

The Effect of Energy Efficiency Obligations on Residential Energy Consumption and the Abatement Cost of Carbon

February 3, 2026

Abstract

We evaluate the French Energy Savings Certificates (CEE) program, under which energy retailers subsidize building retrofits to comply with mandatory energy-efficiency targets. Using municipality-level panel data for 4,774 municipalities over 2018–2020, we estimate the program’s impact on gas and electricity consumption and associated carbon emissions. We find that official reporting overstates energy savings by at least 59%. We then develop a novel method to estimate the corresponding average carbon abatement cost by exploiting the tradability of energy-saving certificates. Combining certificate prices with estimated energy impacts and relevant emissions factors yields a preferred estimate of EUR 150 per ton of CO₂e. Accounting for program-induced energy price effects on demand reduces this cost to EUR 52 per ton, suggesting that the program is cost-effective overall.

Keywords: Energy efficiency, energy efficiency obligations, abatement cost of carbon

JEL codes: L78, Q48, Q58

1 Introduction

Improving the energy efficiency of the building stock is a cornerstone of the energy transition. According to the International Energy Agency, global investment in building energy retrofits averaged more than USD 160 billion annually between 2015 and 2021 (IEA 2022). This represents around 60% of all global energy-efficiency investments, more than twice the amount devoted to the transportation sector (IEA 2022). And much more is expected in the years ahead. In the European Union, the Renovation Wave strategy aims to double the renovation rate in order to support the achievement of the 55% greenhouse gas emissions reduction target by 2030 compared with 1990 levels. Its implementation requires giving a lion's share to energy-efficiency investments in buildings. In France, they are expected to account for around 70% of the total investments necessary to meet the national 2030 climate targets (Pisany-Ferry and Mahfouz 2023).

The central role given to building renovation in decarbonization stems from the recognition of its multiple co-benefits: job creation, health gains, reduced energy poverty, and greater energy independence. It also reflects strong confidence in its energy impacts. As stated by the (International Energy Agency 2018), energy efficiency is the "first fuel", the fuel you do not have to use. Since the late 1970s, insulation measures and the adoption of energy-efficient heating and cooling technologies have been widely promoted as a win-win strategy to reduce energy consumption and associated carbon emissions.

This view has largely been grounded in engineering model projections suggesting that energy savings would be sufficiently large, over time, to more than offset upfront investment costs. The most popular illustration is the so-called McKinsey marginal abatement cost curve which claims that energy efficiency investments in buildings exhibit negative abatement cost of carbon (McKinsey 2009). These results have been challenged by a growing empirical literature documenting that realized energy savings systematically fall short of engineering projections. In the United States, the recent studies estimate the energy performance gap between projected and realized savings to be around 55% (Allcott and Greenstone 2024; Fowlie et al. 2018; Christensen et al. 2023; Zivin and Novan 2016). Papineau et al. (2025) report similar magnitudes for Canada. See also Davis et al. (2020) for Mexico.

That energy savings are lower than expected does not mean *per se* that carbon abatement costs need to be revised upward. Fowlie et al. (2018) derive from their energy impact estimates a cost of

USD 350 per tCO₂e abated through the Weatherization Assistance Program (WAP) in Michigan¹. Similarly, Lang and Lanz (2022) estimate an abatement cost of USD 380 per tCO₂e for a Swiss energy efficiency program.

These cost estimates are, however, not very robust. The approach used to compute abatement costs essentially consists of calculating the private cost of energy savings as the difference between upfront investment expenditures and the discounted stream of realized—rather than projected—energy savings over the lifetime of the measures. Avoided carbon emissions are then obtained by multiplying realized energy savings by the relevant fuel-specific emissions factor. Unsurprisingly, the resulting estimates are highly sensitive to assumptions regarding investment lifetimes and discount rates. For instance, Christensen et al. (2023) show that reducing the assumed lifetime of measures from 30 to 20 years increases the estimated abatement cost by a factor of six. Similarly, Fowlie et al. (2018) document a 40 percent increase when the discount rate is raised from 3% to 7%. There is no straightforward way to improve the robustness of these estimates. Measure lifetimes are not directly observed in the data and therefore rely on engineering assumptions, while the choice of discount rate remains theoretically contested and empirically unresolved.²

A further challenge in conducting these calculations concerns the treatment of non-monetary private costs and benefits. Energy retrofits generate benefits associated with rebound effects in energy service consumption, as well as upfront non-monetary costs linked to program participation and investment. These costs and benefits are generally assumed to be zero and are therefore omitted from most evaluations³.

As pointed out by Allcott and Greenstone (2024), while important, accounting for commercial costs, mental load, improved health and comfort, and overlapping policies requires many assumptions.

In this paper, we estimate the carbon abatement cost of the French energy efficiency program using an approach that departs fundamentally from this accounting-like approach. This program imposes quantitative energy-savings obligations on energy suppliers. In practice, compliance is achieved primarily through the provision of financial incentives to energy consumers to undertake

¹This value is taken from Table 1 in Gillingham and Stock (2018) and corresponds to the private cost per avoided ton of CO₂e. It decreases to USD 200 per tCO₂e when accounting for the benefits from reduced local environmental externalities, as in Fowlie et al. (2018).

²Sébastien Houde and Myers (2019), for example, assume that privately rational discount rates lie between the annual percentage rate on credit cards (12%) and the three-year return on Treasury bonds (2%). This interval is arguably wide

³A notable exception is the study by Fowlie et al. (2018), which accounts for non-monetary benefits arising from increased consumption of energy services by directly measuring changes in indoor temperatures.

energy efficiency investments. Each subsidized investment generates a number of energy savings certificates intended to reflect its projected lifetime energy savings, which determine compliance with the obligation. We exploit a specific design feature of the program: the energy savings certificates are tradable. Their market price then indirectly reveals the cost of the subsidized investments required to generate them. This allows us to infer abatement costs from observed market behavior rather than from engineering or discounted-cash-flow assumptions. Our core strategy is to combine the certificate price with the per-certificate amount of carbon avoided.

We proceed in three steps. First, in order to compute the amount of carbon emissions avoided, we estimate the causal effect of the program on residential gas and electricity consumption. Using municipality-level panel data for 4,774 municipalities over the period 2018–2020, covering 306,035 energy efficiency investments, the amount of investments is measured at the municipality–year level by the number of energy efficiency certificates issued for investments completed in that year. Using certificates rather than a simple count of investments mitigates treatment heterogeneity across observations, which can bias two-way-fixed-effects estimators in the presence of staggered and heterogeneous treatment effects, as shown by Chaisemartin and d’Haultfœuille (2020). This definition also provides a direct mapping between the number of certificates and energy savings, allowing us to interpret the estimated coefficients as a direct measure of the discrepancy between *ex ante* projected and *ex post* realized energy savings.

Identification relies on an instrumental variables strategy exploiting the effect of past temperature shocks on the salience of heating- and cooling-related housing characteristics, which in turn affects households’ investment decisions. Our instrument is the two-year lagged annual heating degree days (HDD). The length of the lag is assumed to roughly correspond to the average delay between investment decisions and retrofit completion. The identifying assumption is that lagged temperature shocks are orthogonal to contemporaneous changes in energy consumption.

Our preferred estimates indicate that investments supported by the CEE program reduce annual municipality-level gas and electricity consumption by 1.25% on average. This realized reduction represents at most 41% of the energy savings predicted by the engineering estimates used to issue certificates. Furthermore, combining the estimated energy savings with fuel-specific carbon emission factors, we find that the program reduces annual carbon emissions by 1.9%.

In a second step, we develop a formal model of the program that links these econometric estimates to certificate prices in order to predict the average cost of saving gas and electricity. The

model describes how obligated parties seeking to minimize their compliance costs compete to source eligible investments and offer financial incentives to households. Under a set of linearity assumptions and assuming a competitive certificate market, we derive a formula that yields the average cost of carbon from the certificate price.

In a third step, the formula is calibrated using the energy savings estimated in the first stage, the corresponding carbon emission factors, and the certificate prices observed during the study period. Our preferred estimate is a cost of EUR 150/tCO₂e.⁴.

In a fourth step, we examine an additional channel through which the program reduces energy use. The grants offered to households, together with the associated commercial and administrative costs, are ultimately financed through marginal increases in retail energy prices (Rosenow et al. 2019). These price increases provide incentives for all energy users—not only those who invest in energy efficiency—to save energy and reduce carbon emissions. Combining our results with external estimates, we show that this energy price effect dominates the investment subsidy channel, as it accounts for 70% of the total energy savings achieved through the program. The implicit carbon price associated with the energy price increase is only EUR 12/tCO₂e. Given its large impact on energy demand, the average abatement cost of the program therefore falls to EUR 53/tCO₂e.

Our first contribution to the literature is the evaluation of an energy efficiency program with a distinct and institutionally specific design. The program is based on energy efficiency obligations imposed on multiple energy retailers that compete to source the least-cost investments. This design stands in contrast to US-based programs. So-called Energy Efficiency Resource Standards (EERSs) generally impose obligations on local distribution monopolies regulated by state public utility commissions, with compliance -costs recovered through regulated charges paid by all customers connected to the network (Aroonruengsawat et al. 2012; Arimura et al. 2012, for evaluations, see). By contrast, European programs rely on obligations imposed on a set of energy retailers operating in liberalized and competitive energy markets. A further distinction of our evaluation is that it explicitly accounts for the pass-through of program costs into retail energy prices and its effect on energy demand.

Second, we contribute to the literature by providing a new estimate of the energy performance gap between projected and realized savings, using a continuous treatment variable, the number of energy efficiency certificates, whose associated energy impact is more homogeneous than a binary

⁴All monetary values referring to the French program are expressed in 2019 euros hereafter

treatment invest/no invest. The estimated effects fall within the range of previous evaluations, but are potentially subject to less bias than standard quasi-experimental results, following the arguments of Chaisemartin and d'Haultfoeuille (2020). Another important feature of our approach is that it allows us to exclude inframarginal investments from the estimation. In this sense, we do not estimate the energy impact of all investments supported by obligated parties, but rather the impact of investments that would not have been undertaken in the absence of this financial support.

A third contribution is to propose a no***vel approach that exploits the tradability of obligations to estimate the private cost of CO₂ emissions abatement. The analysis ultimately rests on a conceptual framework to carefully examining how certificate prices translate into the private costs borne by both obligated parties and subsidized households. This revealed-preference approach broadens the scope of costs and benefits associated with the program compared to the standard accounting-based methodology used in the studies cited above. It captures costs incurred by obligated firms for activities aimed at persuading households to participate in the program. These activities require substantial resources devoted to outreach, information provision, and engagement, which can represent a significant share of total costs. For instance, an experiment conducted by Fowlie et al. (2018) in Michigan shows that such promotional efforts accounted for around 20% of the monetary investment cost. Second, the policy generates administrative costs for obligated firms, which must process energy-efficiency investments into certificates in order to demonstrate compliance.

Through its effect on the level of grants endogenously set by the obligated parties, it also allows inferring the full range of costs and benefits on the household side. This includes the non-monetary costs at the investment stage, such as the time and cognitive effort required to gather and process information, coordinate with contractors, or manage disruptions during the retrofit process, nor the associated stress. Indirect evidence suggests that such “hassle costs” are substantial. Fowlie et al. (2015a) show that inducing participation in the Weatherization Assistance Program requires encouragement expenditures equivalent to roughly 20 percent of investment costs, despite the fact that retrofits are fully subsidized. See also the analysis by (Sebastien Houde et al. 2025, see also)

On the benefit side, once completed, retrofits generate non-monetary gains, notably improved comfort arising from increased use of energy services through rebound effects.

Home retrofits may generate significant disruption and inconvenience during the works. The psychological burden associated with planning, managing, and monitoring renovation projects adds

to household costs.

Our analysis also connects to the behavioral public economics literature on normative implications. Following the terminology of Chetty (2015), our revealed-preference approach captures decision utility, both for obligated firms choosing the intensity of their commercial efforts and the level of energy-efficiency grants, and for households deciding whether to invest. By contrast, the accounting-style methodology aims to approximate experience utility, that is, households' actual well-being.

Our discussion of the robustness of the results obtained using the traditional approach aligns with the arguments developed by Bernheim and Taubinsky (2018), who emphasize that measuring experience utility inevitably requires theoretical assumptions. In our context, these include assuming zero non-monetary costs and benefits, rational expectations about energy prices over the lifetime of the investment—often proxied by the current price⁵—an investment lifetime that depends solely on the type of technology, and specific assumptions about households' discount rates. Under these conditions, it becomes difficult to determine which measure comes closest to true utility.

The paper proceeds as follows. In section 2, we present some background information on the French program. We introduce the data used in the analysis in section 3. The empirical strategy is exposed in section 4. Section 5 provides regression results and some robustness checks. We turn to the estimation of the abatement cost of carbon in the following section, and we conclude in Section 7.

⁵Survey evidence from the United States suggests that car buyers tend to predict future increases in energy prices.

2 Institutional background

Energy efficiency obligations have become a widely used policy instrument to promote end-use energy savings across a broad range of jurisdictions. As of 2022, the International Energy Agency identified at least 48 active programs operating in 31 countries worldwide (IEA 2022). Within the European Union, the Energy Efficiency Directive 2023/1791 establishes energy efficiency obligations as a core mechanism for achieving national energy consumption reduction targets. In the United States, 24 states operate so-called Energy Efficiency Resource Standards (EERSs)⁶. They are energy efficiency obligations primarily imposed on local distribution monopolies regulated by state public utility commissions, with compliance costs recovered through regulated charges paid by all customers connected to the network. In contrast, European programs are obligations imposed on a set of energy retailers operating in liberalized and competitive markets. Comparable schemes have also been implemented in countries such as Australia, Brazil, Canada, China, South Korea, South Africa, and Uruguay (Crampes and Léautier 2020).

The French CEE program⁷ is the largest in Europe with a total investment of nearly EUR 4 billion per year (Broc et al. 2020). It supports retrofit works in the residential, industrial, or tertiary sector, and to a lower extent in agriculture and transport. The residential sector gathers more than two thirds of the total energy savings (DGEC 2022).

The mechanism works as follows. Every four years, individual energy savings targets are assigned to retailers of electricity, gas, and gasoline in proportion to their sales. In practice, obligated suppliers predominantly meet their targets through the provision of grants for residential energy retrofitting. For each investment subsidized, they receive a certain amount of energy savings certificates from the regulator upon providing proof of investment (e.g., an invoice for the installation of insulation). The number of certificates awarded is designed to reflect the discounted stream of expected energy savings over the lifetime of the measure. At the end of each compliance period, suppliers must return enough certificates to cover their obligation.

The standardized calculation of certificates is based on ex ante engineering estimates. In the residential sector, efficiency measures are grouped into 23 categories, such as roof insulation and high-efficiency individual boilers (see Table A2). Each category has a formula linking savings to

⁶This count includes only programs with mandatory energy efficiency requirements. Two additional states have voluntary targets, and two states allow energy efficiency as a compliance option under their renewable portfolio standards. See <https://www.epa.gov/statelocalenergy/energy-and-environment-guide-action>.

⁷CEE stands for "Certificats d'Economie d'Energie", Energy Savings Certificates in english.

project size and location. For example, installing 50 m² of roof insulation in the coldest French climate zone is credited with 85,000 kWh over 30 years, while a high-efficiency boiler in the same zone yields 24,800 kWh over 17 years. Lifetime savings are discounted at a 4% annual rate, and each certificate represents 1 kWh saved.

The presence of multiple obligated firms implies competition in sourcing energy efficiency investments that minimize the cost of producing compliance certificates. The program grant substantial flexibility regarding both the type and location of eligible investments. Obligated energy retailers may target their own customers or other energy users, including customers supplied by competing retailers (Giraudet, Glachant, et al. 2020). They also freely choose the level of grants offered to induce these investments. Compliance costs are ultimately recovered through market adjustments in retail energy prices. In this way, the program do not increase public expenditures as utilities pass on their costs to consumers (Rosenow et al. 2019). While the resulting prices increase contributes to reduced energy consumption, this indirect effect is not counted toward compliance with the program. We quantify its magnitude in subsection 6.3.

An additional source of flexibility arises from the possibility for obligated firms to meet part or all of their obligation by purchasing energy savings certificates from other obligated parties. Trading volumes reached 179 TWhc in 2018 and 288 TWhc in 2019, highlighting the central role of certificate trading in meeting the annual obligation of 533 TWhc. Certificate prices reflect both the underlying marginal cost of generating energy savings and the stringency of the obligation, a feature we exploit to infer the carbon abatement cost implied by the program.

The emphasis on cost minimization is further reflected in the relatively limited requirements for project implementation. Unlike other energy efficiency programs such as the Weatherization Assistance Program in the United States or Germany's Federal Subsidy for Efficient Buildings, the French program does not mandate pre-retrofit energy audits or ex post certified quality controls. To limit inframarginal renovations, obligated suppliers are only required to submit to the regulator an affidavit in which the beneficiary household declares that the financial support was decisive for its investment decision.

Last, the program has also been helping to combat fuel poverty thanks to two social equity provisions: a sub-obligation whereby energy retailers are required to devote at least 25% of their energy-saving operations to low-income households, and a bonus system that doubles the amount of certificates issued for the energy renovation of homes occupied by households in the bottom quartile.

The bonus system has mechanically created a gap between realized energy savings and the number of certificates. Obviously, these bonus certificates are not included when the government reports the quantity of energy savings achieved through the program, and we likewise exclude them from the dataset used in the analysis. We will take the existence of these public subsidies into account in our abatement cost calculations.

3 Data

3.1 Data sources

The analysis builds on three primary data sources: residential electricity and gas consumption data, certificate data detailing the quantity and characteristics of energy retrofits subsidized by the program, and weather and city-level socio-demographic data.

Residential electricity and gas use. The data is provided by the *Opérateurs des Réseaux d'Energie* agency. It gathers information from all households in the distribution of electricity and natural gas at the municipality level from 2018 to 2020.

Energy retrofits. The Energy Efficiency Obligation database is hosted by the Centre d'Accès Sécurisé aux Données (CASD), a French public-interest organization that provides secure access to confidential data for non-profit research purposes (CASD 2023). The dataset includes more than 3.1 million energy efficiency operations carried out in the residential sector between 2018 and 2020. This three-year period corresponds to the program's fourth obligation phase⁸. The dataset provides detailed information on the types of work undertaken, the dates of initiation and completion, the expected lifespan of each retrofit, its geographic location (at the city level), and the number of certificates issued.

This information allows us to estimate the projected energy savings associated with each subsidized retrofit. The calculation begins by converting the number of certificates into lifetime energy savings, after excluding any bonus certificates. These lifetime savings are then transformed into annual savings using data on the expected lifespan of each measure and by applying the standardized 4% discount rate. Since the completion month is known for every renovation, savings

⁸This phase was unexpectedly extended by one year due to the COVID-19 pandemic. However, 2021 is excluded from our analysis as it reflects exceptional conditions related to the pandemic.

are accounted for only from the month following completion. When aggregated at the municipal level, this procedure ensures that annual savings accurately reflect the actual timing of renovation activities.

A key limitation is that these data cannot be matched to household-level energy consumption. Consequently, our empirical analysis is conducted at the municipality level, implying that both treatment and outcomes are measured in aggregate rather than at the individual household level.

Weather data and sociodemographics. Heating degree days (HDD) and precipitation are standard engineering metrics used to approximate heating demand, as they capture the influence of temperature and humidity on energy consumption. The data are provided by Météo France, the French national meteorological service, on a grid of 9,892 cells, each covering 64 km² (8 km × 8 km). For each grid cell and day, the average temperature is recorded. HDD values are then computed at the municipal level, using 17°C as the reference temperature. The detailed matching procedure is described in Appendix A. We also extract data on population and income from official administrative datasets.

3.2 Study sample

The data do not provide information on energy sources other than gas and electricity (such as heating oil, liquefied petroleum gas, or district heating), and the available retrofit data do not indicate the type of fuel used in retrofitted dwellings. To address this issue, we restrict our analysis to municipalities with limited reliance on alternative energy sources. Using data from the 2018 population census (INSEE 2018), we first exclude municipalities where heating oil or liquid gas constitutes the primary heating source for more than 10% of housing units (excluding holiday homes), and second all municipalities equipped with district heating systems operating between 2018 and 2020. In practice, this selection removes rural municipalities with relatively high dependence on heating oil or propane, as well as densely populated urban centers such as Paris, Marseille, and Lyon. The final estimation sample consists of 4,774 municipalities, representing 5.18 million inhabitants. Table 1 presents summary statistics for the resulting sample. It consists of municipalities with a high share of single-family houses (96.3% on average) and where households consume more electricity than gas compared to the national average (see Table A1 in the Appendix). The latter probably reflects the fact that these municipalities, unlike larger cities, generally lack a gas distribution

network.

Table 2 displays the shares of the main retrofit categories observed in our sample. Investment in insulation (roof, floor, wall) accounts for 81% of projected savings and most of these savings are achieved in homes heated by gas.

Table 1: Descriptive statistics of the study sample

	N = 4,774	
	Mean	SD
Panel A: Energy use		
Annual electricity use per capita (kWh)	3,429.959	1,213.841
Annual gas use per capita (kWh)	1,263.306	1,722.556
Panel B: Retrofit works		
Projected lifelong energy savings per capita (kWh)	2,816.795	2,001.76
Annual projected energy savings (kWh)	77.643	61.008
Panel C: Demographics		
Median income per capita (EUR/year)	21,363.438	3,625.951
Population size	1,078	1,365
Panel D: Weather		
HDD	2,066	575
CDD	381	188
Annual precipitation (mm)	928	263

Table 2: Share of projected savings, by type of energy retrofit

Code	Operation	% projected savings	% in gas-heated dwellings
BAR-EN-101	Roof insulation	53.6	81.0
BAR-EN-103	Floor insulation	16.1	88.5
BAR-EN-102	Wall insulation	11.3	79.9
BAR-EN-104	High energy efficient boiler	6.4	n.a.
BAR-EN-106	Heat pump	4.3	n.a.

Notes: Table A2 in the Appendix gives the full distribution of the 25 work categories.

4 Empirical strategy

4.1 Model

To estimate the impact of retrofit works supported by the program on residential gas and electricity, let us begin with a simple Two-Way Fixed-Effects (TWFE) model which leverages year-to-year within-municipality variations in energy use and energy efficiency investment. The baseline estimating equation writes as:

$$Y_{i,t} = \beta X_{i,t} + \lambda \mathbf{W}_{i,t} + \mu \mathbf{D}_{i,t} + \alpha_i + \gamma_{r(i),t} + u_{i,t} \quad (1)$$

The outcome variable $Y_{i,t}$ represents the sum residential electricity and gas consumption in municipality i during year t . Combining these two energy sources allows us to account for potential substitution effects (Giraudet, Sébastien Houde, et al. 2018), such as the replacement of a gas boiler by a heat pump. Municipality fixed effects are denoted as α_i . We also include region-year fixed effects $\gamma_{r(i),t}$ which controls for factors which could influence energy consumption and the supply of energy savings investments.⁹

The variable $X_{i,t}$ represents the cumulative projected savings achieved through works completed until year t . The underlying idea is that the energy savings in a given year are determined by the stock of previous investments, reflecting the persistence of treatment status once a dwelling is retrofitted. In this specification, the coefficient β directly indicates the share of projected savings that are realized ex post. Note that our continuous treatment variable $X_{i,t}$ differs from the

⁹Throughout the paper, “region” refers to the French *département*.

binary treatment variable employed in household-level studies, which captures the occurrence of an energy efficiency investment. A key advantage of this specification is that it mitigates treatment effect heterogeneity across municipality–year cells (i, t) which is a known source of bias in two-way fixed-effects designs as discussed by Chaisemartin and d’Haultfoeuille (2020). At the same time, it helps reduce the gap between the local average treatment effect (LATE) identified in our empirical strategy and the average treatment effect. We return to these points in the results section.

Due to data limitations, the variable X includes only projected savings from investments completed from 2018 onwards. Earlier investments are however implicitly captured through the inclusion of municipality fixed effects.

Another issue is that the impact of an investment made in year t on the quantity of energy consumed over the entire year depends on the timing of its completion. An investment finalized earlier in the year contribute more substantially to Y_{it} as they are active over a greater portion of the year. To account for this heterogeneity in exposure, projected savings from investments completed during year t are weighted by the proportion of heating degree days occurring after the completion month, relative to the total HDD observed over the entire year. For instance, one unit of projected savings from an investment completed at the end of June is weighted by the ratio of HDD between July and December to the total HDD for the entire year.

Last, the equation includes a vector $\mathbf{W}_{i,t}$ of weather variables (contemporaneous annual HDD and precipitations) that influence energy use and may indirectly affect the pace of energy efficiency investments, and a vector $\mathbf{D}_{i,t}$ of demographic controls including median income and population. We apply a logarithmic transformation to population because its effect on energy use is likely non-linear due to agglomeration effects.

4.2 Instrumental Variation

Self-selection is the main threat to identification. Households choose whether to renovate their homes, and unobserved time-varying factors—such as anticipated demand shocks—that influence this decision can bias results if they are correlated with energy consumption. As an illustration, a surge in environmental awareness may simultaneously increase the likelihood of investing in retrofits and prompt short-term behavioral changes to reduce energy use, such as lowering indoor temperatures during winter. Failing to account for such shocks can lead to an overestimation of energy savings.

Aggregating individual behavior to the municipality level attenuates omitted-variable bias only insofar as unobserved individual shocks are idiosyncratic and therefore average out within municipalities. This assumption is unlikely to hold. In our illustration, environmental awareness is unlikely to be randomly distributed across residents of the same municipality—there might be a common municipal component (e.g., local campaigns, political preferences) so its effects need not cancel in aggregate.

A further limitation is that retrofits undertaken without support from the CEE program are not observed, as they do not generate certificates. This issue also applies to most previous studies (**christensen2023**; Allcott and Greenstone 2024; Fowlie et al. 2018; Myers 2020; Papineau et al. 2025) which only account for renovations supported by specific energy efficiency programs. While this omission may appear unimportant given that our focus is on the program’s impact rather than that of energy efficiency investments, CEE-supported and non-CEE retrofits are likely interrelated, being influenced by similar unobserved factors. This interdependence may potentially introduce bias

Our solution is to instrument the year-to-year change in projected savings $X_{i,t}$. We exploit municipality-level data on degree days two years before the investment in energy efficiency is completed. More specifically, the instrument is

$$Z_{i,t} = \text{HDD}_{i,t-2}$$

The assumption is that annual deviations from the average HDD increase the salience of heating- and cooling-related home characteristics, thereby influencing the decision to invest in energy efficiency. The two-year lag is considered a reasonable estimate between the time the investment decision is made and the completion of the retrofits. Exogeneity arises from the fact that past temperature and precipitation shocks are not correlated with changes¹⁰ in energy use two years later through channels other than energy efficiency investments.

The presence of non-CEE investments presents a specific challenge, however. To clarify the issue, we decompose the error term in Eq. (1) as follows: $u_{i,t} = \phi R_{i,t} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ includes all within-municipality dynamics that we do not control for, and $R_{i,t}$ represents projected savings imputable to retrofit investments not generating certificates in municipality i in year t . The second

¹⁰The focus on *changes* in energy use is crucial for identification, as previous temperatures and precipitation may have a persistent effect on energy use behavior.

stage equation thus writes:

$$Y_{i,t} = \beta^{IV} \hat{X}_{i,t} + \delta_2 \mathbf{W}_{i,t} + \lambda_2 \mathbf{D}_{i,t} + \alpha_i + \gamma_t + \phi R_{i,t} + \varepsilon_{i,t}$$

where $\hat{X}_{i,t}$ is the fitted value of $X_{i,t}$.

The exclusion restriction requires

$$\text{Cov}(Z_{i,t}, \varepsilon_{i,t}) + \text{Cov}(Z_{i,t}, \phi R_{i,t}) = 0. \quad (2)$$

The above argument asserts that temperatures from two years prior do not affect current changes in energy use through any channel other than energy retrofits, regardless of whether the investment is subsidized by the program so that $\text{Cov}(Z_{i,t}, \varepsilon_{i,t}) = 0$. However, there is no reason to doubt that past temperature shocks also influence non-CEE energy efficiency investments, leading to $\text{Cov}(Z_{i,t}, R_{i,t}) \neq 0$. As a result, the condition in Eq. (2) no longer holds, resulting in a biased estimate of the coefficient β^{IV} .

The good news is that we can sign the bias. Assuming that the control variables are uncorrelated with the instrument, straightforward calculations give:

$$\beta^{IV} = \beta + \phi \frac{\text{Cov}(R_{i,t}, Z_{i,t})}{\text{Cov}(X_{i,t}, Z_{i,t})}$$

Focusing on the final term of this expression, it is clear that $\phi < 0$ because non-CEE investments naturally reduce energy consumption. Furthermore, since the first-stage effect of the instrument on CEE-funded investments is not driven by any unique characteristic of the CEE program, it can be extended to all types of energy efficiency retrofits. It follows that $\text{Cov}(R_{i,t}, Z_{i,t})$ and $\text{Cov}(X_{i,t}, Z_{i,t})$ exhibit the same sign. These two statements implies a negative bias: $|\beta^{IV}| > |\beta|$. β^{IV} can be interpreted as a lower-bound estimate of the program's impact on energy use.¹¹

¹¹This issue is common in many studies in which non-subsidized investments are typically unobserved. christensen2023 mitigate it by comparing retrofitted homes to not-yet-retrofitted homes, which addresses the concern under the assumption that households renovate at most once over the study period.

5 Econometric results

5.1 Main estimation

We estimate both the OLS and IV regressions for savings, clustering standard errors at the municipality level to account for potential within-municipality correlation patterns.

Table 3: Regression results for the effect of projected savings on energy use

	OLS	IV
Expected Savings	-0.474*** (0.073)	
Fitted Expected Savings		-0.411** (0.137)
Log. of Pop.	746 741.953*** (169 332.700)	740 670.975*** (169 630.600)
HDD	579.140** (219.638)	560.989** (203.402)
Precipitation (mm)	112.085+ (64.536)	109.794+ (62.550)
Num.Obs.	12 207	12 207
R2	0.999	0.999
R2 Adj.	0.998	0.998
R2 Within	0.079	0.078
FE: Code_commune_INSEE	X	X
FE: dep_year	X	X
F-test (1st stage)		318.974

Notes: The dependent variable is the sum of gas and electricity energy use. Standard errors clustered at the municipality level are in parentheses. ***, **, * and + denote statistical significance at the 0.1, 1, 5 and 10 percent levels.

The two columns of Table 3 present the estimated effects of projected savings. The coefficients represent the impact of one kWh of projected savings at time t on energy use in the same year. In column (1), the results indicate that an additional kWh of projected savings at t is negatively correlated with energy use. However, this observed correlation is endogenous due to the potential selection effects among retrofitting households influenced by within-municipality dynamics, as discussed in Section 4. This endogeneity is further exacerbated by the influence of non-CEE investments. Nevertheless, the coefficient is statistically significant, which motivates the search for a better identification strategy.

Column (2) presents the results of the IV estimation, which is based on the framework outlined in Section 4. Compared to the OLS estimate, the magnitude of the IV coefficient decreases by around 15%. This suggests that failing to account for potential confounders leads to an overestimation of the impact of CEE retrofits on energy use. The discrepancy between $\hat{\beta}^{OLS}$ and $\hat{\beta}^{IV}$ likely stems from pre-existing downward trends in energy use within municipalities that implement more retrofits.

We estimate that one kWh of projected savings achieved through a CEE operation reduces actual energy use by no more than 0.411 kWh. This represents an overestimation of engineering predictions by at least 59%. The effect is statistically significant at the 1% level and supported by a strong first-stage F-statistic (319), well above the threshold suggested by Staiger and Stock (1997). We discuss and interpret this result in the next subsection.

We run the same IV regression separately for electricity and natural gas. Table 4, column (1), shows that electricity use remains unaffected by additional savings. The effect measured in our main specification in Table 3 is thus mostly triggered by a decrease in natural gas consumption. This outcome is straightforward to explain: over 80% of the savings are attributed to insulation works in dwellings that do not use electricity for heating. Furthermore, the installation of air-to-water or water-to-water heat pumps – frequently associated with a switch from natural gas to electricity for heating – account for less than 5% of the total savings (see Table A2 in the Appendix). Gas-heated houses tend to be older and less insulated, so retrofits yield larger efficiency gains. This also helps explain their higher renovation rates, as such investments are relatively more cost-effective.

Table 4: Effect of projected savings on electricity and gas

	Electricity	Natural Gas
Fitted Expected Savings	-0.040 (0.051)	-0.371** (0.126)
Log. of Pop.	481 664.692*** (60 217.343)	259 006.283+ (146 045.155)
HDD	183.242** (67.292)	377.747* (190.333)
Precipitation (mm)	-11.767 (25.218)	121.562* (56.313)
Num.Obs.	12 207	12 207
R2	0.999	0.997
R2 Adj.	0.999	0.994
R2 Within	0.005	0.097
FE: Code_commune_INSEE	X	X
FE: dep_year	X	X
F-test (1st stage)	318.974	318.974

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Clustered standard errors at the municipality level

Notes: The dependent variables are electricity and gas consumption. The models are estimated using 2SLS, where the two-year lagged temperature is used as an instrument for projected savings. Standard errors clustered at the municipality level are reported in parentheses. ***, **, *, and + denote statistical significance at the 0.1, 1, 5, and 10 percent levels, respectively.

5.2 Robustness checks

We perform several robustness checks for our IV specification. First, we address potential estimation bias arising from households transitioning away from residential heating oil or liquid gas. While our analysis focuses on municipalities in the lowest decile for the consumption of these fuels, some scope for such behavior remains. To mitigate this, we exclude municipalities where the share of housing units using heating oil (or liquid gas) changed by more than 1 percentage point between 2018 and 2020. The estimation results for these sub-samples are shown in columns (1) and (2) of Table 5. Although the precision of the coefficient on fitted savings slightly decreases, it remains significant at the 5% level for both fuel sources. The coefficients are of a similar magnitude to those in the main regression, suggesting that at best, only 40% of the projected savings are realized.

Table 5: Robustness checks for the effect of savings on energy use

	Fuel Oil	Liq. Gas	SEM 10km	SEM 20km
Fitted Expected Savings	-0.401** (0.155)	-0.392** (0.150)	-0.411** (0.151)	-0.411** (0.158)
Log(population)	722 113.896*** (183 157.870)	728 092.995*** (181 607.367)	740 670.975*** (176 997.319)	740 670.975*** (223 732.967)
HDD	644.666** (224.196)	592.342** (206.189)	560.989* (220.538)	560.989* (269.547)
Precipitation	137.235* (69.587)	114.078+ (63.762)	109.794 (69.517)	109.794 (87.301)
Observations	10 991	11 796	12 207	12 207
R2	0.999	0.999	0.999	0.999
R2 Adj.	0.998	0.998	0.998	0.998
R2 Within	0.074	0.078	0.078	0.078
FE: Code_commune_INSEE	X	X	X	X
FE: dep_year	X	X	X	X
F-test (1st stage)	280.142	313.242	318.974	318.974

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Clustered standard errors at the municipality level (1-2) / Spatial Error Model (3-4)

Second, we examine the potential influence of spatial dependence between individual observations. While clustered standard errors account for within-municipality, cross-period correlation, a spatial-error model (SEM) explicitly addresses contemporaneous cross-municipality correlations. In this context, it is plausible that the error term $u_{i,t}$ and $u_{j,t}$ for two adjacent municipalities i and j are not perfectly orthogonal. This may arise because unobserved non-CEE retrofitting investments $R_{i,t}$ and $R_{j,t}$ are influenced by local supply and demand shocks that span across municipal boundaries. To address this, we apply the variance-covariance matrix estimator proposed by Conley (1999), which incorporates the relative proximity of adjacent municipalities using a defined threshold.

The error term $u_{i,t}$ of our second stage equation is thus a function of contemporaneous adjacent municipalities error terms $u_{j,t}$ and $\vartheta_{i,t} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2)$:

$$u_{i,t} = \xi \sum_{i \neq j} \omega_{ij} u_{j,t} + \vartheta_{i,t} \quad (3)$$

We present results for the 10 km and 20 km thresholds. The only deviation from the baseline estimation lies in the computation of standard errors, which are no longer clustered at the municipality level. Nonetheless, the p-value for the effect of contemporaneous savings remains below 5%

for both thresholds. While this test has limitations – since the spatial diffusion perimeter likely varies across observations, making the optimal radius an empirical question – the consistent significance of the effect of CEE-funded retrofits under this spatial autoregressive specification provides further support for our estimate.

Third, our reference IV model identifies a local average treatment effect (LATE), that is, the impact of certificates on the population of municipalities whose investment behavior responds to past weather shocks. To assess the internal validity of our analysis, we perform an alternative IV estimation using a different shift-share instrument, which potentially target a different subset of compliers.

To construct the instrument, we exploit municipality-level data on the volume of projected energy savings for each of the 23 work categories (e.g., wall insulation, floor insulation, air-to-air heat pumps). Specifically, we decompose the local variation in savings from a work of type s in municipality i into two components: (i) the national growth rate in projected savings for work type s , which may capture global supply chain dynamics or national policy shocks; and (ii) the initial local share of work type s , which reflects municipality i 's exposure to the national shock.

Formally, the instrument writes:

$$\sum_{s=1}^S \alpha_{i,s,t_0} \Delta X_{s,t} \quad (4)$$

where α_{i,s,t_0} denotes the local share of investment of type s in the pre-sample period t_0 , the year 2016 in our case. $X_{s,t}$ is the projected energy savings in year t from work of type s carried out in all municipalities in the sample.

The fact that past α_{i,s,t_0} shares predict future shares may result from local supply dynamics and learning-by-doing. For example, past heat pump installations in municipality i have increased the productivity of local installers. Demand spillovers can also play a role, as a household's choice of renovation type may be influenced by feedback from neighbors who have retrofitted their homes in previous years. This alternative IV strategy yields very similar estimates of the energy performance gap (see 6).

Table 6: Bartik IV

	OLS-FD	2SLS-FD
Expected Savings	−0.438*** (0.060)	
Fitted Expected Savings		−0.414*** (0.067)
Log(population)	633 833.696*** (90 307.486)	629 536.981*** (91 228.938)
Median income	4.059 (3.038)	3.890 (3.093)
HDD	313.655*** (30.266)	318.157*** (27.845)
CDD	−57.471 (93.795)	−51.485 (88.237)
Precipitation	78.218*** (14.553)	75.673*** (16.439)
Observations	8723	8723
R2	0.068	0.068
R2 Adj.	0.067	0.067
F-test (1st stage)		1132.702

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Clustered standard errors at the municipality level

5.3 Discussion

We estimate that realized savings in residential electricity and gas amount to at most 41% of the engineering-projected savings. Two mechanisms can account for this wedge: (i) a gap between engineering projections and actual savings; and (ii) inframarginal subsidization (free-riding), whereby the policy finances retrofits that would have occurred anyway. For this reason, our estimate is not directly comparable to those available in the study by Fowlie et al. (2018) or **christensen2023**, who evaluate the impact of the renovations themselves, whereas we identify the impact of the policy designed to induce them.

The existence of such a gap gives a misleading picture of the degree of compliance with national policy objectives. The European Energy Efficiency Directive requires Member States to report annually on the energy savings achieved to meet their national target. Based on the engineering estimates of the CEE, the government reported an overall energy savings volume of 2.827 TWh over the 2018-2020 period covered by our study, leading to a compliance rate of 114% for the period

2014-2021. If we adjust these estimates with our findings, the realized energy savings actually resulted in a 1.25% annual reduction in energy consumption during the study period, falling short of the -1.5% target set by the Directive (European Commission 2012).

Part of the explanation likely stems from the program's design. Unlike other foreign energy efficiency schemes (e.g. the Weatherization Assistance Program in the US, the Federal subsidy for efficient buildings in Germany), it neither mandates an energy audit before investments nor includes quality checks upon project completion. More fundamentally, the program adopts a market-based approach that grants obligated parties maximum flexibility in deciding how to achieve their targets. However, in the absence of quality controls, this flexibility may incentivize prioritization of lower-quality, less expensive work or a focus on infra-marginal investments.¹²

Another way to interpret these results is to determine the level of subsidy required to achieve a 1 MWh reduction in energy consumption. We estimate an incentive payment of EUR 21.87/MWh for gas savings and EUR 160.14/MWh for electricity savings (reflecting the smaller magnitude of electricity reductions; see Table 4). Aggregating both sources yields an average subsidy of EUR 19.24 per MWh saved.¹³

Among the program's objectives is the reduction of carbon emissions linked to residential energy consumption. This issue is less about electricity consumption, which is mostly decarbonized in France due to nuclear power than about gas consumption. From this perspective, the fact that most of the savings concern gas is not necessarily a negative outcome. To quantify the impact, we just need to combine the estimates reported in Table 4 with relevant carbon emission factors. According to the French Environmental Agency and the Ministry for Ecology, the average carbon intensity is 79 g CO₂/kWh for electricity (ADEME 2020) and 227 g CO₂/kWh for natural gas (CGDD 2019). Over the study period, the program is estimated to have induced an average annual reduction in carbon emissions of 1.9% in the municipalities of the sample.

The country has translated the overall target of a 55% reduction by 2030 into sectoral objectives. For the residential sector, this implies an annual reduction of 6.8% in residential gas consumption between 2015 and 2030, and 4.7% for electricity.¹⁴ The

¹²In this way, the program prioritizes cost minimization over the correction of market failures (e.g., inattention, environmental externalities, and split incentives between landlords and tenants) which could yield substantial gains in social welfare as suggested by Allcott, Knittel, et al. (2015).

¹³Relating these figures to the energy-saving costs presented, we next consider in Section 6 how our results align with the marginal value of public funds (MVPF) framework proposed by Hahn et al. (2024).

¹⁴<https://indicateurs-snbc.developpement-durable.gouv.fr/consommation-d-energie-finale-des-secteurs-a33.html>

6 Estimating the abatement cost of carbon

In this section, we build on the previous results to estimate the cost of reducing carbon emissions achieved through the program. As explained, we develop a novel methodology that exploits the tradability of energy savings certificates.

The underlying premise is that, assuming a competitive market, certificate prices reflect the marginal cost of achieving energy savings within the CEE scheme. As we will show, the main strength of this revealed-preference approach is its ability to capture all private costs and benefits incurred by obligated firms and households. For instance, the costs faced by energy retailers and their subcontractors when generating certificates include not only the grants required to induce households to undertake energy-efficiency investments, but also the transaction and outreach costs associated with identifying and securing these investment opportunities. Interviews with obligated parties suggest that subsidy-related expenditures are particularly substantial. As an illustration, Fowlie et al. (2015b) incorporated an encouragement campaign into their field experiment on the Weatherization Assistance Program in Michigan. The intervention increased participation by 5 percentage points, at a cost of more than USD 1,000 per weatherized household — approximately 20% of the renovation cost — even though the program offered households zero out-of-pocket expenses.

Our core strategy for inferring the implied abatement cost of CO₂ is to combine the certificate price with the amount of carbon avoided per certificate. A central challenge arises from a measurement discrepancy: whereas certificate prices reflect *marginal* costs, our empirical estimates pertain to *average* effects on energy consumption. Likewise, available data on the carbon intensity of gas and electricity yield average values. To address this inconsistency, we propose a simple conceptual framework that maps observed market prices to average certificate generation costs. This framework also helps delineate the scope of costs and benefits covered by the approach adopted.

6.1 Conceptual framework

We consider a regulatory setting in which a central authority determines the total number of energy-saving certificates that must be produced over a given compliance period. Let Ω denote this aggregate obligation, which we treat as exogenous, consistent with our objective of analyzing the cost-efficiency properties of the program. A representative obligated firm may fulfill this requirement either by purchasing certificates at a unit price p on the market or by directly incentivizing

energy efficiency investments among households.

Let x_{\max} , , with $x_{\max} > \Omega$, denote the total potential for energy savings across the population. Importantly, this potential corresponds to projected savings, those corresponding to the variable $X_{i,t}$ in the empirical model, except that we consider individual households instead of municipalities. For simplicity, we normalize these projected energy savings such that each household is associated with one unit of potential savings.

The cost of saving energy varies across households. Formally, let $c(x)$ denote the cost of realizing this unit of savings for a household of type x , net of any program subsidy. It thus corresponds to the household's willingness to accept making the investment.¹⁵ Each realized unit generates one certificate.

This willingness to accept investing in one energy saving unit thus encompasses the full spectrum of benefits and costs influencing the retrofit decision. These include monetary savings on energy expenditures, non-monetary gains such as improved comfort (including rebound effects), as well as various forms of investment costs—financial, psychological, and practical (e.g., the time and inconvenience associated with renovation works, or the “warm-glow” utility derived from energy conservation). In practice, energy retrofitting is often integrated into broader dwelling renovation projects. The complementarities between the energy-related and non-energy-related components of such projects generate positive spillovers on other aspects of the renovation. $c(x)$ implicitly captures the value of these economies. In addition, c may also include the benefit of subsidies or tax credits that overlap with the CEE program and provide households with additional incentives to undertake retrofits. This is the case in our setting, as households may also benefit from tax credits that reduce the monetary investment cost. These transfers will be explicitly accounted for at the calibration stage in order to exclude them from the abatement cost estimation.

We assume household types are ordered such that $c(x)$ is strictly increasing in x . Let x_0 be defined such that $c(x) \leq 0$ for all $x \in [0, x_0]$. This assumption captures the existence of untapped, privately profitable investments within the population, implying that some subsidy-funded projects may be infra-marginal. Finally, the function is assumed to be linear, i.e. the aggregate cost of realizing savings is quadratic, an assumption that enables the derivation of the average cost from the equilibrium certificate price.

¹⁵Note that the dependence of c on x does not imply that households base their decision on projected savings or on any particular belief about the energy impact of their choice. However, survey evidence presented by Allcott and Greenstone (2024) in their evaluation of a Wisconsin program suggests that most households take such projections at face value.

We make two informational assumptions. The first is standard: the firm knows the function $c(x)$ but does not observe the type of individual households. The second reflects the specific context of energy retrofits: households are initially unaware of the program and the possibility of receiving grants; they only become informed when contacted by the firm.¹⁶ The need for outreach to induce investment is a well-documented feature of such programs as discussed above.

Turning to the obligated firm, the cost borne in producing certificates includes two components: (i) the subsidy granted to the investing household, (ii) the cost of identifying and persuading the household to proceed with the retrofit, and converting documentation (e.g., contractor invoices and homeowner attestations of support) into valid certificates once the retrofit is finished. The subsidy amount by unit of projected savings offered to participating households, denoted s , is uniform across recipients, consistent with the firm's inability to observe individual household types.¹⁷ The second component, the effort required to induce and monitor the participation of a household, is captured by a function $\gamma(x)$ with $\gamma'(x) > 0$. That is, the more reluctant a household is to invest, the higher the cost of convincing it. Again, we assume that $\gamma(\cdot)$ is linear.

Last, the process by which the firm meets its obligation unfolds as follows:

1. The firm determines the share α of its obligation Ω to be met through direct subsidization, with the remainder satisfied via certificate purchases on the market.
2. The firm sets the level of the subsidy s so as to induce a volume of projected savings equal to $\alpha\Omega$ and randomly selects a sample of households to whom the subsidy is offered.
3. Each selected household decides whether to accept the offer. Upon acceptance, the retrofit is carried out, and the firm receives the corresponding number of certificates from the regulator.
4. The firm purchases the remaining certificates needed to meet its total obligation.

In the third stage, a sampled household of type x will accept the subsidy if the net cost of the retrofit is non-positive, i.e., if $c(x) \leq s$. This defines a threshold type $x(s)$ such that all sampled households with $x \leq x(s)$ accept the offer. By construction, the threshold satisfies:

$$c(x(s)) = s.$$

¹⁶This assumption is also consistent with situations in which households only become aware of retrofit opportunities or associated costs upon engaging with the obligated firm.

¹⁷We could assume a more flexible subsidy scheme where the firm would learn the individual type when exchanging with the household. The uniformity assumption is however realistic as illustrated by web scraped data collected by Pille-Riin Aja and Louis-Gaetan Giraudet.

In the previous stage, the firm chooses the subsidy level s to minimize its total cost, subject to the constraint that the number of accepted retrofits equals the obligation level Ω . Cost minimization is straightforward in this context, as the uniform subsidy leads to the self-selection of the lowest-cost households. Furthermore, within a random sample drawn from the overall population of mass x^{\max} , the probability that a given household accepts the subsidy offer is $x(s)/x^{\max}$. Compliance with the obligation then requires contacting a mass $[x^{\max} \times \Omega]/x(s^*)$ of households.

Last, under the assumption of a competitive certificate market, the equilibrium price p^* is equal to the marginal cost of savings: $p^* = \gamma(x^*) + s^*$. We collect the equilibrium conditions in a lemma.

Lemma 1. *The obligation is fulfilled by*

1. *setting a subsidy s^* such that $c(x(s^*)) = s^*$*
2. *offering it to a random household sample of mass $\Omega \times x_{\max}/x(s^*)$.*

The resulting certificate price is given by $p^ = \gamma(x(s^*)) + s^*$ and the quantity of certificates produced is equal to $\Omega = [x(s^*)]^2 / x_{\max}$.*

We can now derive the average cost of generating a certificate. We begin by considering the costs borne by households. Importantly, part of the energy savings induced by the CEE program is achieved at negative cost—that is, for all households of type x such that $x \leq x_0$. Since these households would have undertaken the investment even in the absence of the program, their cost is recorded as zero in our calculation. This distinction is crucial: we are evaluating the cost of the policy, not the cost of the investment itself. The net average cost to households, after subtracting the subsidy, is therefore given by:

$$\left(\int_{x^0}^{x(s^*)} \frac{1}{\Omega x_{\max}} c(x) dx \right) - s^* \quad (5)$$

The average cost on the firm's side is

$$\left(\int_0^{x(s^*)} \frac{1}{\Omega x_{\max}} \gamma(x) dx \right) + s^* \quad (6)$$

Note that we sum the marginal cost starting from 0 rather than from x_0 , since generating certificates from inframarginal projects still entails non-negative administrative costs.

The last step of the analysis then consists in relating these costs to the certificate price p^* . From the linearity assumptions of $c(\cdot)$ and $\gamma(\cdot)$ follow that

Proposition 1. *The average cost jointly borne by the obligated firm and the households for achieving one unit of projected savings through the program is equal to $\frac{p^*}{2}$.*

Proof. From the lemma, we have $c(x(s^*)) = s^*$. Since $c(x_0) = 0$ and $c(\cdot)$ is linear, the household's cost, as given by Eq. (5), is equal to $-\frac{s^*}{2}$. Moreover, we know that $p^* = \gamma(x(s^*)) + s^*$, and since $\gamma(\cdot)$ is linear and $c(x) \geq 0$, the firm's cost, as given by Eq. (6), is $\frac{p^*-s^*}{2} + s^*$. Summing both costs, we obtain $\frac{p^*}{2}$. \square

This result naturally relies on assumptions. Two are particularly critical: first, the assumption that the marginal cost functions $c(\cdot)$ and $\gamma(\cdot)$, are linear; and second, that the subsidy enters household surplus linearly, implying the absence of income effects. Under these conditions, the subsidy functions purely as a transfer from firms to households.

6.2 Calibration and results

Relying on Proposition 1, we are in position to calculate the average cost per ton of CO₂ avoided. Let us first specify the certificate price used in the calculation. This choice is not straightforward, as the price varied between 2018 and 2020. As shown by Figure 2, it increased significantly during most of the study period.

Such a pricing pattern is characteristic of the scheme: each compliance period is associated with an increase in the obligation, which raises the marginal cost of compliance. This upward trend was particularly pronounced during the study period, as the fourth compliance period (2018–2021) involved a sharp increase in the obligation level. In this context, this led to a lag in stakeholders' responses to the new market conditions, reflecting a transitional phase in which economic agents revised their understanding of the new market parameters.

Consistent with our theoretical framework, the relevant price is the one influencing the investment decision, that is, the price prevailing when the decision to initiate the works is made. This price reflects the expectations of obligated parties at the moment of investment and therefore serves as the appropriate reference point for the cost of operations initiated at that time. Our dataset records the initiation date for each retrofit

Second, we derive an expression for the abatement cost that is suitable for calibration using our econometric estimates based on municipality-level data. To do so, we characterize the implications of the theoretical framework developed in the previous section at this level of aggregation. Let x_{imt}

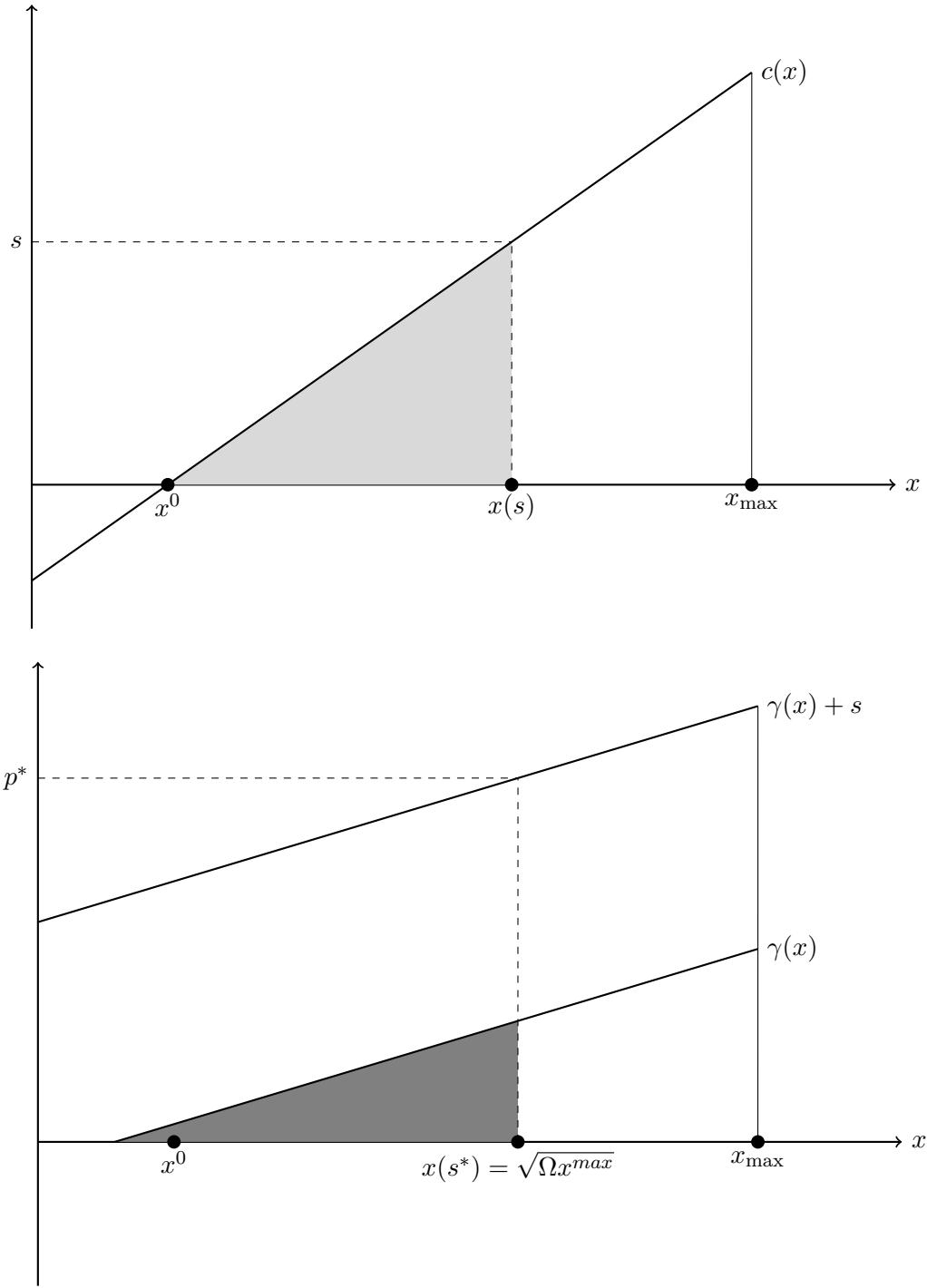
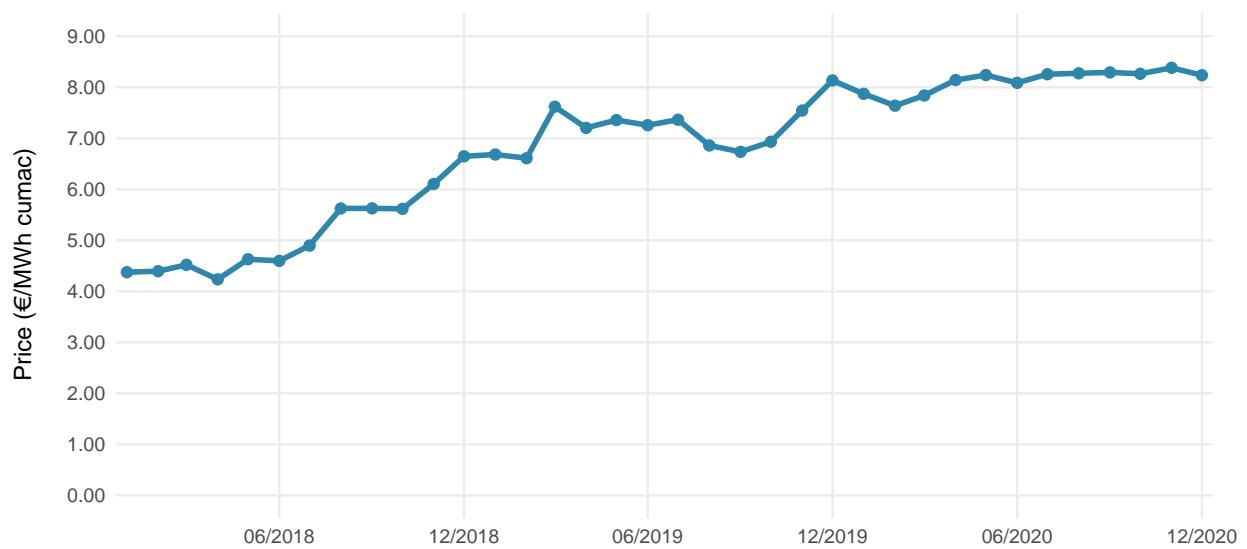


Figure 1: Household response to the CEE subsidy and certificate market equilibrium

Notes: The household response to a uniform subsidy s is shown in the upper panel, with the grey area depicting the corresponding household loss excluding the subsidy. Note that this does not include the positive surplus of infra-marginal households (those with type $x \leq x^0$). The lower panel displays the resulting certificate market equilibrium with an Ω . The dark grey area represents the encouragement cost borne by the obligated firm to induce the necessary investments, excluding grants. See text for details.

denote the number of certificates generated in municipality i from works completed in month m of year t , and let β_{imt}^g and β_{imt}^e be the corresponding average effects on gas and electricity consumption.

Figure 2: Evolution of the certificate spot price, 2018-2020



Notes: Certificates associated with each project are valued using the spot market price on the contract signature date (Emmy 2023). We rely on official records of savings with bonus in this calculation, because the value of each work is defined by the (annualized) amount of certificates it delivers, including bonuses. Certificates are divided into two categories: standard certificates and so-called 'Précarité' certificates, which are issued for investments in dwellings occupied by fuel-poor households. Since early 2018, the prices of both categories have converged, justifying the use of the average price in the graph and subsequent analysis. The reasons for this convergence are detailed by Darmais et al. (2024).

These effects may vary across municipalities and over time due to heterogeneity in contractor quality or in the composition of retrofits undertaken. Let μ_g and μ_e denote the carbon content per kWh of gas and electricity, respectively, which we assume to be constant over the study period because national trends are absorbed by region–year fixed effects.

Under these assumptions, Proposition 1 implies that the carbon abated and total cost associated with these certificates in municipality i , month m , and year t are:

$$x_{imt} \times (\beta_{imt}^g \mu^g + \beta_{imt}^e \mu^e) \quad \text{and} \quad \frac{x_{imt} \times p_{mt}}{2},$$

respectively. Aggregating these costs and abatement quantities across municipalities and over the entire study period, we obtain the average abatement cost of carbon:

$$\frac{1}{2} \left(\sum_{imt} x_{imt} \times p_{mt} \right) \left(\sum_{imt} x_{imt} \times (\hat{\beta}_g \times \mu_g + \hat{\beta}_e \times \mu_e) \right)^{-1} \quad (7)$$

where $\hat{\beta}_g$ and $\hat{\beta}_e$ are the averages of β_{imt}^g and β_{imt}^e , respectively, weighted by certificate quantities x_{it} and estimated in the empirical analysis above.

Moreover, some renovations were cross-subsidized through a tax credit over the period under study (DGFIP 2016). Recall that this benefit is included in $c(x)$. It must therefore be subtracted from $c(x)$, as it corresponds to a pure transfer between investing households and taxpayers.

To quantify the magnitude of this transfer, we rely on official estimates of overlapping support provided by the French government (ONRE 2022). These data indicate that a share $\pi = 22\%$ of retrofit projects were also supported by the tax credit, with an average subsidy of $s = \text{EUR}18.6$ per MWh of projected energy savings.¹⁸

The term to be added to Eq. (5) to obtain the average household surplus net of this transfer is given by:

$$\pi s \times (\hat{\beta}_g \mu_g + \hat{\beta}_e \mu_e)^{-1}. \quad (8)$$

An additional complexity arises from the incentivization of certain renovation investments through a tax credit over the period (DGFIP 2016). For the sake of simplicity, we incorporate this benefit into $c(x)$ above. However, it must be excluded from the calibration, as it essentially corresponds to a transfer between investing households and taxpayers. To quantify the magnitude

¹⁸Details on the underlying assumptions are provided in Appendix X.

of this transfer, we rely on official estimates of overlapping support provided by the French government (ONRE 2022). We find that a share $\pi = 22\%$ of renovation works were also supported by the tax credit, receiving an average subsidy of $s = \text{EUR } 18.59$ per MWh of projected energy savings.

The corresponding increase in the household cost per unit of realized energy savings induced by this overlap is then given by:

$$\pi s \times \left(\hat{\beta}_g \times \mu_g + \hat{\beta}_e \times \mu_e \right)^{-1} \quad (9)$$

We are now able to compute the average abatement cost, which is the difference between the expressions in Eq. (7) and (9), using the estimates $\hat{\beta}_g$ and $\hat{\beta}_e$ in Table 4, emission factors from the French environmental agency and the Ministry for Ecology, and monthly certificate price data. This yields an estimate of EUR 150/tCO₂e.

This estimate per ton is significantly higher than the official French carbon value set for 2020, which was EUR 90/tCO₂e. This reference value does not correspond to the social cost of carbon, but rather to the shadow cost of achieving the national abatement target included in France's Nationally Determined Contribution (NDC). It has since been substantially revised upward to reflect the updated target of a 55% reduction in greenhouse gas emissions by 2030 and now amounts to EUR 250/tCO₂e. Relative to this benchmark, the average energy retrofit measures included in the study sample meet the cost-effectiveness criterion within the French climate policy mix.

Last, it mostly falls below the other empirical estimates available in the literature. is below that of Fowlie et al. (2018), who estimate it at USD 200 per ton in the context of the Weatherization Assistance Program. The results are however not directly comparable. First, the scope of the costs and benefits are different. Fowlie and coauthors account for the impact of the energy use reductions on the emission of local pollutants and the private benefits associated of increasing indoor temperatures after retrofit (i.e., the rebound effect), the other non-monetary costs benefits as well as the encouragement cost. Last, they include in their estimation the costs and benefits of the inframarginal renovations while they are set to zero in our analysis.

Our revealed preference approach does not impose such a restriction. Second, our estimate covers all non-monetary costs and benefits that are priced by the market for certificates, including the discomfort incurred during installation, comfort gains, and the transaction and commercialization costs. To the best of our knowledge, we are the first to estimate such a comprehensive cost of abatement, specifically for energy retrofit investments.

It is important to emphasize that $c(x)$ reflects households' ex ante payoffs based on the information set available to households before the investment. It does not correspond to ex post realizations, which may diverge from expectations owing to systematic misperceptions of costs and benefits. This distinction is salient in the energy efficiency literature, where these misperceptions are frequently cited as a source of the discrepancy between the investments households actually undertake and those that would appear privately profitable, a phenomenon commonly referred to as the "energy efficiency gap".

6.3 Effect of energy price increases through the CEE Program

The analysis conducted thus far provides only a partial assessment of the program's carbon impact. As outlined in introduction, the cost borne by energy retailers to generate certificates is ultimately transmitted to end-user energy prices. This pass-through mechanism induces all households, rather than solely those undertaking energy efficiency investments, to reduce their energy consumption. In this subsection, we seek to quantify this indirect effect, which amplifies the overall carbon impact of the program, and the associated abatement cost. The analysis is conducted within the empirical scope of our study, namely the municipalities included in our sample and their residential consumption of gas and electricity.

To compute the energy user welfare loss due to the energy price increase, we rely on a standard demand framework. Let $m_{f,t}$ denote the price of fuel f in year t with $f \in \{e, g\}$ and $m_{f,t}^0$ the counterfactual price in the absence of the program. Assuming (locally) linear demand functions for gas and electricity, the total consumer welfare loss due to the program-induced increase in fuel prices is

$$\frac{1}{2} \times \sum_{f,i,t} (m_{f,t} - m_{f,t}^0) (Y_{f,i,t}^0 - Y_{f,i,t}) , \quad (10)$$

This Harberger-type distortion corresponds to the hatched area in Figure 3.

By applying appropriate emission factors to the reduced consumption of gas and electricity corresponding quantity of carbon abated is given by:

$$\sum_{f,i,t} \mu_f \times (Y_{f,i,t}^0 - Y_{f,i,t}) ,$$

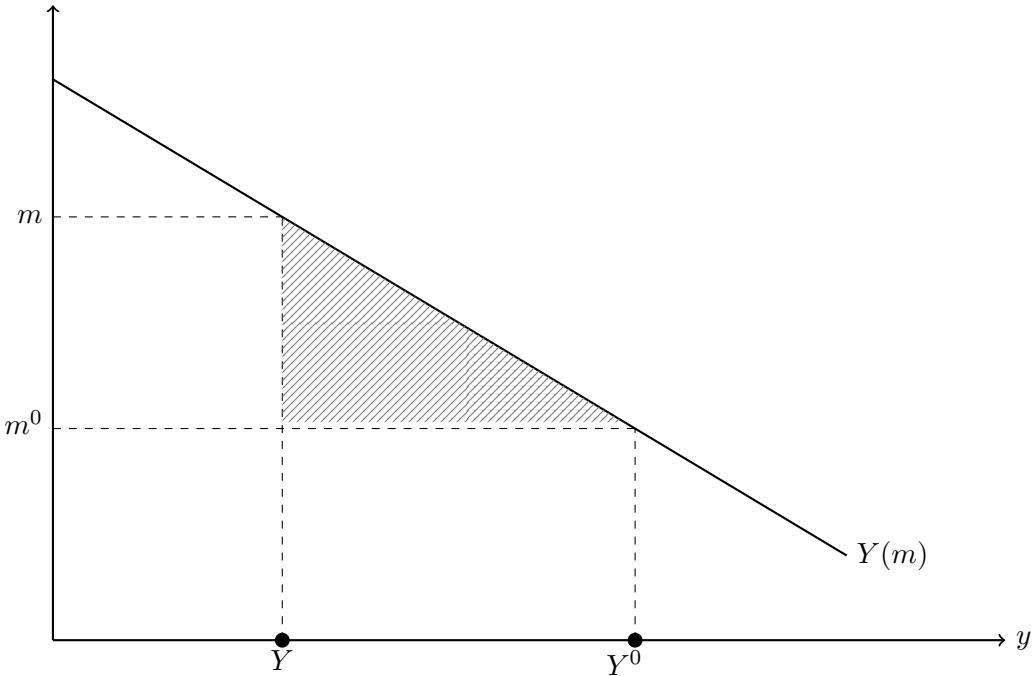


Figure 3: Impact of the program on energy demand

Notes: The graph shows the effect of the program-induced increase in energy prices on energy demand and the resulting decline in consumer surplus (the hatched area).

so that the average abatement cost of carbon is

$$C := \frac{1}{2} \times \frac{\sum_{f,i,t} (m_{f,t} - m_{f,t}^0) (Y_{f,i,t}^0 - Y_{f,i,t})}{\sum_{f,i,t} (Y_{f,i,t}^0 - Y_{f,i,t}) \times \mu_f} \quad (11)$$

However, this expression does not permit the direct computation of abatement costs, since counterfactual fuel prices $m_{f,t}^0$ and fuel consumption levels $Y_{f,i,t}^0$ are not observed. To address this limitation, we rely on external estimates of pass-through rates and energy-demand elasticities from the existing literature.

Relying on administrative data, Darmais et al. (2024) estimate the difference $m_{f,t} - m_{f,t}^0$ for the year 2019. They find that the program led to a 4.61% increase in residential gas prices and a 3.16% increase in electricity prices relative to the counterfactual. These rates cannot, however, be applied uniformly over the entire study period. As shown in Figure 2, certificate prices exhibit substantial variation over time, implying corresponding changes in their impact on energy prices. We therefore infer program-induced fuel price increases for 2018 and 2020 by scaling the 2019 estimates according to the relative changes in certificate prices observed in those years. Details are provided in Appendix

C.

Ultimately, we can compute the price difference using the following expression:

$$m_{f,t} - m_{f,t}^0 = m_{f,t} \left(\frac{\delta_{f,t}}{1 + \delta_{f,t}} \right), \quad (12)$$

where $\delta_{f,t}$ denotes the program-induced price increase rate of fuel f in year t .

Turning next to the estimation of the difference $Y_{f,i,t}^0 - Y_{f,i,t}$, we rely on demand elasticity estimates from Douenne (2020). For municipalities with a size comparable to the average in our sample, the relevant elasticity is -0.34^{19} . A limitation of this estimate is that it does not distinguish between gas and electricity consumption. We therefore assume identical elasticities across fuels, an assumption supported by Labandeira et al. (2017), whose meta-analysis finds no statistically significant difference between electricity and gas price elasticities.

Denoting this price elasticity by ϵ , we have by definition

$$-\epsilon = \left(\frac{Y_{f,i,t}^0 - Y_{f,i,t}}{Y_{f,i,t}^0} \right) \left(\frac{m_{f,t} - m_{f,t}^0}{m_{f,t}^0} \right)^{-1}. \quad (13)$$

We then substitute Eqs. (12) and (13) into Equation (11) and rearrange leading to a computable expression for the average carbon abatement cost:

$$C = \frac{1}{2} \left(\sum_{f,i,t} \frac{m_{f,t} Y_{f,i,t} (\delta_{f,t})^2}{(1 + \delta_{f,t})(1 + \epsilon \delta_{f,t})} \right) \left(\sum_{f,i,t} \frac{\mu_f Y_{f,i,t}}{1 + \epsilon \delta_{f,t}} \delta_{f,t} \right)^{-1} \quad (14)$$

Finally, we parameterize the model by combining demand elasticity estimates and program-induced price increase rates from the literature with observed certificate prices and energy consumption quantities in our dataset. The resulting average cost of carbon abatement induced by the increase in energy prices amounts to EUR 11.95/tCO₂e.

We compute the overall average cost of carbon abatement as the sum of the subsidy and price effects of the policy, weighted by their respective carbon abatement. According to the denominators in Eq. (7) and (14), energy efficiency investments supported by the policy abated 162,748 tons of CO₂e, while the induced increase in energy prices lead to an additional abatement of 384,416 tons. The resulting overall cost is equal to EUR 53/tCO₂e.

¹⁹The estimated elasticity is -0.34 for rural municipalities, -0.27 for medium-sized cities, and -0.08 for large cities.

7 Conclusion

Relying on a new administrative dataset recording all CEE-supported energy efficiency retrofits in the French residential sector between 2018 and 2020, we investigate their impact on gas and electricity consumption in 4,774 peri-urban municipalities. We compare our econometric estimates associated to these operations to measure the wedge between projected and realized savings. We document two primary findings. First, each kWh of savings predicted by engineering models yields in the best case scenario only 0.411 kWh of realized savings. The French CEE is therefore plagued by a minimum 59% energy performance gap. Second, the average cost of carbon abatement through CEE retrofits is equal to 150 EUR per ton of CO₂ equivalent. This estimate however gives a partial view on the program outcome as it ignores its effect on the energy prices. When accounting for this energy price channel, the abatement cost falls to EUR 53/tCO₂e.

We acknowledge several important limitations of the present study. First, we are unable to provide a definitive estimate of the actual energy savings induced by the French program. This limitation mainly stems from our inability to control for contemporaneous energy retrofits not supported by the program. As a result, our estimates should be interpreted as a lower bound on the energy performance gap, and we remain agnostic regarding its underlying determinants. In particular, we do not investigate the two information asymmetries highlighted in the literature: moral hazard arising from information asymmetries between beneficiaries and installers, and behavioral responses by beneficiary households, commonly referred to as the rebound effect.

Second, the estimation of abatement costs relies on a structural model that rests on several assumptions. While these assumptions differ from those underlying accounting-style calculations—typically concerning investment lifetimes and discount rates—they are also open to debate. Data limitations prevent us from formally testing the robustness of the results derived from this model.

On a broader point of view, one should also keep in mind that energy efficiency works may have other effects than energy reduction and carbon emissions reductions, such as health improvements or unemployment reduction through the creation of green jobs.

References

- ADEME (2020). *Positionnement de l'ADEME sur le calcul du contenu CO₂ de l'électricité, cas du chauffage électrique*. URL: <https://librairie.ademe.fr/ged/84/fiche-technique-ademe-contenu-co2-electricite-2020-v2.pdf>.
- Allcott, Hunt and Greenstone, Michael (May 2024). *Measuring the Welfare Effects of Residential Energy Efficiency Programs*. Working Paper 23386. National Bureau of Economic Research. DOI: 10.3386/w23386. URL: <http://www.nber.org/papers/w23386>.
- Allcott, Hunt, Knittel, Christopher, and Taubinsky, Dmitry (May 2015). “Tagging and Targeting of Energy Efficiency Subsidies”. In: *American Economic Review* 105.5, pp. 187–91. DOI: 10.1257/aer.p20151008. URL: <https://www.aeaweb.org/articles?id=10.1257/aer.p20151008>.
- Arimura, Toshi H. et al. (2012). “Cost-effectiveness of electricity energy efficiency programs”. In: *The Energy Journal* 33.2, pp. 63–99.
- Aroonruengsawat, Anin, Aufhammer, Maximilian, and Sanstad, Alan H. (2012). “The impact of state-level energy efficiency programs on electricity consumption in the United States”. In: *The Energy Journal* 33.1, pp. 159–198.
- Bernheim, B. Douglas and Taubinsky, Dmitry (July 2018). *Behavioral Public Economics*. Working Paper 24828. National Bureau of Economic Research. DOI: 10.3386/w24828. URL: <http://www.nber.org/papers/w24828>.
- Broc, Jean-Sébastien, Stańczyk, Wojciech, and Reidlinger, Bettin (May 2020). *Snapshot of Energy Efficiency Obligation Schemes in Europe*. Report Provisional version.
- CASD (2023). *CEE : Energy saving certificates*. URL: <https://www.casd.eu/en/source/energy-saving-certificates/>.
- CGDD, Commissariat général au développement durable (2019). *Les facteurs d'émission de gaz à effet de serre*. URL: <https://www.notre-environnement.gouv.fr/themes/climat/les-emissions-de-gaz-a-effet-de-serre-et-lempreinte-carbone-ressources/article/les-facteurs-d-emission-de-gaz-a-effet-de-serre/>.
- Chaisemartin, Clément de and d'Haultfœuille, Xavier (2020). “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects”. In: *American Economic Review* 110.9, pp. 2964–2996. DOI: 10.1257/aer.20181169. URL: <https://www.aeaweb.org/articles?id=10.1257/aer.20181169>.

Chetty, Raj (May 2015). “Behavioral Economics and Public Policy: A Pragmatic Perspective”. In: *American Economic Review* 105.5, pp. 1–33. DOI: 10.1257/aer.p20151108. URL: <https://www.aeaweb.org/articles?id=10.1257/aer.p20151108>.

Christensen, Peter et al. (July 2023). “Decomposing the Wedge between Projected and Realized Returns in Energy Efficiency Programs”. In: *The Review of Economics and Statistics* 105.4, pp. 798–817. ISSN: 0034-6535. DOI: 10.1162/rest_a_01087. eprint: https://direct.mit.edu/rest/article-pdf/105/4/798/2142634/rest_a_01087.pdf. URL: https://doi.org/10.1162/rest_a_01087.

Conley, T.G. (1999). “GMM estimation with cross sectional dependence”. In: *Journal of Econometrics* 92.1, pp. 1–45. ISSN: 0304-4076. DOI: [https://doi.org/10.1016/S0304-4076\(98\)00084-0](https://doi.org/10.1016/S0304-4076(98)00084-0). URL: <https://www.sciencedirect.com/science/article/pii/S0304407698000840>.

Crampes, Claude and Léautier, Thomas-Olivier (2020). *White certificates and competition*. TSE Working Papers 20-1167. Toulouse School of Economics (TSE).

Darmais, Amélie, Glachant, Matthieu, and Kahn, Victor (2024). “Social equity provisions in energy efficiency obligations: An ex-post analysis of the French program”. In: *Energy Policy* 195, p. 114348. ISSN: 0301-4215. DOI: <https://doi.org/10.1016/j.enpol.2024.114348>. URL: <https://www.sciencedirect.com/science/article/pii/S0301421524003689>.

Davis, Lucas W., Martinez, Sebastian, and Taboada, Bibiana (2020). “How effective is energy-efficient housing? Evidence from a field trial in Mexico”. In: *Journal of Development Economics* 143, p. 102390. ISSN: 0304-3878. DOI: <https://doi.org/10.1016/j.jdeveco.2019.102390>. URL: <https://www.sciencedirect.com/science/article/pii/S0304387818312756>.

DGEC (2022). *BILAN DE LA 4EME PERIODE DES CEE, 2018-2021*. Tech. rep. Direction Générale de l’Energie et du Climat.

DGFiP, Direction générale des Finances publiques (Sept. 2016). *Crédit d’impôt transition énergétique*. Web page. URL: <https://www.impots.gouv.fr/particulier/credit-dimpot-transition-energetique>.

Douenne, Thomas (2020). “The Vertical and Horizontal Distributive Effects of Energy Taxes: A Case Study of a French Policy”. In: *The Energy Journal* 41.3, pp. 231–254. DOI: 10.5547/01956574.41.3.tdou.

Emmy, Registre National des Certificats d’Economie d’Energie (2023). *Cotation du kWh cumac*. URL: <https://www.emmy.fr/public/donnees-mensuelles>.

European Commission (2012). “Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/EC and 2006/32/EC”. In: *Off Journal of the European Union, E. Parliament, Editor.*

Fowlie, Meredith, Greenstone, Michael, and Wolfram, Catherine (May 2015a). “Are the Non-monetary Costs of Energy Efficiency Investments Large? Understanding Low Take-Up of a Free Energy Efficiency Program”. In: *American Economic Review* 105.5, pp. 201–04. DOI: 10.1257/aer.p20151011. URL: <https://www.aeaweb.org/articles?id=10.1257/aer.p20151011>.

— (2015b). “Are the non-monetary costs of energy efficiency investments large? Understanding low take-up of a free energy efficiency program”. In: *American Economic Review* 105.5, pp. 201–204.

— (2018). “Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program”. In: *The Quarterly Journal of Economics* 133.3, pp. 1597–1644. URL: <https://academic.oup.com/qje/article-abstract/133/3/1597/4828342>.

Gillingham, Kenneth and Stock, James H. (2018). “The Cost of Reducing Greenhouse Gas Emissions”. In: *The Journal of Economic Perspectives* 32.4, pp. 53–72. ISSN: 08953309. URL: <https://www.jstor.org/stable/26513496> (visited on 12/12/2025).

Giraudet, Louis-Gaëtan, Glachant, Matthieu, and Nicolaï, Jean-Philippe (2020). “Selling and Saving Energy: Energy Efficiency Obligations in Liberalized Energy Markets”. In: *The Energy Journal* 41.Special I. URL: <https://ideas.repec.org/a/aen/journl/ej41-si1-giraudet.html>.

Giraudet, Louis-Gaëtan, Houde, Sébastien, and Maher, Joseph (2018). “Moral Hazard and the Energy Efficiency Gap: Theory and Evidence”. In: *Journal of the Association of Environmental and Resource Economists* 5.4, pp. 755–790. URL: <https://EconPapers.repec.org/RePEc:ucp:jaerec:doi:10.1086/698446>.

Hahn, Robert W et al. (July 2024). *A Welfare Analysis of Policies Impacting Climate Change*. Working Paper 32728. National Bureau of Economic Research. DOI: 10.3386/w32728. URL: <http://www.nber.org/papers/w32728>.

Houde, Sébastien et al. (2025). *Big Hassle on the Decarbonization Frontier*. Tech. rep. 12326. CESifo Working Paper. DOI: 10.2139/ssrn.5908870.

Houde, Sébastien and Myers, Erica (Apr. 2019). *Heterogeneous (Mis-) Perceptions of Energy Costs: Implications for Measurement and Policy Design*. Working Paper 25722. National Bureau of Economic Research. DOI: 10.3386/w25722. URL: <http://www.nber.org/papers/w25722>.

- IEA (2022). *Energy Efficiency*. Tech. rep. International Energy Agency.
- INSEE (2018). *Logement en 2018, Recensement de la population - Base infracommunale (IRIS)*. URL: <https://www.insee.fr/fr/statistiques/4799305>.
- International Energy Agency (2018). “Energy Efficiency and Demand”. In: *World Energy Outlook 2018*. Paris: IEA.
- Labandeira, Xavier, Labeaga, José M., and López-Otero, Xiral (2017). “A meta-analysis on the price elasticity of energy demand”. In: *Energy Policy* 102, pp. 549–568. ISSN: 0301-4215. DOI: <https://doi.org/10.1016/j.enpol.2017.01.002>. URL: <https://www.sciencedirect.com/science/article/pii/S0301421517300022>.
- Lang, Ghislaine and Lanz, Bruno (2022). “Climate policy without a price signal: Evidence on the implicit carbon price of energy efficiency in buildings”. In: *Journal of Environmental Economics and Management* 111, p. 102560. ISSN: 0095-0696. DOI: <https://doi.org/10.1016/j.jeem.2021.102560>. URL: <https://www.sciencedirect.com/science/article/pii/S0095069621001121>.
- McKinsey (2009). *Pathways to a low-carbon economy: Version 2 of the global greenhouse gas abatement cost curve*. Tech. rep. McKinsey Company.
- Myers, Erica (2020). “Asymmetric information in residential rental markets: Implications for the energy efficiency gap”. In: *Journal of Public Economics* 190, p. 104251. ISSN: 0047-2727. DOI: <https://doi.org/10.1016/j.jpubeco.2020.104251>. URL: <https://www.sciencedirect.com/science/article/pii/S0047272720301158>.
- ONRE (2022). *La rénovation énergétique des logements : Bilan des travaux et des aides entre 2016 et 2019*. Tech. rep. Ministère de la Transition Ecologique (MTE).
- Papineau, Maya, Rivers, Nicholas, and Yassin, Kareman (2025). “Household benefits from energy efficiency retrofits: Implications for net zero housing policy”. In: *Energy Economics* 143, p. 108245. ISSN: 0140-9883. DOI: <https://doi.org/10.1016/j.eneco.2025.108245>. URL: <https://www.sciencedirect.com/science/article/pii/S0140988325000684>.
- Pisany-Ferry, Jean and Mahfouz, Selma (2023). *Les incidences économiques de l'action pour le climat*. Tech. rep. France Stratégie. URL: <https://www.strategie-plan.gouv.fr/publications/incidences-economiques-de-laction-climat>.
- Rosenow, Jan, Cowart, Richard, and Thomas, Samuel (2019). “Market-based instruments for energy efficiency: a global review”. In: *Energy Efficiency* 12.5, pp. 1379–1398.

Staiger, Douglas and Stock, James H. (1997). "Instrumental Variables Regression with Weak Instruments". In: *Econometrica* 65.3, pp. 557–586. ISSN: 00129682, 14680262. URL: <http://www.jstor.org/stable/2171753> (visited on 09/06/2023).

Zivin, Joshua Graff and Novan, Kevin (2016). "Upgrading Efficiency and Behavior: Electricity Savings from Residential Weatherization Programs". In: *The Energy Journal* 37.4, pp. 1–23. ISSN: 01956574, 19449089. URL: <http://www.jstor.org/stable/44075492> (visited on 02/02/2026).

A Descriptive statistics

Table A1: Per capita municipal residential energy use, retrofit works, and demographics

	Estimation sample (N = 4,774)		Mainland France (N = 34,868)	
	Mean	SD	Mean	SD
Panel A: Annual energy use				
Electricity (kWh)	3,429.959	1,213.841	3,168.284	830.544
Gas (kWh)	1,263.306	1,722.556	745.262	1,384.025
Panel B: Retrofit works				
Projected lifelong savings (kWh)	2,816.795	2,001.76	3,416.708	2,945.592
Projected annual savings (kWh)	77.643	61.008	96.349	84.181
Panel C: Demographics				
Median annual income (€/yr)	21,363.438	3,625.951	21,833.585	3,692.437
Population	1,078	1,365	1,991	8,262
Panel D: Weather				
Annual HDD	2,066	575	2,143	435
Annual precipitation (mm)	928	263	881	210

Table A2: Summary statistics on the 23 standardized energy retrofit operations used in the residential sector

Operation	Life exp. (years)	Mean (MWh c.)	Median (MWh c.)	Sum 2017–19 (GWh c.)	Total (%)	Rank
Roof insulation	30	240.11	207.000	49527.841	52.82	1
Floor insulation	30	354.38	308.000	16694.019	17.80	2
Wall insulation	30	350.58	209.000	8163.930	8.71	3
HP air-water / water-water	17	489.80	454.500	7494.935	7.99	4
High EE individual boiler	17	124.01	109.100	6669.954	7.11	5
Window w/ insulated glazing	24	51.62	32.800	1361.083	1.45	6
Wood-burning system	12	29.53	29.600	1178.195	1.26	7
HP air-air	17	54.06	44.590	869.218	0.93	8
Individual biomass boiler	17	442.72	454.500	716.768	0.76	9
Hygro-adjustable CMV	17	62.11	46.357	209.885	0.22	10
Hot water network insulation	20	2217.54	899.810	175.185	0.19	11
Hybrid individual HP	17	576.96	454.500	167.317	0.18	12
Water network insulation	20	8861.70	9259.200	150.649	0.16	13
HP water-heater	17	21.21	21.100	138.965	0.15	14
Rooftop insulation	30	566.98	148.500	86.180	0.09	15
Comprehensive renovation	30	13384.10	8029.547	53.536	0.06	16
Heating network insulation	20	3146.14	1848.000	34.608	0.04	17
High EE collective boiler	22	1219.98	805.806	29.280	0.03	18
Low-temperature radiator	35	33.73	16.932	27.219	0.03	19
Insulating closure	24	4.63	3.900	5.362	0.01	20
Individual solar water heater	20	33.21	27.600	4.882	0.01	21
Dual-flow ventilation	17	50.59	43.890	4.047	0.00	22
Collective boiler w/ contract	22	1230.54	1251.188	3.692	0.00	23
Underfloor heating system	50	31.51	27.000	1.733	0.00	24
Connection to a heating network	30	72.10	63.085	0.505	0.00	25

Computation of Heating Degree Days

Heating Degree Days (HDD) are based on the principle that no heating or cooling is required when the outdoor temperature equals 17°C. Degree days measure the deviation of daily mean temperatures from this base value. When the daily mean temperature exceeds 17°C, the difference represents Cooling Degree Days (CDD); when it falls below 17°C, the difference represents Heating Degree Days (HDD).

Formally, for each node n and day d , we compute HDD following the SDES methodology as:

$$HDD_{n,d} = \begin{cases} 17 - T_{n,d}, & \text{if } T_{n,d} < 17^\circ\text{C} \\ 0, & \text{otherwise.} \end{cases}$$

We then aggregate HDD values at the annual level for each node:

$$HDD_{n,y} = \sum_{d=1}^{365} HDD_{n,d},$$

and subsequently compute annual HDD for each municipality ($HDD_{m,y}$).

Mapping HDD to the municipal level is performed according to the following rule:

$$HDD_{m,y} = \begin{cases} HDD_{n,y}, & \text{if } n \subset m \text{ and there is no other node within } m, \\ \frac{1}{k} \sum_{i=1}^k HDD_{n_i,y}, & \text{if } \exists k > 1 \text{ such that } n_i \subset m, \\ HDD_{n^*,y}, \quad n^* = \arg \min_n \|C_m - n\|, & \text{if no node lies within } m, \end{cases}$$

where C_m denotes the centroid of municipality m , used to assign HDD values via one-nearest-neighbor matching when no temperature node falls within the municipal boundaries.

B Robustness analysis

Table B1: Alternative Instrumental Variable specification

	HDD (t-2)	Rain (t-2)	[HDD + Rain] (t-2)
Fitted Expected Savings	-0.417*** (0.111)	-0.411* (0.199)	-0.415*** (0.122)
Log. of Pop.	741 278.602*** (165 266.373)	740 729.911*** (173 162.622)	741 038.689*** (168 504.516)
HDD	562.806* (224.841)	561.165** (186.463)	562.088** (207.029)
Precipitation (mm)	110.024+ (64.876)	109.817+ (60.667)	109.933+ (62.970)
Num.Obs.	12 207	12 207	12 207
R2	0.999	0.999	0.999
R2 Adj.	0.998	0.998	0.998
R2 Within	0.078	0.078	0.078
FE: Code_commune_INSEE	X	X	X
FE: dep_year	X	X	X
F-test (1st stage)	219.63	175.123	179.164

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Clustered standard errors at the municipality level

Table B2: Placebo estimation: lead & lagged expected savings

	Lead	Lagged
Fitted Expected Savings	0.783** (0.264)	-1.072** (0.360)
Log. of Pop.	622 186.101*** (162 610.886)	694 864.260*** (166 261.586)
HDD	822.115*** (184.158)	603.932** (197.419)
Precipitation (mm)	77.263 (70.303)	106.573+ (62.817)
Num.Obs.	12 207	12 207
R2	0.999	0.999
R2 Adj.	0.998	0.998
R2 Within	-0.071	0.067
FE: Code_commune_INSEE	X	X
FE: dep_year	X	X
F-test (1st stage)	80.304	201.415

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Clustered standard errors at the municipality level

C Calibration of program-induced energy price increases

By definition, the price increase rate of fuel f in year t , denoted by $\delta_{f,t}$, satisfies

$$m_{f,t} = (1 + \delta_{f,t}) m_{f,t}^0. \quad (15)$$

The value of $\delta_{f,t}$ is observed for the year 2019. Our objective is to recover the corresponding price increase rates for electricity and natural gas in 2018 and 2020.

To do so, we express the fuel price as a function of the certificate price:

$$m_{f,t} = m_{f,t}^0 + \lambda_f p_t,$$

where λ_f denotes the fuel-specific pass-through rate, assumed to be constant over the study period.

Combining this expression with Eq. (15) and rearranging yields

$$\lambda_f = \frac{m_{f,t}}{p_t} \left(\frac{\delta_{f,t}}{1 + \delta_{f,t}} \right). \quad (16)$$

We compute λ_f using observed certificate prices and fuel prices in 2019, together with program-induced price increases of $\delta_g, 2019 = 0.461$ for natural gas and $\delta_e, 2019 = 0.316$ for electricity.

Finally, we invert Eq. (16) to recover the price increase rate:

$$\delta_{f,t} = \frac{\lambda_f p_t}{m_{f,t} - p_t}.$$

We apply this expression to the years 2018 and 2020 to obtain the corresponding values of $\delta_{f,t}$. The resulting estimates are reported in Table C1.

Table C1: Estimated parameters

	f	e	g
λ_f	0.7106	0.4100	
$\delta_{f, 2018}$	0.0248	0.0350	
$\delta_{f, 2020}$	0.0350	0.0628	