emissions label with the same categories. We focus our analysis on the energy efficiency label, which is more directly correlated with household energy costs than the GHG label.[5] As one can see on Figure 1, which shows an example of an EPC document, the presentation makes the category of the energy label very prominent, in addition to the information on energy consumption. In addition, the label category is usually the only information about energy efficiency provided in property advertisements, which increases its salience for potential buyers.

In July 2021, the French government adopted a significant reform of the EPC, adjusting its calculation method and making it a fully enforceable real estate diagnosis. There were no serious legal consequences of providing an inaccurate EPC before 2021.[6] Our study focuses on the period between January 2013 and July 2021, which corresponds to a stable legal and technical framework with weak enforcement regulation.

2.2 Market structure and incentives for manipulation

We focus on the EPCs of homes sold or rented on the real estate market. The main actors involved in the market for EPC assessments of homes include owners (clients), EPC certifiers (service providers), and real estate agents. Owners must provide an up-to-date EPC with other mandatory technical diagnoses when selling or renting a home.[7] Certifiers usually offer to provide all certificates together for a fixed fee, paid by homeowners. Estate agents, who may recommend a certifier to the seller, are likely to be aware of the potential premium in the sale price of a home with a higher EPC, as property websites regularly publish articles on the subject.[8]. As the main source of realtors' revenue is derived from

[5] The energy efficiency label and the greenhouse gas emissions label are correlated because they vary with the level of energy consumption, but the GHG label is worse for houses with fuel or gas heating compared to houses with only electricity.

[6] The reform led to an update of the model used to calculate EPCs and the generalization of its use for the assessment of all homes, along with a new simplified design for the presentation of the EPC

[7] Such as assessment of electricity and gas installations, exposure to lead and asbestos, climatic and industrial risks in the area, etc. Some of these diagnoses, including EPC, have a limited validity period, which implies that most sales require a new assessment.

[8] See for example the article https://edito.seloger.com/actualites/villes/vraiment-l-impact-dpe-prix-d-un-logement-article-39526.html published by the main real estate website SeLoger September 2020

broker fees, which are calculated as a percentage of the transaction price (MEF, 2020), it is reasonable to assume that both realtors and homeowners would have a preference for certifiers that give a favorable EPC label for the house.

In a competitive market, certifiers may feel compelled to manipulate EPC assessments if they anticipate that competitors will use such practices to attract customers. If the legal consequences of issuing inaccurate certificates are limited, competitive pressures may increase the incentives for firms to engage in deceptive practices. Several features of the certification market may exacerbate such behavior. First, manipulation is inherently complex to detect because energy performance is not readily observable. Second, providing an inaccurate EPC rating has limited legal consequences during the study period, thereby reducing the costs of fraudulent practices. Third, the services offered by certifiers are pretty standardized, and barriers to entry are relatively low, which may exacerbate the competitive pressure.[9] In France, during the study period, there were almost 15,000 certifiers who were active in many local areas (see descriptive statistics in Table I).

Given the market's organization, we hypothesize that more competitive markets will lead to higher levels of manipulation. To test this hypothesis, we first need to develop a method to detect manipulation in the absence of audit data that would allow for a direct detection of fraud.

3 Data and evidence of manipulation

3.1 Data and summary statistics

Our main analysis is based on the database covering all EPCs for homes, provided in open access by the French Agency for Energy Transition (ADEME). Our primary sample of interest, which contains 3,18 million EPCs for houses issued between January 2013, and June 2021 includes all the variables that certifiers were required to fill in when assessing buildings (including geolocation data).[10] It also provides detailed information on the

[9]Training costs are limited, as training centers typically offer fast-track course packages, where prospective certifiers can acquire all the qualifications to become a certifier within a few weeks.

[10]We chose to restrict our sample to single-family homes, excluding flats because the quality of the statistical merge based on geolocation is lower for multi-dwelling units, but the results (available upon

EPC assessment for each dwelling unit, including the expected annual primary energy consumption in kilowatt hours per square meter, the EPC label awarded, the certifier's identifier, and the assessment date. Summary statistics (see column 1 of table II), show that less than 4% of homes are rated as high energy-efficient dwellings (classes A and B), while more more than a third (35.5%) are rated D and 15% are rated low (class F) or very low (class G). This distribution roughly represents the energy performance of the stock of homes in France, as evaluated by Le Saout et al. (2022).[11]

To measure the housing price premium of a better label, we construct a second sample with information on all houses sold in France between 2014 and 2022, for which we can retrieve the associated Energy Performance Certificate. The dataset on real estate transactions comes from the French Ministry of Finance (DGFiP, 2023). It includes variables related to each transaction, including geolocation information of the dwelling, property characteristics, and the transaction price. We match the two datasets using geolocation information and property characteristics available in the two databases (see appendixA for a detailed description of the datasets and merging method.). The resulting merged database contains 568,436 house transactions matched with EPC observations. Summary statistics (see column 3 in table II) show that the distribution of characteristics in the merged sample is relatively close to the sample of all EPC homes, with an average price of 226,000 euros.

3.2 Detecting manipulation in EPC certification

In the absence of audit data to detect fraudulent EPCs, we examine the distribution of EPC labels to detect anomalies. We focus on a specific type of manipulation, which can be inferred from the data: bunching at EPC label cutoffs. While several forms of fraudulent practices can coexist in the EPC market, manipulation at the threshold is potentially significant because it directly benefits the buyer. Indeed, the label is a salient feature of the EPC, and, as we show later, exceeding the threshold is associated with a

request) are similar if we include flats.

[11] Among the existing stock of houses, Le Saout et al. (2022) tend to find a slightly higher share (17%) of low to very low energy performing homes, as houses in the worst condition are less likely to be sold or rented and to appear in the EPC database.

significant house price premium.

To generate an EPC label, the certifier must first calculate the predicted theoretical energy consumption based on the characteristics of the dwelling, and then assign an energy class based on the energy thresholds defined by law. Without manipulation, we should expect the distribution of theoretical energy consumption at the thresholds for each label to be continuous, reflecting the diversity of dwelling characteristics and the exogenous nature of the threshold definitions. However, Figure 2 shows systematic deformations in the distribution of theoretical energy consumption at the thresholds between different EPC classes for the entire sample of EPCs issued for houses over 2013-2021. More specifically, we observe a bunching of EPCs on the favorable side of the threshold, corresponding to a better energy class, and a missing mass on the other side of the cutoff. We observe a deformation in the distribution at the 151, 231, 331, and 450 kWh thresholds, corresponding to the thresholds for classes C/D, D/E, E/F, and F/G.

To assess whether this visual evidence is statistically significant, we perform the density continuity test developed in Cattaneo et al. (2020), which is based on a McCrary sorting test (McCrary, 2008) widely used in the empirical literature. The results, shown in column 1 of table III, confirm that four of the six cutoffs exhibit significant discontinuities in the distribution of EPCs, corresponding, as in the figure, to the thresholds for classes C/D, D/E, E/F, and F/G. As a robustness check, we test for discontinuities at the placebo cutoffs, defined as the midpoints between two actual thresholds. We find no significant discontinuities at these placebo cutoffs (see column 2 of table III). These results confirm that substantial deformations in the distribution mainly occur at the cutoffs between two EPC classes.

An important question is whether the observed bunching can indeed be interpreted as a fraudulent practice. Two alternative interpretations could be put forward: bunching could be an artifact of the method used to model theoretical consumption, or it could reflect actual renovations households undertake to achieve a target EPC label. To investigate whether the model used to predict theoretical energy consumption could generate bunching, we exploit the co-existence of two methods to assess this value in France before

2021. For most homes (over 80%), energy consumption is calculated using a predictive model called “3-CL”, but homes built before 1949 are assessed based on past energy bills. When using past bills, the certifier calculates energy consumption based on the average consumption over the past 3 years. We would therefore not expect that this method of calculation would generate any specific discontinuity in the distribution of energy consumption. Figure 3 reveals, however, the same deformation of the distribution of EPC labels, irrespective of the method used to calculate theoretical consumption. This suggests that the model used to estimate consumption is not the primary driver of bunching.

Another possible explanation for the observed bunching might be optimization by households, making improvements to their dwellings to achieve a better energy class. Collins and Curtis (2018), who find evidence of bunching for EPCs after dwelling renovations in Ireland but not before, argue that this ex-post bunching could be evidence of a genuine response by households undertaking renovations to reach a salient EPC threshold. In the UK context, Sejas-Portillo et al. (2025) shows that dwellings with predicted energy costs close to the more unfavorable side of an EPC threshold are more likely to be re-certified within a short period and to achieve a better subsequent rating. They argue that this is evidence that a small number of potential sellers are making strategic investments to improve their property’s energy performance. However, they do not detect significant discontinuities for the entire sample of EPCs. In the case of France, clear bunching is found for the sample of all EPCs, most of which were carried out for dwellings that had not undergone renovation. We can also exploit that the values of the thresholds defining the energy performance classes were modified by the 2021 reform, to analyze how bunching evolves before and after the reform. Figure 4, which reproduces the distribution of EPCs as a function of predicted theoretical energy consumption for certifications carried out after July 2021, shows that the distribution adjusts to the new thresholds. The excess mass of EPCs previously observed at the old threshold values disappears, while bunching appears at the new threshold values. Such a massive adjustment in the distribution after a change in the legal values defining the thresholds suggests that the response is more likely due to changes in reporting practices by certifiers than by actual actions taken by households.

In addition, we uncover a channel for adjusting the EPC score without renovation, to manipulate the reported size of dwellings. The thermal model used to calculate most EPCs is based on software that predicts absolute conventional energy consumption by assessing the energy lost through the building envelope due to heat transfer. The expected energy consumption is then divided by the surface area to get energy consumption per square meter, which is used to attribute the energy class. A simple way to manipulate the final EPC result is to reduce the house's dimensions slightly. Since a slight reduction in the floor area of a house results in a more considerable decrease in its envelope area, a reduction in the declared size of the house will result in a reduction in conventional consumption per square meter.[12] Consistent with this intuition, Figure 7 shows evidence that houses whose energy consumption is just below an EPC cutoff have a significantly smaller reported size than houses just above. We estimate, using regression discontinuity techniques (see below for a detailed explanation of the method), that these discontinuities in size are significant for most cutoffs, but not at placebo points (see results in table VI). Since we can assume that households carrying out renovations would not do so to reduce the size of their dwelling, this finding adds to the evidence that the observed bunching at the EPC cutoffs is mainly caused by manipulation in France.

3.3 Competition and manipulation: graphical evidence

Having established that bunching is likely to be due to an overly lenient assessment of energy consumption at the threshold, we seek to understand whether it can be related to the incentive structures in the third-party certification market. More specifically, we want to investigate whether manipulation is more likely to occur in markets with higher levels of competition. To do so, we focus on houses whose theoretical consumption is close to an EPC cutoff where bunching has been detected. We restrict our sample to the

[12] In France, while there is a legal obligation to provide a floor area certificate when selling a flat, there is no such legal obligation for the sale of a house. It is therefore very easy to manipulate the reported dimensions of a house in the EPC certificate.

EPCs within 5kWh/m2/year above or below the following cutoffs: C/D, D/E, E/F and F/G. This represents a sample of 328,478 EPCs in these "areas of manipulation". The descriptive statistics (see column 2 of table II) show that, despite the sample restrictions on the distribution of labels, the other characteristics of the houses located at these cutoffs are quite similar to the full sample of houses in the EPC database. The raw analysis of the distribution of EPCs in this sample (see table VIII in the appendix) shows that, on average, only 33% are above the cut-off, and 67% (twice as many) are below it and get a better EPC class. Compared to a random allocation, where we would expect 50% of observations on each side, this sample has considerable bunching.

We provide some descriptive evidence of the relationship between competition and the manipulation of EPCs. We then construct a measure of bunching at the local level by calculating the relative excess mass of EPCs to the left of the cut-off, aggregated at the local level of the *département*, corresponding to administrative areas similar to English counties.[13] Competition is measured using a Herfindahl-Hirschman Index (HHI) centered on the property's location for which the EPC is issued. We include all certifiers operating in the same postcode as the property and active in the year the EPC is issued. The HHI is calculated in the standard way by summing the squares of the market shares of each certifier that has operated in that market. This results in a specific HHI for each postcode and year, which reflects the concentration faced by the owner of a property when searching for certifiers.[14] Figure 5, which represents the distribution of the HHI within our sample, shows that there is considerable variation in the level of competition at the zip code and year level, with a mean value of 0.21 and a standard deviation of 0.21. While most areas exhibit low to moderate levels of concentration, a significant number of areas are very concentrated, with only one certifier active in a given year. To provide first evidence of the link between competition and manipulation, we construct an aggregate measure of competition at the department level, by taking the average HHI of the

[13]More precisely, for each threshold, we calculate the difference between the number of EPCs to the left of the threshold and the number to the right, normalized by the total number of EPCs in the interval. We take the average for the thresholds C to G by department. Metropolitan France has 96 *départements*.

[14]Alternatively, we can define the HHI at the certifier level. See Appendix B for robustness checks using this alternative definition.

certifiers operating in a department/year. Figure 6 plots aggregate bunching, as a function of average competition at the department level. We observe a negative correlation between bunching and HHI: more competition (lower levels of HHI) is associated with more manipulation. To test the robustness of this correlation, we develop an econometric model in the next section.

4 Econometric analysis

4.1 Empirical specification

We focus on the sample of certificates whose theoretical energy consumption is located close to a cutoff where we detect manipulation, as defined in the previous subsection: all EPCs with energy consumption within 5k Wh/m2/year above or below the following cutoffs: C/D, D/E, E/F and F/G.

We consider the benefit Y_{ij}^* that a certifier j gets from issuing a certificate i with an energy consumption close to the thresholds, as a linear function of the vector of explanatory variables X, with β the vector of coefficients, and the error term ϵ_i:

$$Y_{ij}^* = X \cdot \beta + \epsilon_i \tag{1}$$

We can define the probability that the predicted energy consumption falls just below the threshold of one label, defined by the binary variable Y_i, which equals 1 if the theoretical energy consumption of the EPC takes a value just below the cutoff :

$$Y_{ij} = 1 \text{ if } Y_{ij}^* \geq 0 \text{ and } Y_{ij} = 0 \text{ if } Y_{ij}^* < 0 \tag{2}$$

Assuming that the error term follows a standardized normal distribution $\epsilon_i \sim \mathcal{N}(0, 1)$, we can use a probit model for estimation:

$$Pr(Y_{ij} = 1 \mid X_i) = \Phi(X_i \cdot \beta) \tag{3}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

In the main specification, our explanatory variable of interest is the level of competition faced by the certifier in the market in which it operates, measured by the individualized HHI. We also include the number of certificates issued by the certifier to date as a control variable to proxy for experience. In addition, we include controls related to the characteristics of the EPC: the method of certification (energy bill or thermal model) and the date of realization. To control for local property market characteristics, we also include the local number of heating degree days and the local average yearly square meter price at the zip code level. We also add cutoff fixed effects in all specifications.

4.2 Results

The results of the main specification, presented in the first column of table IV, show a negative relationship between HHI and manipulation: a higher level of competition (*i.e.* a smaller HHI) results in more manipulation. The marginal effects, shown in column 2 of Table IV, suggest that a decrease of the HHI by 1 standard deviation (0.21) increases manipulation by 2.24 percentage points.[15] This corresponds on average to a 13% decrease in manipulation at the cutoff.[16] These results are consistent with the prediction from the industrial organization literature that more competition may reduce the quality of certification.

The results on the coefficients of the other control variables also provide some interesting insights. Certifiers' use of thermal modelling seems to lead to more manipulation, which makes sense as certifiers have more freedom to adjust parameters in such a model than when taking the average of past energy bills. Areas with higher average house prices, where the premium for more efficient homes tends to be lowest, as found in Civel (2019), are also associated with lower levels of manipulation.

[15]This number is calculated by multiplying the coefficient of the marginal effect from column (2) of the HHI, which is -0.116, by 0.205,the standard deviation of the HHI.

[16]Compared to a 50% random probability, the probability to be below the cutoff is on average 67% in the sample, i.e. 17 p.p. higher. A decrease of 2.24 p.p. corresponds to a 13% decrease.

4.3 Robustness checks

We perform a series of checks to assess the robustness of our results. First, we run the same probit model at placebo cut-offs. To do so, we replicate the previously described method on EPCs that are not in the "areas of manipulation" but in the middle of EPC classes. Placebo cutoffs selected are 121, 191, 281, 401 kWh/m2/year, the bandwidth is still set at 5kWh/m2/year. EPCs below these respective cut-offs are again attributed a value of 1, and 0 otherwise. Results, presented in column (2) of table V, show no significant effect of competition on bunching at the placebo cut-offs. These results suggest that competition only increases the likelihood of manipulation when it matters to sellers. Second, we check that the results are not sensitive to the definition of the level of competition. To do so, we compute an HHI at the certifier/year level (rather than at a transaction/year level), defining the relevant market for each certifier as all the zipcodes where she is active in a given year (see appendix for a detail of the calculation). Alternative measures of competition lead to a similar negative and significant relationship between concentration and certification (column (3) of table V). Finally, we check that the choice of the bandwidth around the cut-off used to measure the manipulation does not affect the results. Results confirm that choosing a larger bandwith of 10Kwh instead of 5KWh yields similar results (column (4) of table V). Overall, these results confirm the robustness of the finding that markets with higher levels of competition for certifiers have higher levels of manipulation. These results are consistent with predictions from theoretical models that certifiers have incentives to offer more favorable ratings to property owners to increase their market share in the presence of competitors. In the next section, we examine the welfare consequences of manipulation by providing new evidence that a better EPC class does indeed trigger a significant housing premium.

5 Assessing the welfare effects of manipulation: Measuring the willingness to pay for better EPCs

Many studies have measured the green premium associated with energy-efficient homes using hedonic regression models, in which the price of houses is assumed to be a function of their various characteristics, including energy efficiency indicators. However, the main difficulty in interpreting estimates from hedonic models is the potential correlation of the green premium with other unobservable factors affecting house prices. In addition, it is difficult in these models to disentangle the value associated with achieving a particular EPC class from a broader green premium due to the better energy efficiency of the dwelling.

Our aim here is not to measure the house price premium associated with energy-efficient homes but to assess whether there is an effect of "crossing the threshold" between two EPC classes. More specifically, we want to compare the house prices of houses with similar energy consumption that have been assigned different EPC labels, to assess whether the salience of the label has a specific effect on house prices.

Empirically, we can measure the impact of crossing the threshold in a regression discontinuity (RDD) framework, restricting the sample to houses located near an EPC label cutoff that are sold between 2014 and 2024. Figure 8 shows how the log of house prices evolves around each cutoff. We observe a clear discontinuity in house prices when crossing the cutoffs for a better EPC class, suggesting that households are willing to pay a higher price for houses with a better label, even if they have very similar levels of predicted energy consumption. To measure the price premium empirically, we apply a RDD regression model, following the literature (Lee and Lemieux (2010) and Cattaneo and Titiunik (2022)):

$$ln(P_i) = \hat{\alpha} + \hat{\beta} \cdot X_i + \hat{\tau} \cdot D_i + \hat{\gamma} \cdot X_i \cdot D_i + \hat{\epsilon}, \qquad (4)$$

where the dependent variable is the logarithm of the price of houses $ln(P_i)$ located just below and above each cutoff, $\hat{\beta}$ and $\hat{\gamma}$ are the estimated coefficients for energy consumption X_i and the interaction effect between energy consumption and treatment status $X_i \cdot D_i$ of house i, respectively. $\hat{\epsilon}$ is the estimated random error term and $\hat{\alpha}$. The important underlying assumption on which relies RDD is the density continuity of the running variable. The observed manipulation occurring at the thresholds poses, therefore, a threat to identification, as we might be concerned that houses located close to the cutoff, but on different sides, might be different in unobservable characteristics. If these unobserved characteristics are positively linked to the dwelling's quality, the previously observed premiums might be misallocated to EPC classes. To overcome this problem, we adopt a donut-hole RDD strategy, which consists of dropping observations near the cutoff that have potentially been manipulated and conduct the RDD only on observations out of this window. This is a standard strategy adopted in the literature to treat similar situations (Barreca et al. (2011), Cattaneo and Titiunik (2022) and Barr et al. (2022)).[17]

The results in table VII confirm the visual evidence: crossing an RDD threshold is associated with a significant house price premium. For the thresholds B/C C/D, D/E, E/F, a better energy class is related to an increase in house prices of around 6%. The effect is even higher for the extreme thresholds (A/B and F/G), with increases close to 0.15 and 0.20 of the log or price, respectively. We run the same RDD analyses at placebo cutoffs corresponding to the mid-points between each class as a robustness check. We find no significant price premium from crossing a placebo cutoff.

While these effects might seem significant, they align with the behavioral literature showing inattention biases may lead consumers to focus on salient product information features. In the market for used homes, Civel and Cruz (2018) shows that a substantial share of individuals have difficulty processing information about energy efficiency and that they focus their attention on the EPC class, which is the most salient element of the EPC document. Our results show that this focus on the label translates into a significant price premium for a better label, even after controlling for the predicted energy performance

[17] Bandwidth selection and confidence intervals adjustment for robust bias-correction are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017) to accommodate for the potential misspecification bias. The nearest-neighbor method is used for variance estimation.

of the house.

6 Conclusion

This paper explores the relationship between competition and certification quality in the Energy Performance Certificates (EPCs) market. Leveraging French administrative data, we uncover evidence of bunching in the distribution of EPCs at the thresholds between energy performance classes, signaling potential manipulation to secure more favorable ratings. Our empirical findings reveal that the likelihood of manipulation increases as competition among certifiers intensifies. Furthermore, we demonstrate that higher energy performance labels are associated with substantial house price premiums. These findings highlight the distributional consequences of manipulation, as informed sellers reap benefits at the expense of uninformed buyers.

These findings have significant policy implications, as accurately identifying energy-inefficient homes is crucial for prospective buyers or tenants and is a key step in renovating residential buildings and transitioning to a low-carbon economy. The results underscore the challenge and importance of designing labels resistant to manipulation and communicating information clearly and transparently. Compared to the existing literature, our results for France point to larger incentives for manipulation than in other countries. Indeed, existing analyses on energy performance certificates, their manipulation, and the price premium associated with higher ratings reveal significant heterogeneity in results. One possible explanation for this variability is the lack of harmonized EPC rules across countries, which creates very different market incentives. Energy efficiency is a cornerstone of the European decarbonization policy, so we suggest that implementing standardized rules at the European level, based on the characteristics of non-manipulable certificates (for instance, preventing sellers from freely shopping for certifiers, or limiting threshold effects), would effectively address the inefficiencies and welfare losses caused by current certifier practices.

References

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

Andor, M. A., A. Gerster, and S. Sommer (2020). Consumer inattention, heuristic thinking and the role of energy labels. *The Energy Journal 41*(1), pp. 83–112.

Atasoy, A. (2020). Behavioral responses of green builders to discontinuous certification schemes. *Resource and Energy Economics 60*(C), S0928765518300708.

Aydin, E., D. Brounen, and N. Kok (2020, May). The capitalization of energy efficiency: Evidence from the housing market. *Journal of Urban Economics 117*, 103243.

Barr, A., J. Eggleston, and A. A. Smith (2022). Investing in Infants: the Lasting Effects of Cash Transfers to New Families. *The Quarterly Journal of Economics 137*(4), 2539–2583.

Barreca, A. I., M. Guldi, J. M. Lindo, and G. R. Waddell (2011). Saving Babies? Revisiting the effect of very low birth weight classification. *The Quarterly Journal of Economics 126*(4), 2117–2123.

Becker, B. and T. Milbourn (2011). How did increased competition affect credit ratings? *Journal of Financial Economics 101*(3), 493–514.

Bennett, V. M., L. Pierce, J. A. Snyder, and M. W. Toffel (2013). Customer-driven misconduct: How competition corrupts business practices. *Management Science 59*(8), 1725–1742.

Blonz, J. A. (2023). The costs of misaligned incentives: Energy inefficiency and the principal-agent problem. *American Economic Journal: Economic Policy 15*(3), 286–321.

Bolton, P., X. Freixas, and J. Shapiro (2012). The credit ratings game. *The Journal of Finance 67*(1), 85–111.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022). Salience. *Annual Review of Economics 14*(Volume 14, 2022), 521–544.

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.

Cattaneo, M. D., M. Jansson, and X. Ma (2020, July). Simple Local Polynomial Density Estimators. *Journal of the American Statistical Association 115*(531), 1449–1455.

Cattaneo, M. D. and R. Titiunik (2022). Regression discontinuity designs. *Annual Review of Economics 14*(Volume 14, 2022), 821–851.

Cattaneo, M. D. and G. Vazquez-Bare (2017). The Choice of Neighborhood in Regression Discontinuity Designs. *Observational Studies 3*(2), 134–146.

Civel, E. (2019). *The Red and the Green: essays on the economics of information in the sustainable habitat market.* Ph. D. thesis, Université de Nanterre-Paris X.

Civel, E. and N. Cruz (2018). Green, yellow or red lemons? Artefactual field experiment on houses energy labels perception. Working Paper 1809, Chaire Economie du climat.

Collins, M. and J. Curtis (2018). Bunching of residential building energy performance certificates at threshold values. *Applied Energy 211*(C), 662–676.

Comerford, D. A., I. Lange, and M. Moro (2018). Proof of concept that requiring energy labels for dwellings can induce retrofitting. *Energy Economics 69*, 204–212.

Davis, L. W., S. Martinez, and B. Taboada (2020). How effective is energy-efficient housing? evidence from a field trial in mexico. *Journal of Development Economics 143*.

Davis, L. W. and G. E. Metcalf (2016). Does better information lead to better choices? evidence from energy-efficiency labels. *Journal of the Association of Environmental and Resource Economists 3*(3), 589–625.

DGFiP (2023). Direction générale des Finances publiques. *Demandes de valeurs foncières géolocalisées (DVF géolocalisées) - data.gouv.fr*.

Dranove, D. and G. Z. Jin (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature 48*(4), 935–63.

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

Fack, G. and C. Landais (2016). The effect of tax enforcement on tax elasticities: Evidence from charitable contributions in france. *Journal of Public Economics 133*(C), 23–40.

Flynn, S. and A. Ghent (2018). Competition and credit ratings after the fall. *Management Science 64*(4), 1672–1692.

Fowlie, M., M. Greenstone, and C. Wolfram (2018). Do energy efficiency investments deliver? evidence from the weatherization assistance program*. *The Quarterly Journal of Economics 133*(3), 1597–1644.

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.

Goeschl, T. (2019). Cold case: The forensic economics of energy efficiency labels for domestic refrigeration appliances. *Energy Economics 84*.

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

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

Houde, S. (2018b). The incidence of coarse certification: Evidence from the energy star program.

Hubbard, T. N. (1998). An empirical examination of moral hazard in the vehicle inspection market. *The RAND Journal of Economics 29*(2), 406–426.

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

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.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics 8*(Volume 8, 2016), 435–464.

Kleven, H. J., M. B. Knudsen, C. T. Kreiner, S. Pedersen, and E. Saez (2011). Unwilling or unable to cheat? evidence from a tax audit experiment in denmark. *Econometrica 79*(3), 651–692.

Lanz, B. and E. Reins (2021). Asymmetric information on the market for energy efficiency: Insights from the credence goods literature. *The Energy Journal 42*(4), 91–110.

Le Saout, R., B. Mesqui, and R. Jean-Philippe (2022, July). Le parc de logement par classe energétique au 1er janvier 2022. Working Paper, Observatoire National de la Transition Energétique.

Lee, D. S. and T. Lemieux (2010, June). Regression Discontinuity Designs in Economics. *Journal of Economic Literature 48*(2), 281–355.

Lerner, J. and J. Tirole (2006). A model of forum shopping. *American economic review 96*(4), 1091–1113.

Lizzeri, A. (1999). Information revelation and certification intermediaries. *The RAND Journal of Economics 30*(2), 214–231.

Mahenc, P. (2017). Honest versus misleading certification. *Journal of Economics & Management Strategy 26*(2), 454–483.

McCrary, J. (2008, February). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics 142*(2), 698–714.

MEF (2020). L'agent immobilier. *Ministère de l'Économie et des Finances.*

Myers, E., S. L. Puller, and J. West (2022). Mandatory energy efficiency disclosure in housing markets. *American Economic Journal: Economic Policy 14*(4), 453–87.

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.

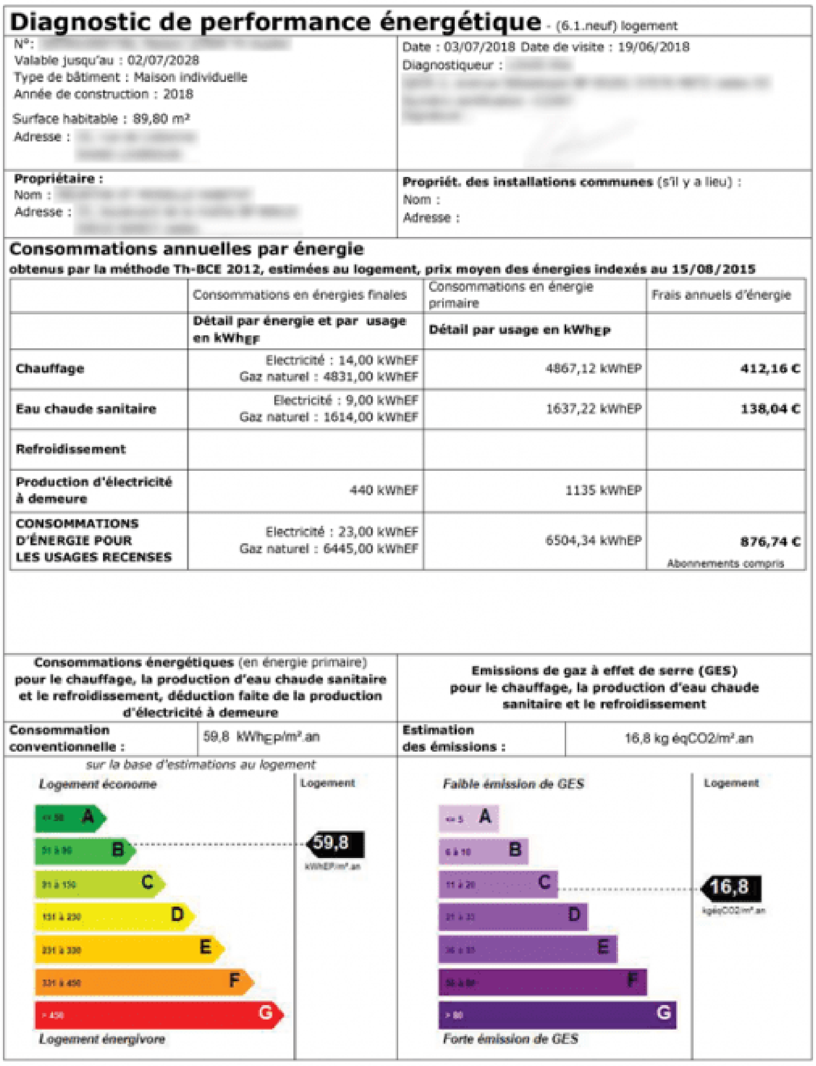
Sejas-Portillo, R., M. Moro, and T. Stowasser (2025). The simpler the better? threshold effects of energy labels on property prices and energy-efficiency investments. *American Economic Journal: Applied Economics.*

Strausz, R. (2005). Honest certification and the threat of capture. *International Journal of Industrial Organization 23*(1-2), 45–62.

Tirole, J. (1986). Hierarchies and bureaucracies: On the role of collusion in organizations. *JL Econ. & Org. 2*, 181.

Zheng, Y. and T. Bar (2021). Certifier competition and audit grades: An empirical examination using food safety certification. *Applied Economic Perspectives and Policy.*

Figures and Tables



Diagnostic de performance énergétique - (6.1.neuf) logement

N°:
Valable jusqu'au : 02/07/2028
Type de bâtiment : Maison individuelle
Année de construction : 2018
Surface habitable : 89,80 m²
Adresse :

Date : 03/07/2018 Date de visite : 19/06/2018
Diagnostiqueur :

Propriétaire :
Nom :
Adresse :

Propriét. des installations communes (s'il y a lieu) :
Nom :
Adresse :

Consommations annuelles par énergie
obtenus par la méthode Th-BCE 2012, estimées au logement, prix moyen des énergies indexés au 15/08/2015

	Consommations en énergies finales	Consommations en énergie primaire	Frais annuels d'énergie
	Détail par énergie et par usage en kWh$_{EF}$	**Détail par usage en kWh$_{EP}$**	
Chauffage	Electricité : 14,00 kWhEF Gaz naturel : 4831,00 kWhEF	4867,12 kWhEP	**412,16 €**
Eau chaude sanitaire	Electricité : 9,00 kWhEF Gaz naturel : 1614,00 kWhEF	1637,22 kWhEP	**138,04 €**
Refroidissement			
Production d'électricité à demeure	440 kWhEF	1135 kWhEP	
CONSOMMATIONS D'ÉNERGIE POUR LES USAGES RECENSES	Electricité : 23,00 kWhEF Gaz naturel : 6445,00 kWhEF	6504,34 kWhEP	**876,74 €** Abonnements compris

Consommations énergétiques (en énergie primaire) **pour le chauffage, la production d'eau chaude sanitaire et le refroidissement, déduction faite de la production d'électricité à demeure**

Consommation conventionnelle : 59,8 kWh$_{EP}$/m².an

sur la base d'estimations au logement

Emissions de gaz à effet de serre (GES) pour le chauffage, la production d'eau chaude sanitaire et le refroidissement

Estimation des émissions : 16,8 kg éqCO2/m².an

Figure 1: Example of an EPC label issued before July 2021

Source: French Minister for Ecological Transition

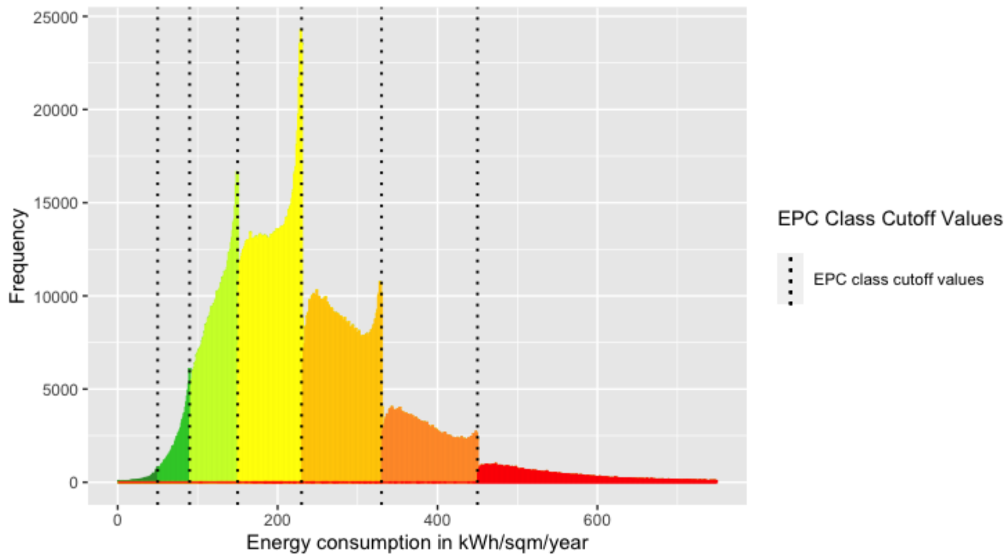


Figure 2: Distribution of EPCs for houses (Jan 2013 - June 2021)

Notes: This figure shows the distribution of EPC energy labels as a function of theoretical energy consumption for the period January 2013 to June 2021. Each colour corresponds to a different EPC class. The dotted lines correspond to cut-off values between two classes, as defined by the French regulation before July 2021. Sample: All EPC issued for houses in France between January 2013 and June 2021, from the ADEME EPC database.

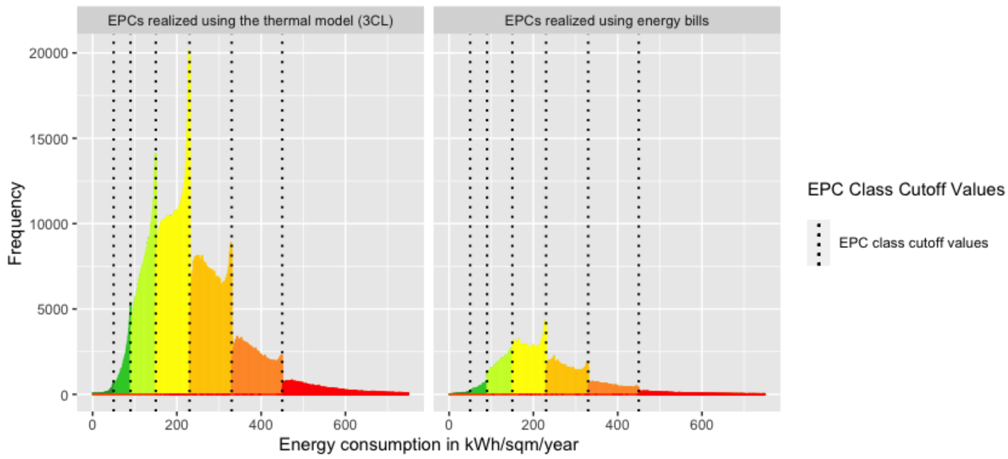


Figure 3: Distribution of EPCs for houses, by method used for computation

Notes: This figure shows the distribution of EPC energy labels as a function of theoretical energy consumption and the method used for computation from January 2013 to June 2021. The left panel corresponds to EPCs issued using the thermal model 3CL (80% of the sample), and the right panel corresponds to EPCs issued using the method based on past energy bills for houses constructed before 1949 (20% of the sample). Each color corresponds to a different EPC class. The dotted lines correspond to cut-off values between two classes, as defined by the French regulation before July 2021. Sample: All EPC issued for houses in France between January 2013 and June 2021, from the ADEME EPC database.

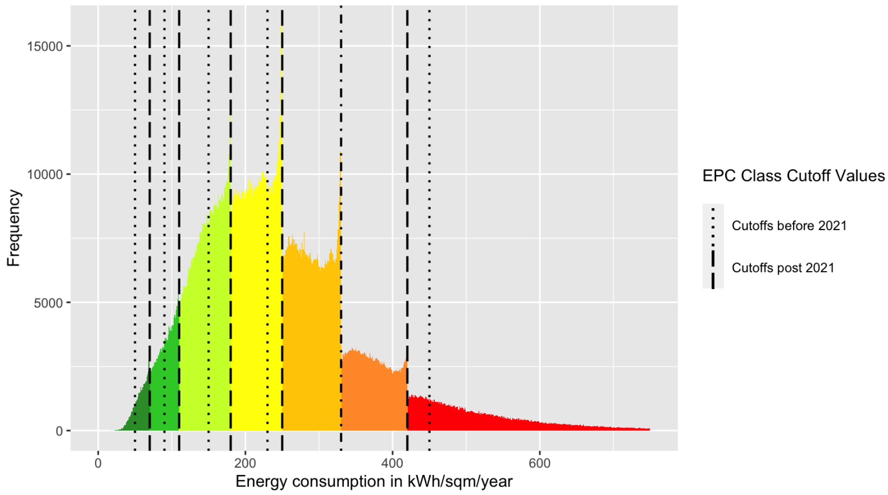


Figure 4: Distribution of EPCs for houses (July 2021-April 2024)
fromsize Notes: This figure shows the distribution of EPC energy labels as a function of theoretical energy consumption from July 2021 to April 2024. Each colour corresponds to a different EPC class. The thin dotted lines correspond to cut-off values between two classes, as defined by the French regulation before July 2021, and the thick dotted lines correspond to the new cutoff values, as defined by the regulation after the July 2021 reform. Sample: All EPC issued for houses in France between July 2021 and April 2024, from the ADEME EPC database.

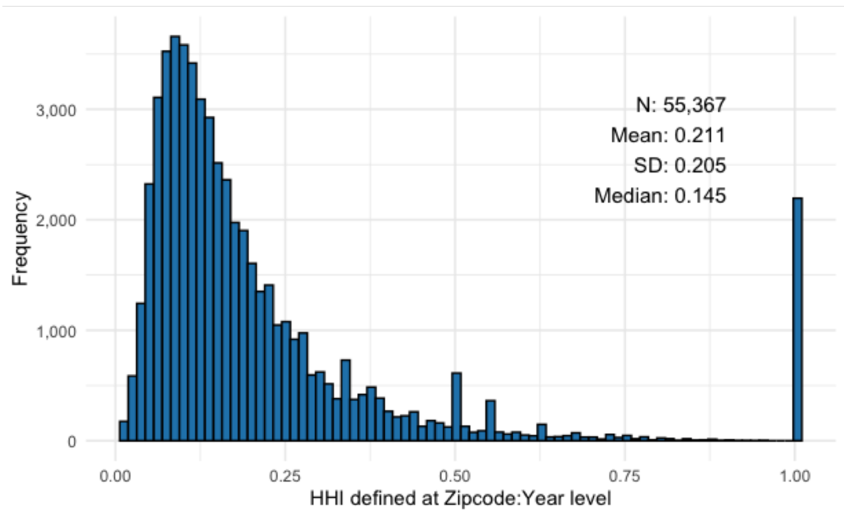


Figure 5: Herfindahl-Hirschman Index per Zipcode

Notes: This figure shows the distribution of HHI computed at the zipcode level for a given year, for the period 2013 to 2021. Calculations from the authors, using the database for all EPCs for houses and flats issued in France between January 2013 and June 2021, taken from the ADEME EPC database.

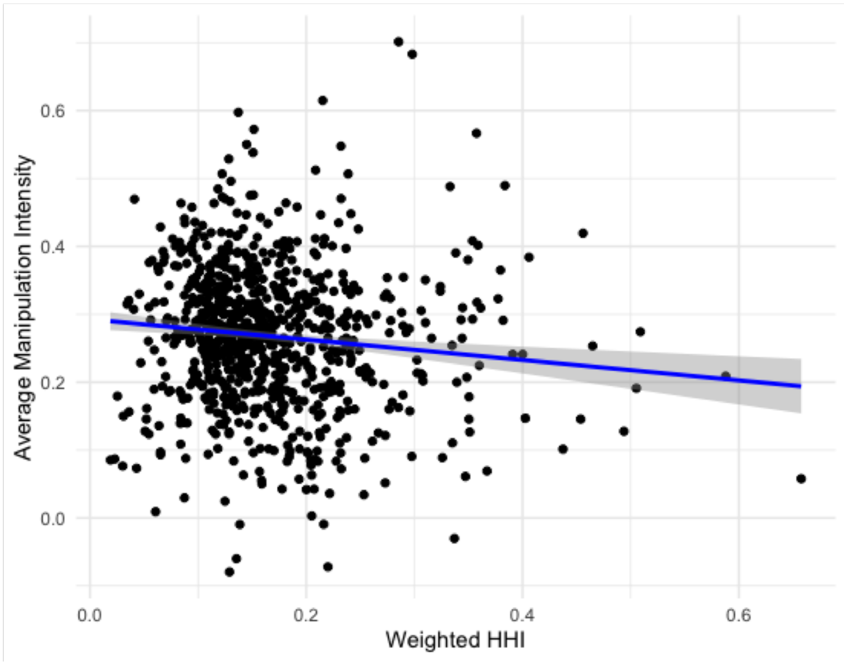
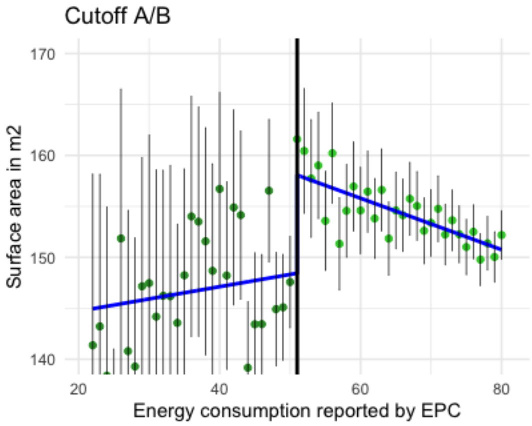
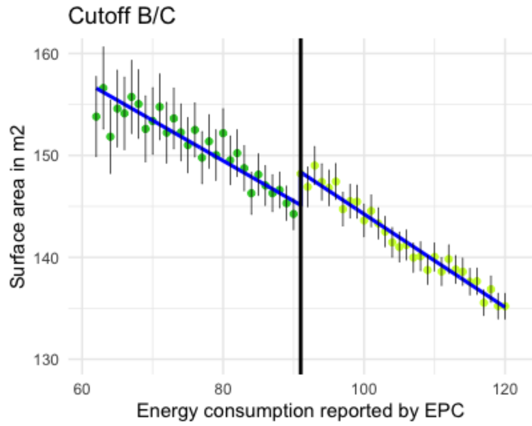


Figure 6: Manipulation intensity vs weighted HHI defined by zipcode:year

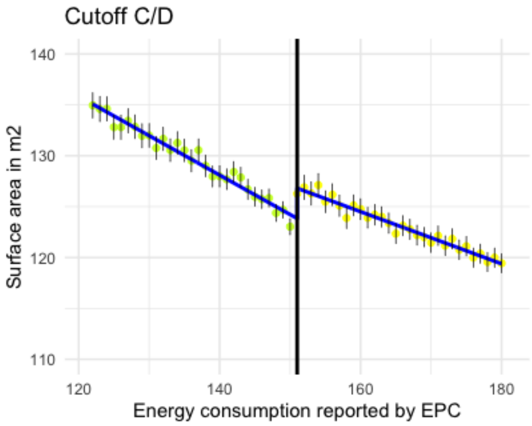
Notes: This figure shows the relationship between the average concentration of certifiers at departmental level and the intensity of manipulation of EPC certificates at the same level. Metropolitan France is divided into 96 departments, administrative areas similar to English counties. Manipulation is calculated as the average at the departmental level at cutoffs from C to G for a given year. For each cut-off, we calculate the difference between the number of EPCs to the left of the threshold in the department and the number to the right, normalized by the total number of EPCs in the interval. Average concentration at the department level is computed as the weighthed HHI of certifiers operating in each zip code of the department and year (with weights taking into account the certifier activity in each zip code). The corresponding fitted linear model gives a significant negative effect of weighted HHI on manipulation intensity (coefficient : -0.11003**). Calculations from the authors, using the database for all EPCs for houses and flats issued in France between January 2013 and June 2021 taken from the ADEME EPC database.



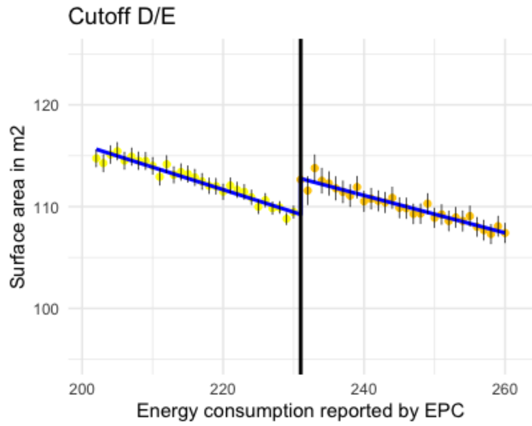
(a) Cutoff between class A and B



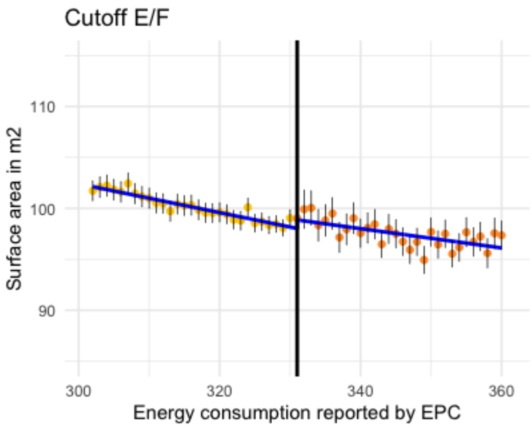
(b) Cutoff between class B and C



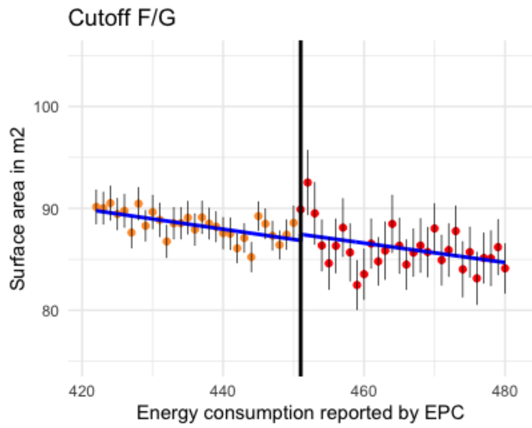
(c) Cutoff between class C and D



(d) Cutoff between class D and E



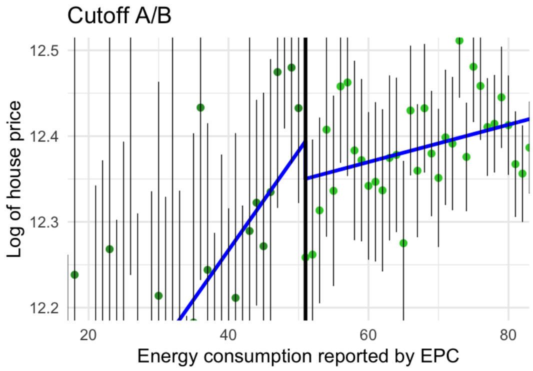
(e) Cutoff between class E and F



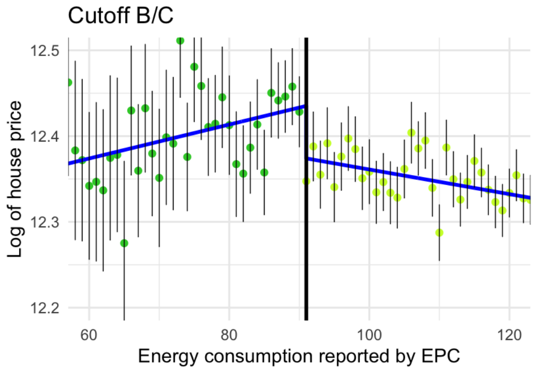
(f) Cutoff between class F and G

Figure 7: Reported Surface area of the house at the cutoffs between energy classes

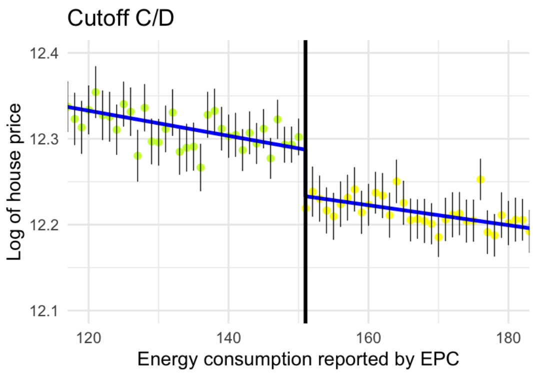
Notes: This figure plots the binned averages and confidence intervals of the surface area of houses (in square meters) reported by EPC certifiers as a function of the predicted energy consumption of the house in the vicinity of each of the cut-off between two neighboring energy consumption classes. The thick vertical lines represent the value of the energy consumption cut-off between two energy classes. The blue lines represent the linear fit computed separately on either side of the cut-off. Calculations from the authors, using the database for all EPCs for houses issued in France between January 2013 and June 2021 taken from the ADEME EPC database. Bandwidths are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017).



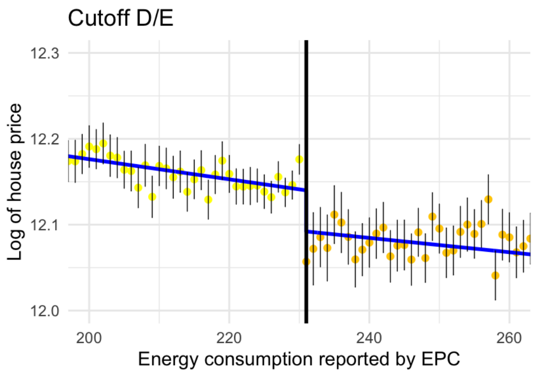
(a) Cutoff between class A and B



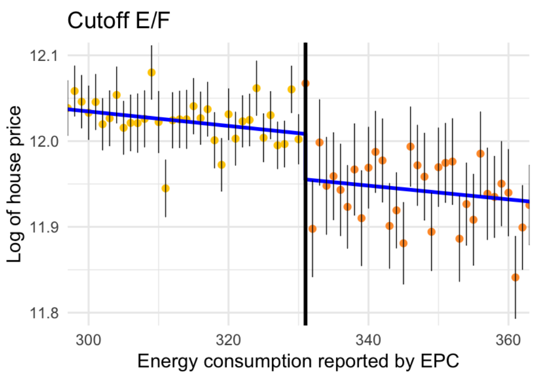
(b) Cutoff between class B and C



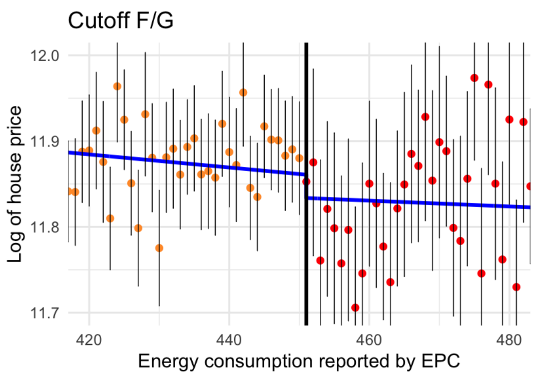
(c) Cutoff between class C and D



(d) Cutoff between class D and E



(e) Cutoff between class E and F



(f) Cutoff between class F and G

Figure 8: RDplots - Log of house price vs energy consumption.

Notes: This figure plots the binned averages and confidence intervals of the log of house price, as a function of the predicted energy consumption of the house in the vicinity of each of the cut-off between two neighbouring energy consumption classes. The thick vertical lines represent the value of the energy consumption cut-off between two energy classes. The blue lines represent the linear fit computed separately on either side of the cut-off. Calculations from the authors, using the database of houses sold in France between 2014 and 2022 houses merged with a corresponding EPC from the ADEME database database. Bandwidths are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017).

Table I: Summary Statistics - Certifiers

Statistic	**Value / Mean (SD)**
Number of Certifiers	14,443
Mean number of Certificates per certifier	473.0 (836.0)
Mean number of departments of intervention	4.24 (3.25)
Mean number of zipcodes of intervention	41.0 (38.6)
Mean number of active years	3.92 (2.36)

Notes: Calculations from the authors, using the certifier's identifier from the ADEME database for all EPCs for houses and flats issued in France between January 2013 and June 2021.

Table II: Summary statistics - EPCs

Variable	(1) **All EPCs**	(2) **Manipulated Cutoffs EPCs**	(3) **EPCs with Price Data**
Certification method:			
Thermal model (3CL)	80.6%	80.8%	80.1%
Energy bills	19.4%	19.5%	19.2%
EPC Class:			
A	0.3%	0.0%	0.3%
B	3.0%	0.0%	2.6%
C	18.5%	20.7%	17.7%
D	35.5%	46.6%	36.3%
E	27.7%	23.9%	28.3%
F	11.3%	7.7%	11.5%
G	3.7%	1.1%	3.3%
Year of certification			
2013	5.9%	5.7%	6.7%
2014	10.7%	10.6%	18.6%
2015	11.0%	11.1%	17.5%
2016	11.5%	11.5%	17.0%
2017	12.4%	12.3%	16.0%
2018	13.3%	13.3%	14.2%
2019	14.2%	14.3%	9.5%
2020	12.8%	12.7%	0.6%
2021	8.4%	8.3%	0.0%
Construction period			
Before 1945	4.2%	4.0%	8.5%
1945-1974	40.0%	38.7%	43.8%
1974-1981	18.0%	18.1%	17.6%
1982-2000	20.0%	21.7%	17.2%
2001-2004	4.2%	4.4%	3.1%
2005-2012	11.3%	11.2%	8.2%
2012-2022	2.3%	1.8%	1.6%
Unknown	0.1%	0.1%	0.0%
Av. floor space (in m^2)	111.4 (47.2)	110.6 (45.3)	105.7 (38.9)
Av. nb of heating degree days	2,220.5 (391.1)	2,225.7 (389.7)	
Av. property value (in euros)			226,227 (159,888)
Av. number of rooms:			4.2 (1.3)
Av. land area (in m^2)			394.7 (281.5)
Observations	3,179,609	328,478	568,436

Notes: Statistics are calculated on the different samples used in the paper. Standard deviations are shown in parenthesis. Column (1): all EPCS for houses issued in France between January 2013 and June 2021 from ADEME. Column (2): EPCs with predicted energy consumption between -5 and $+5$ KWh of a manipulated cutoff. Column (3): all recorded houses sales in France between 2014 and 2022 merged with a valid EPC.The ADEME database on energy performance certificates (EPCs) provides information on the method used to predict energy consumption (thermal model or energy bills-for houses built before 1949), the EPC class, the year of certification, the construction period, number of heating degree days in the department, and floor space of the dwelling, as reported by the certifier. Other variables are only available for the sample of EPCs merged with data on property sales.

Table III: Density Discontinuity Tests

Cutoff	**Robust T-value**	
	(1) **All EPCs**	(2) **EPCs with price**
51 (A/B)	-1.7319*	0.4841
91 (B/C)	-10.667**	2.1698*
121 (Placebo)	1.0018	1.1663
151 (C/D)	-47.5297***	-20.9581***
191 (Placebo)	1.3488	1.1315
231 (D/E)	-140.1038***	-65.6055***
281 (Placebo)	-0.428	0.9061
331 (E/F)	-89.1625***	-37.5676***
401 (Placebo)	-0.7387	-0.656
451 (F/G)	-38.9022***	-13.2896***

Notes: this table shows the results of the test for discontinuity in density from Cattaneo et al. (2020), testing for discontinuities at the thresholds between each EPC class as well as at placebo cut-offs. Column (1): sample of all EPCs issued between January 2013 and June 2021, Column (2): sample of EPCs matched with a house sale. Significance of the test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table IV: Probit Model for EPC manipulation

	Probability of EPC value being below cutoffs:	
	(1)	(2)
	Probit Coefficients	Marginal Effects
Herfindahl-Hirschman Index (HHI)	-0.325^{***}	-0.116^{***}
	(0.022)	(0.008)
Certification method:		
• Energy bill	Reference	Reference
• Thermal model	0.268^{***}	0.099^{***}
	(0.006)	(0.002)
Heating degree days	-0.00002^{***}	-0.000007^{***}
	(0.00001)	(0.000002)
Number of certificates realized	-0.00000	-0.000000
	(0.00000)	(0.000001)
Zipcode average price/m^2	-0.00001^{***}	-0.000005^{***}
	(0.00000)	(0.000001)
Date of realization	0.00000	0.000000
	(0.00000)	(0.000001)
Constant	0.046	–
	(0.053)	
Cutoff Fixed Effects	Yes	Yes
Observations	328,478	328,478
Log Likelihood	−199,815.700	
Akaike Inf. Crit.	399,651.300	

Notes: this table shows the results of the estimation of the probit model for the sample of EPCs within $-/+5$ Kwh/m^2 of a manipulated cut-off (C to G), where the dependent variable is an indicator for the EPC falling below the cut-off. The main variable of interest is the Herfindahl-Hirschman Index (HHI), defined at the zipcode/year level. Control variables include the certification method used to calculate the EPC, the number of certificates already realized by the certifier, the date of realization of the EPC, the number of heating degree days at the departement level, the average house price per/m^2 at the zipcode level and cut-off fixed effects. Column (1): results of the probit regression and , Column (2): Marginal effects. Standard errors in parenthesis. Significance of the test: *** p < 0.01, ** p < 0.05, * p < 0.1. Calculations by the authors from the ADEME database of EPC for houses (January 2013-June 2021).

Table V: Probit Model for EPC manipulation - Robustness checks

	Probability of EPC value being below cutoffs:			
	(1)	(2)	(3)	(4)
	Main specification	Placebo cutoffs	Alternative HHI (per certifier)	Bandwidth of 10kWh
Herfindahl-Hirschman Index	-0.325^{***}	0.017	-0.754^{***}	-0.285^{***}
	(0.022)	(0.021)	(0.066)	(0.015)
Certification method:				
• Energy bill	Reference	Reference	Reference	Reference
• Thermal model	0.268^{***}	-0.022^{***}	0.269^{***}	0.183^{***}
	(0.006)	(0.005)	(0.006)	(0.004)
Heating degree days	-0.00002^{***}	-0.00003^{***}	-0.00002^{***}	-0.00004^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00000)
Number of certificates realized	-0.00000	-0.00001^{***}	-0.00001^{**}	0.00001^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Zipcode average price/m^2	-0.00001^{***}	-0.00000	-0.00001^{***}	-0.00001^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Date of realization	0.00000	0.00001^{**}	0.00000	0.00000^{*}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	0.046	-0.093^{*}	-0.045	0.019
	(0.053)	(0.049)	(0.052)	(0.037)
Cutoff Fixed Effects	Yes	Yes	Yes	Yes
Observations	328,478	346,093	328,478	662,026
Log Likelihood	−199,815.700	−239,428.900	−199,859.800	−417,434.300
Akaike Inf. Crit.	399,651.300	478,877.700	399,739.500	834,888.700

Notes: this table shows the results of the estimation of the probit model for the sample of EPCs , where the dependent variable is an indicator for the EPC falling below the cut-off. The main variable of interest is the Herfindahl-Hirschman Index (HHI), defined at the zipcode/year level. Control variables include the certification method used to calculate the EPC, the number of certificates already realized by the certifier, the date of realization of the EPC, the number of heating degree days at the departement level, the average house price per/m^2 at the zipcode level and cut-off fixed effects. Column (1): results of main specification, on the sample of EPCs within $-/+5$ Kwh/m^2 of a manipulated cut-off (C to G); Column (2): results of the probit on the sample of EPCs within $-/+5$ Kwh/m^2 of a placebo cut-off; Column (3): results of the probit on the same sample as column (1) but with an alternative definition of the HHI at the certifier/year level; Column (4) results of the probit on the sample of EPCs within $-/+10$ Kwh/m^2 of a manipulated cut-off. Standard errors in parenthesis. Significance of the test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Calculations by the authors from the ADEME database of EPC for houses (January 2013-June 2021).

Table VI: RD Estimates on House Surface

Cutoff	Model	Coefficient	Std.Err.	P>|z|	CI.Lower	CI.Upper
51	Conventional	13.5789***	2.6771	0.0000	8.3319	18.8260
51	Bias-Corrected	13.4265***	2.6771	0.0000	8.1794	18.6736
51	Robust	13.4265***	3.2602	0.0000	7.0367	19.8164
91	Conventional	4.5694***	0.7552	0.0000	3.0893	6.0496
91	Bias-Corrected	4.8285***	0.7552	0.0000	3.3484	6.3087
91	Robust	4.8285***	0.8969	0.0000	3.0707	6.5864
131 (Placebo)	Conventional	-0.3531	0.8541	0.6793	-2.0272	1.3209
131 (Placebo)	Bias-Corrected	-0.4213	0.8541	0.6218	-2.0953	1.2527
131 (Placebo)	Robust	-0.4213	1.0779	0.6959	-2.5340	1.6914
151	Conventional	3.8542***	0.4423	0.0000	2.9874	4.7210
151	Bias-Corrected	4.0498***	0.4423	0.0000	3.1830	4.9166
151	Robust	4.0498***	0.5154	0.0000	3.0397	5.0600
201 (Placebo)	Conventional	-0.3240	0.4226	0.4432	-1.1523	0.5043
201 (Placebo)	Bias-Corrected	-0.3771	0.4226	0.3722	-1.2054	0.4511
201 (Placebo)	Robust	-0.3771	0.5103	0.4599	-1.3773	0.6230
231	Conventional	4.0098***	0.3611	0.0000	3.3021	4.7176
231	Bias-Corrected	4.1555***	0.3611	0.0000	3.4478	4.8633
231	Robust	4.1555***	0.4137	0.0000	3.3447	4.9663
281 (Placebo)	Conventional	-0.0341	0.5581	0.9513	-1.1279	1.0597
281 (Placebo)	Bias-Corrected	-0.0757	0.5581	0.8921	-1.1695	1.0181
281 (Placebo)	Robust	-0.0757	0.6865	0.9122	-1.4212	1.2698
331	Conventional	1.1648***	0.3669	0.0015	0.4457	1.8839
331	Bias-Corrected	1.2583***	0.3669	0.0006	0.5392	1.9774
331	Robust	1.2583***	0.4345	0.0038	0.4068	2.1098
401 (Placebo)	Conventional	-1.0947	0.8809	0.2140	-2.8213	0.6319
401 (Placebo)	Bias-Corrected	-1.2820	0.8809	0.1456	-3.0086	0.4446
401 (Placebo)	Robust	-1.2820	1.0778	0.2342	-3.3944	0.8304
451	Conventional	0.6586	0.5859	0.2610	-0.4897	1.8069
451	Bias-Corrected	0.8230	0.5859	0.1601	-0.3252	1.9713
451	Robust	0.8230	0.6896	0.2327	-0.5286	2.1747

Notes: This table present the coefficient of the RDD doughnut estimation, where the dependent variable is the house surface. Each row corresponds to a different local polynomial regression discontinuity estimation at a different threshold. Actual cut-offs are located at 51 Kwh/m^2 (A/B), 91 Kwh/m^2 (B/C),151 Kwh/m^2 (C/D), 231 Kwh/m^2 (D/E), 331 Kwh/m^2 (E/F) and 451 Kwh/m^2 (F/G). The thresholds 131, 201, 281 and 401 Kwh/m^2 correspond to placebo cut-offs. The coefficients report the magnitude of the jump at each threshold, with three different methods for estimation (Conventional, Bias-Corrected and Robust). Bandwidth selection and confidence intervals adjustment for robust bias-correction are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017) to accommodate for the potential misspecification bias. Observations between within $-/+5$ Kwh/m^2 of each threshold are excluded from the regression to account for potential manipulation. The nearest-neighbor method is used for variance estimation. Standard errors in parenthesis. Significance of the test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Calculations by the authors from the ADEME database of EPC for houses, merged with price data (2014-2022).

Table VII: RD Estimates on the log of House Price

Cutoff	Model	Coefficient	Std.Err.	P>|z|	CI.Lower	CI.Upper
51	Conventional	-0.1993***	0.0458	0.0000	-0.2890	-0.1096
51	Bias-Corrected	-0.2191***	0.0458	0.0000	-0.3088	-0.1294
51	Robust	-0.2191***	0.0524	0.0000	-0.3217	-0.1165
91	Conventional	-0.0652***	0.0157	0.0000	-0.0959	-0.0345
91	Bias-Corrected	-0.0700***	0.0157	0.0000	-0.1007	-0.0392
91	Robust	-0.0700***	0.0188	0.0002	-0.1067	-0.0332
121 (Placebo)	Conventional	0.0055	0.0101	0.5856	-0.0143	0.0254
121 (Placebo)	Bias-Corrected	0.0097	0.0101	0.3397	-0.0102	0.0295
121 (Placebo)	Robust	0.0097	0.0121	0.4245	-0.0140	0.0334
151 (donut)	Conventional	-0.0625***	0.0160	0.0001	-0.0938	-0.0312
151 (donut)	Bias-Corrected	-0.0679***	0.0160	0.0000	-0.0993	-0.0366
151 (donut)	Robust	-0.0679***	0.0190	0.0004	-0.1052	-0.0306
191 (Placebo)	Conventional	0.0041	0.0071	0.5669	-0.0099	0.0180
191 (Placebo)	Bias-Corrected	0.0021	0.0071	0.7698	-0.0119	0.0161
191 (Placebo)	Robust	0.0021	0.0084	0.8034	-0.0143	0.0185
231 (donut)	Conventional	-0.0639***	0.0123	0.0000	-0.0880	-0.0398
231 (donut)	Bias-Corrected	-0.0690***	0.0123	0.0000	-0.0931	-0.0449
231 (donut)	Robust	-0.0690***	0.0140	0.0000	-0.0964	-0.0416
281 (Placebo)	Conventional	-0.0094	0.0085	0.2702	-0.0261	0.0073
281 (Placebo)	Bias-Corrected	-0.0103	0.0085	0.2252	-0.0271	0.0064
281 (Placebo)	Robust	-0.0103	0.0102	0.3120	-0.0304	0.0097
331 (donut)	Conventional	-0.0568***	0.0119	0.0000	-0.0801	-0.0334
331 (donut)	Bias-Corrected	-0.0609***	0.0119	0.0000	-0.0843	-0.0376
331 (donut)	Robust	-0.0609***	0.0137	0.0000	-0.0877	-0.0342
401 (Placebo)	Conventional	0.0049	0.0122	0.6872	-0.0190	0.0289
401 (Placebo)	Bias-Corrected	0.0021	0.0122	0.8656	-0.0219	0.0260
401 (Placebo)	Robust	0.0021	0.0145	0.8863	-0.0263	0.0304
451 (donut)	Conventional	-0.1553***	0.0406	0.0001	-0.2348	-0.0758
451 (donut)	Bias-Corrected	-0.1737***	0.0406	0.0000	-0.2533	-0.0942
451 (donut)	Robust	-0.1737***	0.0448	0.0001	-0.2615	-0.0860

Notes: This table present the coefficient of the RDD doughnut estimation, where the dependent variable is the log of house price. Each row corresponds to a different local polynomial regression discontinuity estimation at a different threshold. Actual cut-offs are located at 51 Kwh/m^2 (A/B), 91 Kwh/m^2 (B/C),151 Kwh/m^2 (C/D), 231 Kwh/m^2 (D/E), 331 Kwh/m^2 (E/F) and 451 Kwh/m^2 (F/G). The thresholds 131, 201, 281 and 401 Kwh/m^2 correspond to placebo cut-offs. The coefficients report the magnitude of the jump at each threshold, with three different methods for estimation (Conventional, Bias-Corrected and Robust). Bandwidth selection and confidence intervals adjustment for robust bias-correction are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017) to accommodate for the potential misspecification bias. Observations between within $-/+5$ Kwh/m^2 of each threshold are excluded from the regression to account for potential manipulation. The nearest-neighbor method is used for variance estimation. Standard errors in parenthesis. Significance of the test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Calculations by the authors from the ADEME database of EPC for houses, merged with price data (2014-2022).

(For Online Publication)

Appendix to

XXX
Certification, manipulation and competition: evidence from Energy Performance Certificates

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December 2024

A Appendix A - Detailed description of the datasets

A.1 EPC database

In France, certifiers must register each EPC with the French Agency for Energy Transition (ADEME) to be considered officially valid. The resulting EPC database, produced by ADEME, is available in open access on the French government open data portal.[18] It contains the universe of EPCs carried out since between January 2013 and July 2021 by 14,443 different certifiers. This comprehensive CPE database includes more than 90 variables that certifiers are required to fill in when assessing buildings. These variables provide detailed information about the building, including geolocation data (latitude and longitude) for most entries and the year of construction. They also provide detailed information on the EPC assessment for each dwelling unit: the expected annual primary energy consumption in kilowatt hours per square metre, the EPC label awarded, the EPC assessment method (based on the dwelling's heating bills or a thermal model), the certifier's identifier, and the date of the assessment. After excluding entries containing missing or incorrect information (such as incorrect geolocation data, inaccurate postal zone information or inconsistent energy consumption figures), we refined the dataset to include dwellings with a primary energy consumption between 0 and 700 kWh/m^2/year.

A.2 Real Estate Data

Real Estate data comes from the transaction data *"Demande de valeur Foncieres"* produced by the French Department of the Treasury, which provides information on property transactions in mainland France (except Alsace and Moselle). The information contained in the dataset comes from official deeds of sale and cadastral information. This dataset comprises variables related to each transaction, including geolocation information of the dwelling, property characteristics, and the transaction price. The last five years of the datasets are available in open access on the French government's open data portal.[19]. Researchers can request access to historical archives of the data from CEREMA.[20]

We use the registry of all real estate transactions from January 1st, 2014, to December 31st, 2022. Key entries with missing or inconsistent information were removed. Additionally, luxury buildings valued over 2 million euros and dwellings priced below 10,000 euros were excluded from the analysis.

A.3 The method to merge the two datasets

To carry out our analysis, we merged the two datasets. Laking a common identifier, we used geolocation variables (latitude and longitude) to link EPCs to transaction records. Given the differences in the registration of coordinates in each database, a direct match with specific latitude and longitude values was not sufficient. Our matching strategy was to draw a circle with a radius of 20 metres around each property transaction location

[18]see https://www.data.gouv.fr/fr/posts/la-base-des-diagnostics-de-performance-energetique-dpe/
[19]see https://www.data.gouv.fr/fr/datasets/demandes-de-valeurs-foncieres/
[20]https://datafoncier.cerema.fr/dv3f

and use an algorithm to identify EPCs within this area. From the pre-selected EPCs, we assigned the one that contained consistent information about the property characteristics (such as the house size in square metres). Where more than one EPC matched the property characteristics, the most recent pre-sale valuation was selected. We chose to restrict the analysis to houses, as the geographical accuracy of the match is better for houses than for multi-family dwellings.

The resulting merged database contains 568,550 house transactions matched with their EPC. Summary statistics (see Table II), is roughly similar to the original EPC databases, indicating that the merged database accurately represents the initial sample. Moreover, the sample of EPC and houses sold restricted to the manipulated cutoffs are also roughly similar.

B Appendix B - Robustness checks

B.1 Calculation of the HHI

Our main measure of concentration is the Herfindahl-Hirschman Index (HHI), calculated at the zipcode year level, reflecting the local level of competition faced by property owners. To check that the results are robust to the definition of the concentration measure, we also compute the HHI at the certifier level for the entire period under study. To do this, we define each certifier's relevant market as all combinations of years and postcodes in which she has issued at least one EPC, whether for a house or an apartment. Then, within this defined market, the HHI is calculated in the standard way by summing the squares of the market shares of each certifier that has operated in that market. This process results in a specific HHI for each certifier, reflecting the concentration of the market in which she operates, rather than the concentration of the market in the area where the property is located. The results using this alternative measure of HHI (see Table V) are similar to the main results: a higher level of concentration (lower HHI) is associated with less manipulation.

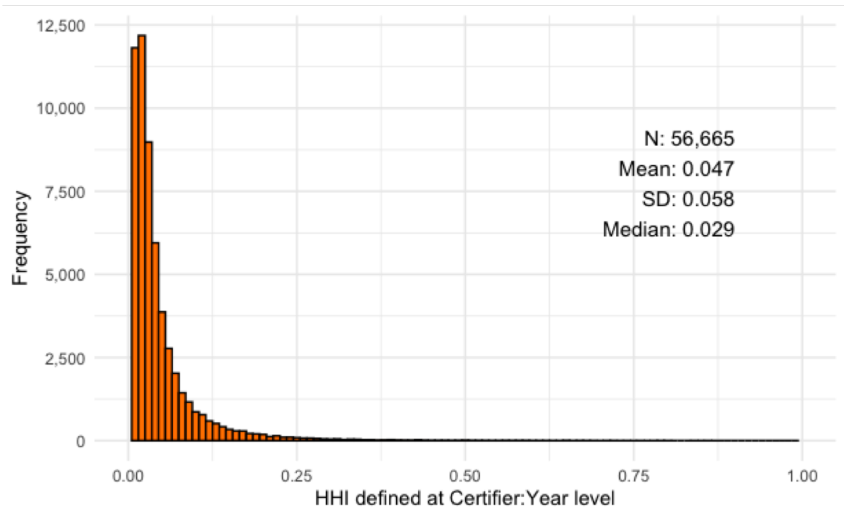

Figure 9: Herfindahl-Hirschman Index defined per Certifier and per year

Notes: This figure shows the distribution of HHI computed at the certifier level for a given year, from 2013 to 2021. Calculations from the authors, using the database for all EPCs for houses and flats issued in France between July 2021 and April 2024, taken from the ADEME EPC database.

C Appendix C - Additional Tables

Table VIII: EPC count 5kWh below and above cutoffs

Cutoff	**Below**	**Above**
C/D	67,930	55,053
D/E	98,509	34,238
E/F	44,073	14,317
F/G	10,680	3,678
Total	**221,192**	**107,286**

Notes: this table shows the number of EPCs issued above and below each EPC cut-off, for a bandwidth of -5 to $+5$ kWh of predicted energy consumption per m^2, from the ADEME database.

Table IX: RD Estimates - House Price in level

Cutoff	Model	Coefficient	Std.Err.	P>|z|	CI.Lower	CI.Upper
51	Conventional	-26,997**	11,868	0.0229	-50,259	-3,735
51	Bias-Corrected	-33,579***	11,868	0.0047	-56,841	-10,317
51	Robust	-33,579**	13,824	0.0151	-60,674	-6,484
91	Conventional	-10,806***	4,071	0.0080	-18,787	-2,826
91	Bias-Corrected	-10,758***	4,071	0.0082	-18,738	-2,777
91	Robust	-10,758**	5,126	0.0359	-20,806	-709.5
151 (donut)	Conventional	-8,085**	3,913	0.0388	-15,755	-414.9
151 (donut)	Bias-Corrected	-9,839**	3,913	0.0119	-17,509	-2,168
151 (donut)	Robust	-9,839**	4,887	0.0441	-19,417	-260.5
231 (donut)	Conventional	-5,834*	3,017	0.0531	-11,747	79.16
231 (donut)	Bias-Corrected	-7,119**	3,017	0.0183	-13,032	-1,205
231 (donut)	Robust	-7,119**	3,629	0.0498	-14,232	-6.533
331 (donut)	Conventional	-6,396**	2,507	0.0107	-11,311	-1,481
331 (donut)	Bias-Corrected	-7,365***	2,507	0.0033	-12,279	-2,450
331 (donut)	Robust	-7,365**	2,920	0.0117	-13,088	-1,641
451 (donut)	Conventional	-24,794***	7,329	0.0007	-39,160	-10,429
451 (donut)	Bias-Corrected	-27,890***	7,329	0.0001	-42,255	-13,525
451 (donut)	Robust	-27,890***	8,902	0.0017	-45,338	-10,442

Notes: This table present the coefficient of the RDD doughnut estimation, where the dependent variable is the house price in level. Each row corresponds to a different local polynomial regression discontinuity estimation at a different threshold. Actual cut-offs are located at 51 Kwh/m^2 (A/B), 91 Kwh/m^2 (B/C),151 Kwh/m^2 (C/D), 231 Kwh/m^2 (D/E), 331 Kwh/m^2 (E/F) and 451 Kwh/m^2 (F/G). The thresholds 131, 201, 281 and 401 Kwh/m^2 correspond to placebo cut-offs. The coefficients report the magnitude of the jump at each threshold, with three different methods for estimation (Conventional, Bias-Corrected and Robust). Bandwidth selection and confidence intervals adjustment for robust bias-correction are selected following the procedure developed in Cattaneo and Vazquez-Bare (2017) to accommodate for the potential misspecification bias. Observations between within $-/+5$ Kwh/m^2 of each threshold are excluded from the regression to account for potential manipulation. The nearest-neighbor method is used for variance estimation. Standard errors in parenthesis. Significance of the test: *** p < 0.01, ** p < 0.05, * p < 0.1. Calculations by the authors from the ADEME database of EPC for houses, merged with price data (2014-2022).

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