When Eligibility is Not Enough

Lessons from France's Energy Voucher Policy

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February 24, 2026

Abstract

Incomplete take-up persists in means-tested programs, even when benefits are allocated automatically. This paper examines why eligible households do not use the energy voucher in France, which is sent directly to beneficiaries. The results show that the determinants of non-take-up differ across the income distribution through two effects. Among modest-income households, non-use is driven by a size effect. Take-up increases sharply when the voucher represents a larger share of household income, with a probability of use by up to 94 percentage points. Among the poorest households, non-use reflects a learning effect linked to administrative familiarity. Households who received the voucher the previous year are about 25 percentage points more likely to use it. Overall, take-up follows a non-linear pattern across income levels, reflecting the joint effect of administrative constraints and the relative value of the benefit.

Keywords: Automatic allocation, Energy voucher, France, Poverty, Take-up

JEL codes: D91, H31, I32, I38, Q48

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I am grateful to Illan Barriola, Antoine Baud, Pierre Cahuc, Marie Gauthier, Cyrian Hallermeyer, Alida Johannsen, Chloé Le Coq, and Marion Leroutier, as well as to seminar participants at the Climate Policy - Research in Action Day workshop organized by DIW, the Law, Economics, and Regulation Conference of CRED-HEC, the CNRS Thematic School on Public Policy Evaluation, and the FAEE PhD Students Workshop — where this paper received the award for Best PhD Paper — for their helpful comments and suggestions. All errors are mine.

1 Introduction

Incomplete take-up remains a persistent issue in many means-tested programs (Hernanz et al., 2004; Finkelstein and Notowidigdo, 2019; Ko and Moffitt, 2024; Castell et al., 2025). Its determinants have been studied across programs and countries, and the literature identifies three main explanations. First, stigma may discourage eligible individuals from claiming benefits because of negative perceptions associated with participation in assistance programs (Moffitt, 1983). Second, imperfect information about eligibility and application rules may prevent potential beneficiaries from recognizing their entitlement (Daponte et al., 1999). Third, transaction costs arising from complex and time-consuming administrative procedures may reduce participation (Currie, 2004). Automatic allocation is intended to address imperfect information and transaction costs by removing the need for active enrollment and thereby increasing take-up (Currie, 2004). However, most evidence remains limited, as most empirical work focuses on programs that require active application. In this context, France's energy voucher program provides a proper case study. Although introduced as an automatically allocated subsidy to help households pay their energy bills, the program exhibits a non-take-up rate around 20%, a high level for a means-tested benefit. (French Court of Audit, 2022).[2]

In this paper, we study the determinants that may drive non-take-up of the French 2022 energy voucher program, despite its automatic allocation. The results show that effects vary across the poverty spectrum. Households among the middle-class are more affected by a benefit size effect, whereas take-up decisions among poor households are driven more by a learning effect and administrative burdens. The analysis relies on microdata from the European Union Statistics on Income and Living Conditions (EU-SILC), a longitudinal survey covering a four-year period that collects household-level information on income, poverty, and living conditions. This dataset allows the measurement of both eligibility for the energy voucher and actual usage, as well as detailed household characteristics and behaviors. To identify the determinants of incomplete take-up across the income distribution, the analysis compares eligible households that used the energy voucher with those that did not.

In France, the energy voucher is a mean-tested transfer for low-income households intended to help pay energy bills. During the 2022-2023 energy crisis, the eligibility has been extended to middle-incomes. It is automatically sent to eligible households once a year. However, the scheme is not entirely free of complexity as the amount is not directly credited to the bank account. Instead, households must manually activate the voucher (online or by post). As a result, using the voucher still requires administrative effort, such as understanding the procedure or creating an online account, which may reduce take-up, particularly relative to the amount received. This policy design removes

[2] The take-up rate was around 78% in 2016 and 2017, during the experimental phase of the scheme. The Ministry for Ecological Transition and Territorial Cohesion (2017) commissioned an evaluation report to assess the program's benefits and limitations. Since 2019, the usage rate has remained close to 80% (French Court of Audit, 2022).

most enrollment barriers while leaving administrative effort at the usage stage, allowing the remaining sources of non-take-up to be clearly identified.

We first provide a simple framework inspired by Moffitt (1983), in which participation in social programs is modeled as a utility-maximization decision. Rather than emphasizing stigma as the primary cost of participation in means-tested programs, we assume a cost-benefit decision, weighing the size of the benefit against administrative costs. Two main hypotheses follow from this framework. First, administrative costs vary across the income distribution. Because low-income households face high financial constraints, they experience financial stress and cognitive load, which reduce mental resources available for administrative decision-making. Cognitive load is further exacerbated by barriers such as lack of information, limited internet skills, and administrative difficulties (Mani et al., 2013; Bhargava and Manoli, 2015). As a result, the perceived effort required to use the voucher is higher among the poorest households. Second, take-up reflects the comparison between perceived administrative costs and the expected benefit from the energy voucher. At low income levels, the potential utility gain from the voucher is large, but also the perceived administrative costs. As income rises, these costs tend to decline, which may increase take-up. However, at higher income levels, the voucher amount becomes smaller, and even modest administrative effort may outweigh the expected benefit. Taken together, these mechanisms imply an inverted U-shaped relationship between income and take-up.

The empirical strategy builds on a logistic model to identify barriers to non-take-up by estimating the probability of using the energy voucher after receipt. The model compares users and non-users among households that received the voucher, conditional on socio-economic characteristics. The amount of the energy voucher received and total gross income are used as proxies for the benefit size effect, while prior receipt of the 2021 energy voucher and previous applications for social benefits as proxies for households' ability to mitigate administrative costs. Consistent with Castell et al. (2025), transaction costs — all kinds of physical and administrative effort required to apply for a benefit — emerge as the main obstacle to take-up. On average, households that received the 2021 energy voucher are 24 percentage points more likely to use the current voucher than households without prior experience, illustrating a clear learning effect. In contrast, the role of financial incentives differs across the income distribution. Overall, a one-unit increase in income reduces the probability of using the voucher by 30 percentage points, reflecting the declining relative value of the benefit as income rises. When households are analyzed by income decile, the benefit size effect is not statistically significant among poor households but is strongest for modest households, for whom the voucher's share of income increases take-up by 93 percentage points. For these households, using the voucher depends on whether the monetary gain justifies the administrative effort required. The results also indicate that low-income households are more affected by administrative burdens. Among them, prior experience with the 2021 voucher is the main determinant, suggesting that reducing administrative frictions is particularly important for the poorest. This distinction between households by income level is motivated by findings from Bertrand et al. (2006) and Mani et al. (2013), who highlight that poverty affects decision-making by imposing cognitive and psychological constraints, leading to systematic behavioral differences across poverty levels. These conclusions are similar between poor and the middle-class.

Given the extent of non-take-up, a subsequent question is whether this has affected the impact of the energy voucher policy among households that used it. To address this, the paper employs a doubly robust difference-in-differences estimator (Sant'Anna and Zhao, 2020), taking voucher-user households as the treatment group. This method estimates the effect of the energy voucher on energy well-being indicators. By comparing eight outcomes related to economic and energy conditions between voucher users and non-users, the results suggest that voucher use had no significant effect on the targeted dimensions. The absence of significant policy effects may be explained by the size of the benefit and by the nature of data. Because the voucher is issued only once per year, its impact on bill payment capacity or indoor heating is likely to be limited, particularly when assessed using annual data.

This paper contributes to the literature on public policy aimed at increasing benefit take-up. Consistent with existing studies, administrative complexity, limited information, and procedural burdens are key determinants of non-take-up, particularly among low-income households (Currie and Gahvari, 2008; Hernanz et al., 2004; Kleven and Kopczuk, 2011). Non-take-up reflects the combined effect of low perceived gains, stigma, behavioral biases, and imperfect information (Ko and Moffitt, 2024), and the computerization of claiming processes can further intensify these barriers. Evidence from France and the United States shows that personalized support increases participation, whereas reliance on online tools (Castell et al., 2025) or the closure of local offices reduces it (Deshpande and Li, 2019). By documenting the importance of prior exposure to the energy voucher in reducing administrative frictions, this study reinforces the view that administrative simplification and clearer communication can improve take-up, even if they do not fully eliminate non-take-up (Kleven and Kopczuk, 2011; Meyer and Mittag, 2019).

The paper also relates to recent work emphasizing behavioral and cognitive constraints explaining heterogeneity in non-take-up across income groups. Bhargava and Manoli (2015) show that take-up depends on the simplicity and the frequency of benefit information, while reducing stigma or lowering small claiming costs has more limited effects. A growing body of research further highlights that low-income households face higher cognitive load, which amplifies the impact of administrative burdens and imperfect information (Mani et al., 2013; Christensen et al., 2020; Baekgaard et al., 2021; Herd et al., 2023). Consistent with this perspective, the results point to heterogeneous responses to administrative frictions and benefit incentives across income levels. Beyond access barriers, the literature also emphasizes the role of financial incentives and the cost–benefit trade-off in claiming decisions. Participation depends not only on eligibility but also on whether the perceived monetary gain justifies the administrative effort needed (Hernanz et al., 2004; Meyer and Mittag, 2019; Ko and Moffitt, 2024). Empirical evidence shows that in Germany, the degree of financial need and the expected duration of eligibility are decisive determinants of benefit request (Bruckmeier and Wiemers, 2012). When perceived benefits are small relative to claiming costs, eligible households may forgo or not use support (Bargain et al., 2012).

Furthermore, the paper's results contribute to the discussion on the effectiveness of energy voucher schemes, which have been widely studied in European contexts. While the French literature has largely focused on energy price caps and related policies (Langot et al., 2023; Rüdinger, 2023; Chaton, 2025), evaluations of the French energy voucher remain scarce, with most studies examining market-level effects rather than household outcomes (Podesta et al., 2021). The findings align with international evidence, which generally shows the limited impact of energy voucher programs. For example, Spain's *Bono Social Eléctrico* shows modest and uneven reductions in energy poverty, with effects weakening over time and remaining lowest for the poorest households (Alvarez and Tol, 2021; Bagnoli and Bertoméu-Sánchez, 2022; Cadaval et al., 2022; Jové-Llopis and Trujillo-Baute, 2024; Llorca and Rodriguez-Alvarez, 2025). Reductions in energy poverty or arrears affect only a limited share of eligible households, with little effect on thermal comfort or housing quality (Bagnoli and Bertoméu-Sánchez, 2022; Alvarez and Tol, 2021; Jové-Llopis and Trujillo-Baute, 2024). Evidence from the United Kingdom similarly indicates that income-support schemes, such as the Winter Fuel Payment, create modest and short-term effects, as vulnerable households often redirect resources to other essential needs (Galvin et al., 2024; Angelini et al., 2019; Beatty et al., 2014). More generally, energy vouchers rarely address structural constraints or incentivize energy-efficiency investments, limiting their effectiveness (Angelini et al., 2019; Kröger et al., 2023). Exceptions arise when vouchers are combined with targeted informational support, as in New Zealand's Warm Homes for Elder New Zealanders program, which increased winter electricity use among low-use households (Viggers et al., 2019). Overall, the literature suggests that energy vouchers provide only partial and temporary relief from energy poverty, constrained by benefit size, targeting, and households' competing financial priorities.

The remainder of the paper is organized as follows. Section 2 presents a simple framework to analyze households' take-up decisions. Section 3 describes the empirical setting and the identification strategy used to uncover the determinants affecting the probability that households use their energy voucher. Section 4 reports the results. Section 5 discusses additional findings, and Section 6 concludes.

2 Model

This section provides a simple framework to illustrate households' take-up decisions in the French Energy Voucher program. The model builds on the framework of Moffitt (1983), which models non-participation in social programs as a utility-maximizing decision. While Moffitt (1983) emphasizes stigma as the main cost of participation in means-tested programs, the present model instead assumes two types of costs that limit take-up: a fixed administrative cost (Currie, 2004; Kleven and Kopczuk, 2011) and a variable administrative cost that depends on household characteristics, reflecting hassle (Bertrand et al., 2006; Bhargava and Manoli, 2015).

2.1 Setup

The model focuses exclusively on households eligible for the energy voucher. Suppose that a household has an exogenous private income y that allows it to cover its daily needs, including energy expenditures. In the absence of the energy voucher program, household utility is a function of income, $U = U(y)$, where U satisfies the standard assumptions of a monotonic and concave utility function in y, with $U'(y) > 0$ and $U''(y) < 0$.

When an eligible household gets an energy voucher, the amount received, denoted $b(y) > 0$, decreases with income, such that $b'(y) < 0$. Utility is proportionally increased by the voucher amount, households eligible for larger benefits are therefore more likely to take them up (Daponte et al., 1999). However, using the voucher entails a non-monetary cost associated with the effort required to use it. Moffitt (1983) distinguishes between *flat stigma*, a fixed cost associated with program participation, and *variable stigma*, which depends on the size of the social benefit received. The present model retains the distinction between fixed and variable costs but interprets them as two separate components: a fixed administrative cost (c_v) common to all households, and a variable administrative cost (c_v) that reflects the intensity of administrative burden, which varies with household characteristics such as education level or hassle.

Applying for social benefits involves substantial transaction costs arising from application processes that are complex, laborious, and time-consuming (Currie, 2004; Moffitt, 2007; Kleven and Kopczuk, 2011). Here, the fixed administrative cost, denoted c_f, represents the effort required to use the energy voucher, either online (creating an account or logging into the supplier's website) or by post (printing the bill, purchasing a stamp, and mailing the document). This cost is assumed to be fixed and identical across households because the procedure for using the voucher is fully standardized and does not vary with household income or socio-demographic characteristics.

Accordingly, household's incentive to complete the program's administrative requirements may depend on the size of the social benefit relative to the costs associated with applying or using. However, evaluating the expected costs and benefits of using the energy voucher may be constrained by cognitive limits in administrative decision-making, especially among low-income households (Bertrand et al., 2006). In the context of benefit programs, these constraints imply that non-take-up may result from cognitive overload that amplifies administrative burdens. In the model, the variable administrative cost, denoted $c_v(y, X_i)$, captures cognitive load, financial stress, and other administrative burdens linked to household characteristics X_i that generate decision fatigue. Households facing higher hassle costs may find it more difficult to understand the procedure, create an online account, or contact a helpline. Mani et al. (2013) show that poverty itself reduces cognitive capacity, as poverty-related concerns (e.g., financial worries) consume mental resources, leaving fewer resources for other tasks. Consequently, the variable administrative cost decreases with income, since higher income alleviates financial pressure and scarcity effects, implying $\frac{\partial c_v}{\partial y}(y, X_i) < 0$.

The total cost of using the benefit is therefore the sum of the fixed and the variable administrative cost:

$$C(y, X_i) = c_f + c_v(y, X_i) \tag{1}$$

A household compares its utility from using the energy voucher with its utility in the absence of the program. It chooses to complete the administrative process to use the voucher, $d^*(y, X_i) = 1$, if the net utility gain exceeds the total cost:

$$d^*(y, X_i) = \begin{cases} 1, & \text{if} \quad U\big(y + b(y)\big) - U(y) \geq C(y, X_i), \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The net gain from using the energy voucher is defined as:

$$G(y, X_i) = U\big(y + b(y)\big) - U(y) - c_f - c_v(y, X_i) \tag{3}$$

The derivative of the net gain with respect to income is therefore:

$$\frac{\partial G}{\partial y}(y, X_i) = U'(y + b(y))(1 + b'(y)) - U'(y) - \frac{\partial c_v}{\partial y}(y, X_i) \tag{4}$$

This derivative captures the marginal effect of income on the propensity to use the energy voucher. It reflects three competing forces that shape household behavior across the income distribution.[3]

[3] In the special case of additive utility, $U(y + b(y)) = U(y) + U(b(y))$, the derivative of the net gain with respect to income simplifies to $\frac{\partial G}{\partial y}(y, X_i) = U'(b(y)) - \frac{\partial c_v}{\partial y}(y, X_i)$. This expression makes the trade-off explicit: the marginal utility derived from the voucher must outweigh the reduction in hassle cost (variable administrative cost) associated with higher income for take-up to remain attractive.

2.2 Empirical Predictions

The overall sign of $\frac{\partial G}{\partial y}(y, X_i)$ is ambiguous, as it reflects three opposing forces. The first term, the gain derived from the benefit, is positive but attenuated by means-testing, the second term captures declining marginal utility and is negative, and the third term is positive and reflects reduced administrative costs. Whether take-up increases or decreases with income therefore depends on which effect dominates across different segments of the income distribution.

2.2.1 Size effect

The gain derived from the social benefit and the declining marginal utility operate through the size of the energy voucher received. Since the voucher is means-tested and declines with income, the utility gain from usage is higher for lower-income eligible households.

Prediction 1. *Take-up of the energy voucher decreases with income.*

Because the voucher amount decreases with income, $b'(y) < 0$, higher-income eligible households receive smaller voucher amounts. Combined with diminishing marginal utility of income, this implies that the utility gain from the energy voucher declines as income rises. The first term of the derivative of the net gain, $U'(y + b(y))(1 + b'(y))$, captures the marginal effect of income on utility when the household receives the voucher, accounting for the mechanical reduction in the voucher amount as income increases. As income rises, the decline in the benefit offsets part of the utility gain from higher income, resulting in a lower net utility gain from usage for wealthier eligible households.

Implication 1a. *Households entitled to larger voucher amounts are more likely to take up the benefit.*

Households entitled to larger vouchers experience a higher utility gain from voucher use. For a given income level, a larger benefit directly increases utility through $U(y + b(y))$. Moreover, due to diminishing marginal utility of income, a given benefit generates a larger utility gain for lower-income households. The term $-U'(y)$ represents the marginal utility of income in the absence of the voucher and serves as the benchmark against which the utility gain from voucher use is evaluated. Consequently, an additional euro of benefit increases the net utility gain from take-up more strongly for poorer households, implying higher take-up rates among households entitled to larger voucher amounts.

Implication 1b. *The relationship between income and take-up is inverted U-shaped.*

The model allows for a non-monotonic relationship between income and take-up rates. Take-up may be relatively low among the poorest eligible households if high administrative costs offset the potentially large utility gain from the voucher. As income increases, administrative costs decline while the voucher amount remains substantial, leading to higher take-up among middle-income eligible households. At higher income levels, take-up may decline as the voucher amount becomes too small to compensate for the remaining administrative effort, even when administrative burdens are low. This inverted U-shaped pattern arises when the reduction in administrative costs dominates at low income levels, whereas the decline in the utility gain from the voucher — driven by smaller benefit amounts and diminishing marginal utility — dominates at higher income levels.

The model also predicts heterogeneity by vulnerability characteristics captured by X_i. Since $\frac{\partial c_v}{\partial(X_i)} > 0$, households with characteristics associated with vulnerability face higher variable administrative costs at all income levels. For these households, take-up is expected to be lower throughout the income distribution.

2.2.2 Learning effect

While the energy voucher amount affects take-up through the utility gain, the usage rate also depends on administrative burdens. Households with prior experience applying for social benefits face lower variable administrative costs. Through learning, they are better able to complete procedures, and reducing hassle and procedural difficulties.

Prediction 2. *Prior administrative experience generates learning effects that reduce administrative costs and increase take-up.*

The variable administrative cost $c_v(y, X_i)$ captures cognitive load, financial stress, and other non-monetary barriers to completing program administrative tasks. Households facing higher hassle are therefore less likely to take up the energy voucher, even when the potential utility gain $U(y + b(y)) - U(y)$ is large. This mechanism helps explain why some very low-income eligible households do not use the benefit despite high financial need. The fixed administrative cost c_f constitutes a particularly binding constraint for households experiencing scarcity. The term $-\frac{\partial c_v}{\partial y}(y, X_i)$ reflects the effect of income on the variable administrative costs: higher income alleviates financial pressure and cognitive constraints, thereby reducing administrative costs and increasing the likelihood of take-up.

Moreover, this mechanism can be interpreted as a learning effect. Households with prior experience in administrative procedures or with greater familiarity with social benefits face lower costs when applying for the voucher. In contrast, households lacking such experience encounter higher cognitive and procedural barriers, which reduce participation even when the voucher provides substantial utility gains. This interpretation implies that administrative costs are not purely financial or time-consuming but also reflect the experience of households with administrative complexity.

Implication 2a. *Learning effects are stronger for low-income households, who face particularly high administrative costs.*

At very low income levels, the utility gain from the energy voucher is potentially large because the voucher amount $b(y)$ is high and marginal utility of income is strong. However, households at the bottom of the income distribution also face the highest administrative costs, reflecting severe financial stress, cognitive load, and limited administrative capacity. As a result, high administrative burdens may offset the large potential utility gain and prevent take-up among the poorest eligible households.

Since administrative costs decrease with income ($\frac{\partial c_v}{\partial y} < 0$), rising income alleviates financial pressure and reduces cognitive and psychological barriers to participation, increasing take-up at intermediate income levels.

By contrast, at income levels close to the eligibility threshold, the voucher amount $b(y)$ becomes very small due to means-testing, substantially reducing the utility gain from participation. In addition, diminishing marginal utility implies that even small transfers generate limited additional utility for these households. Although administrative costs are low at these income levels, the fixed administrative cost c_f represents a relatively large burden compared to the benefit size. Consequently, the decline in the utility gain from the voucher dominates the reduction in administrative costs, leading to lower take-up among higher-income eligible households.

3 Empirical Setting

This section describes the empirical framework and identification strategy used to estimate the determinants of households' decisions to use energy vouchers. Additional information on the French Energy Voucher policy is provided in Appendix A, and further methodological details are presented in Appendix B.

3.1 The French Energy Voucher Policy

The energy voucher was introduced in 2018 to help low-income households pay their energy bills[4] and has been exceptionally expanded to support middle-income households from the energy crisis in 2021 and 2022. This scheme replaces the social electricity and gas tariff, which provided a discount on energy subscription prices for low-income households. The policy change was intended to address two major drawbacks: the social tariff applied only to households using electricity or gas as energy sources, and its non-take-up rate was high (French Court of Audit, 2022).

The energy voucher is a means-tested payment allocated according to the household's financial resources — measured by reference tax income[5] (RTI) per consumption units[6] (CU), calculated using income from year n-2. Since its introduction, the RTI per CU eligibility threshold has been progressively increased to 10,800 euros per CU in 2022, in order to cover the 30% poorest French households (General Directorate of Public Finances, 2024).[7] Importantly, beneficiaries do not need

[4] The energy voucher can also be used to cover expenditures related to energy-saving renovation work, but only 0.001% vouchers are used for this purpose per year (French Court of Audit, 2022).

[5] The reference tax income is the total income of the tax household, including both taxable and non-taxable revenues. Service public (2025). Available at: https://www.service-public.fr/, last accessed August 1, 2025.

[6] The consumption unit (CU) allows for comparison of living standards between households of different sizes and compositions from year n-2. It is calculated as follows: 1 CU for the first adult in the household, 0.5 CU for each additional person aged 14 or over, and 0.3 CU for each children under 14. The French consumption unit follows the OECD equivalence scale. INSEE (2022). Available at: https://www.insee.fr/, last accessed August 1, 2025.

[7] Residents of social housing without private use of their accommodation are eligible for the energy voucher. It is

to take any action to receive the energy voucher, which helps limit non-take-up. The General Directorate of Public Finances automatically compiles the list of households that meet the eligibility criteria.[8] After receiving the voucher, households can use it in two ways: either by sending it to their energy supplier together with an energy bill, or by using the official energy voucher website. Beneficiaries have one year to make use of the energy voucher (DREES, 2023).

The amount of the energy voucher depends on both the household's annual reference tax income (RFR) per consumption unit (CU) and the number of CU in the household. In 2022, the value of the standard energy voucher ranged from 48 to 277 euros (Table 5). Eligibility in 2022 required the household's 2020 reference tax income per CU to be below 10,800 euros. In addition, in response to the sharp rise in electricity and gas prices, exceptional energy vouchers were issued in 2021 and 2022, increasing both the allowance amount and the scope of eligibility. Distributed in December, the 2022 exceptional energy voucher provided an additional payment of 200 euros to standard energy voucher beneficiaries, and 100 euros to households with a reference tax income per CU between 10,800 and 17,400 euros (Table 5). Thereby extending the policy up to the sixth decile of the income distribution, thus covering the middle class as well. According to French Ministry for the Ecological Transition (2023), a total of 5,773,000 households received the standard energy voucher in 2022, and 11,900,000 exceptional energy vouchers were issued (Table 6).

3.2 Data

This paper uses a representative sample of French households from the European Statistics on Income and Living Conditions (EU-SILC) survey conducted by Eurostat.[9] The EU-SILC data contain self-reported information on income, poverty, social exclusion, and living conditions. For the analysis, an annual panel covering four years (2020–2023) is constructed. The outcome of interest captures whether households report having benefited from the energy voucher, including the exceptional one, and is based on a variable indicating whether a household's utility bill costs were reduced or fully covered by a public authority. In France, the energy voucher is the only nationwide program specifically designed to reduce households' energy bills.[10] Over this period, dwelling

paid directly to the residence manager and passed on as a reduction in rent or fees. Since 2021, residents of certain establishments, including residential care homes for the elderly, have also been eligible for the energy allowance.

[8] The scheme is managed by the Services and Payment Agency, which mails the vouchers to eligible households. Each year, vouchers for year n are sent in spring or autumn.

[9] The data used in this article come from the French section of the EU-SILC system, available upon request from Quetelet-Progedo-Diffusion — a portal providing access to data distributed by the Archives des Données Issues de la Statistique Publique (ADISP) and the data lab of the Institut national d'études démographiques (Ined) These data are equivalent to those provided by Eurostat but include around one hundred additional variables, allowing for more detailed analysis.

[10] The Housing Solidarity Fund (HSF) is another program that can provide financial assistance to households facing difficulties in paying housing-related expenses. This program targets the same low-income population as the energy voucher but involves more restrictive eligibility criteria and higher administrative requirements. As a result, households benefiting from the HSF are also eligible for the energy voucher, and the presence of this program is unlikely to bias the proxy for energy voucher take-up.

characteristics, energy consumption, and socio-demographic variables — such as age, education, household composition, and sex — are also observed.

In each survey wave, respondents report whether they received the energy voucher during the previous year (n–1), while socio-demographic characteristics are observed in the survey year n. Energy vouchers are sent in the spring of year n and can be used until March of year n+1. Households interviewed in February of year n therefore report vouchers allocated in year n–1, shortly before the end of the usage period. For example, the 2023 French EU-SILC wave, collected in February 2023, reports energy vouchers allocated for 2022, which are based on 2020 income. Accordingly, the analysis focuses on households observed from 2021 to 2023, ensuring consistency between reported voucher receipt and eligibility information for the 2022 energy voucher allocation.

To identify non-take-up behavior, eligibility to the energy voucher must be distinguished from its use ; the methodical steps are presented in Appendix B. In the EU-SILC database, households self-report whether they received assistance for energy expenditures. Because the energy voucher is automatically sent to eligible households, those with a reference tax income per consumption unit below the eligibility threshold (17,400 euros per UC) should have received the voucher and reported it in the survey. However, when comparing the income distribution with voucher declarations, a substantial share of low-income households report not having benefited from the policy (Figure 3). Given the automatic allocation process, this discrepancy is interpreted as non-use rather than non-allocation.[11] Following the framework of Kleven and Kopczuk (2011), households are classified according to take-up errors : true positives (TP), eligible households reporting receipt; false negatives (FN), eligible households reporting non-receipt; true negatives (TN), non-eligible households reporting non-receipt; and false positives (FP), non-eligible households reporting receipt. Table 1 reports the distribution of these groups.

Table 1: Confusion matrix of 2022 energy voucher use

	N	**%**
True positive	1,789	24.14
False positive	98	1.32
True negative	2,962	39.96
False negative	2,563	34.58
Observations	7,412	100.00

[11] According to Ministry for Ecological Transition and Territorial Cohesion (2017), fewer than 1% of energy vouchers fail to reach households because of delivery issues. All other reasons for non-use occur after households have received the voucher (forgetting, misunderstanding, losing the voucher, or choosing not to use it). This implies that eligible low-income households who report not receiving the voucher could not be missing it due to allocation errors.

3.3 Empirical Strategy

By exploiting differences between energy voucher users and non-users among eligible households, the analysis aims to identify the determinants of social program non-participation among low-income and middle-income households. The identification strategy relies on estimating the probability that an eligible household uses the energy voucher. To this end, a logistic model is used to analyze the determinants of non-take-up in the context of the Energy Voucher Policy. By estimating the probability that an eligible household uses the energy voucher after receipt, this framework isolates the partial effects of transaction costs and administrative costs on voucher use, while controlling for socio-demographic characteristics, housing conditions, and indicators of energy vulnerability. The analysis is restricted to eligible households and compares those who report having used the energy voucher (true positives) with those who report not having used it (false negatives). The model assumes that all eligible households received the voucher, but only true positives used it, while false negatives did not. The following logistic model is estimated:

$$\log\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta_1 \ln A_i + \beta_2 \ln I_i + \beta_3 V_i + \beta_4 S_i + \gamma' \mathbf{X}_i + \delta' \mathbf{D}_i + \eta_{c(i)} + \varepsilon_i \tag{5}$$

The dependent variable indicates whether an eligible household used its energy voucher. It is defined as a dummy equal to 1 if the household reports reduced utility bill costs due to the energy voucher, and 0 otherwise.

The explanatory variables in Equation 5 capture two dimensions of non-take-up. The benefit size effect is proxied by A_i, the logarithm of the energy voucher amount received (in euros), and by I_i, the logarithm of total gross income per consumption unit (in euros). Because the relationship between income and take-up is expected to be non-linear, a quadratic term in log income is included. Learning effects are approximated by indicators of familiarity with social benefit procedures: V_i, a dummy equal to 1 if the household received the energy voucher in 2021, and S_i, a dummy equal to 1 if the household applied for at least one social benefit in the previous year (family allowances, minimum income, scholarship, activity bonus, or disability allowance). Prior experience with social programs is expected to lower administrative barriers and increase voucher use. Finally, $\gamma' X_i$ captures a set of economic and socio-demographic controls. These variables account for heterogeneity in energy vulnerability, housing conditions, and household characteristics that may affect the effective cost of using the voucher. The model is estimated in latent variable form as specified in Equation 5, and results are reported as marginal effects.

Two sets of control variables are included. First, individual/household characteristics such as household size, household type (one-person household, lone parent with at least one child, couple without any children, couple with at least one child, and other), computer ownership , and sex, age, education (no diploma, high school diploma, bachelor's degree, and master's degree or higher) occupation status (employed, unemployed,retired, and other), and citizenship (1 = French, 0 = other) of the respond person. Then, dwelling characteristics including dwelling size in m^2, tenure status (owner, tenant with a rent, and tenant rent-free), type of dwelling (apartment, house, and other kind of accommodation), share of income spent on energy expenses (%), year of housing construction (before 1919, 1919 - 1945, 1946 - 1970, 1971 - 1990, 1991 - 2005, and after 2006), energy source used (electricity, gas, oil, wood logs, and other), energy poverty indicator (1 = yes, 0 = no), and the size of city of residence (rural areas, small towns < 20 000 inhabitants, medium towns < 200 000 inhabitants, and big cities). The energy poverty indicator is defined as a household reporting at least one of the following: (i) leaking roofs, damp walls or rotting windows, (ii) delays in electricity bill payments, or (iii) inability to keep the dwelling adequately warm. This composite measure is consistent with standard practice in the energy poverty literature (Alvarez and Tol, 2021; Bagnoli and Bertoméu-Sánchez, 2022; Cadaval et al., 2022; Cadoret et al., 2024). Finally, spatial fixed effects $\eta_{\mathbf{c(i)}}$ are included in the model to capture unobserved regional differences, such as average temperature, which affect energy demand and household utility costs.

3.4 Summary Statistics

Before presenting the regression output, this section discusses summary statistic of main variables between energy voucher users (true positive) and energy voucher non-users (false negative). Table 12 provides the summary statistics of the outcome, explanatory and control variables for both groups in Appendix C.

On average, households in the true positive group appear significantly more disadvantaged than those in the false negative group, both in terms of income and broader socioeconomic characteristics. Their total gross income per consumption unit is substantially lower — around 20,900 euros on average, compared with more than 30,000 euros among false negatives, a gap of roughly 6,000 euros for a year. Labor market participation also differs: 8% of true positives are unemployed, compared with only 2% among false negatives, while employment rates are lower (47% versus 55%). Educational attainment is weaker among true positives, with 36% having no diploma, compared with 24% in the false negative group, and lower shares holding tertiary degrees. Differences in household structure further reinforce this pattern: true positives are more likely to live alone or to be lone parents, whereas false negatives are more often couples without children. Overall, these descriptive statistics indicate that households who use the energy voucher tend to face more severe economic and social constraints than eligible households who do not use it.

Differences in dwelling and program characteristics could explain why true positives are more likely to use their energy voucher. True positive households are much more likely to be tenants: 50% rent their dwelling, compared with only 28% among false negatives, while homeownership is substantially higher among false negative households (70% versus 49%). TP households also live in smaller dwellings on average (84 m^2 compared with 97 m^2), consistent with lower income levels and tighter budget constraints. Indicators of energy-related difficulties point to a more vulnerable situation among true positives. 9% report arrears on electricity bills, compared with 4% among false negatives. Energy expenditures per square meter are slightly higher for true positive households, suggesting lower energy efficiency or greater exposure to energy costs.

Turning to program-related characteristics, the results highlight the role of information and administrative familiarity. Reference tax income per consumption unit is markedly lower among true positive households, and 39% report having received the energy voucher in 2021, compared with only 6% among false negative households. This large gap suggests that many non-users households are recent entrants into the program — particularly with the Exceptional Energy Voucher — and may not yet be fully aware of their entitlement or of how to use the voucher. Finally, voucher user households receive higher amounts of energy vouchers on average, both for the standard and exceptional schemes. Higher benefit levels likely strengthen incentives to use the voucher and support the interpretation that greater energy vulnerability combined with stronger familiarity with administrative procedures contributes to higher take-up among true positives.

4 Results

This section analyzes the impact of the size effect and the learning effect on the probability of using the energy voucher after a household has received it. Results are first presented for the full sample, and then for subsamples distinguishing between poor and modest eligible households. The coefficients for control variables are presented in Table 13 and 14 in Appendix D, along with other robustness checks in the same Appendix.

4.1 Determinants Driving Non-Take-Up

This part presents pooled estimates for all eligible households and distinguishes determinants between the benefit size effect and the learning effect, in line with the model's predictions. The probability of take-up is estimated using the logistic model in Equation 5. Table 2 reports the marginal effects of the estimated coefficients β. Results are robust across specifications, including a model without controls (Column 1), a model with individual controls only (Column 2), and a model with dwelling controls only (Column 3).

4.1.1 Size Effect

The results show that the probability of using the energy voucher is strongly linked to its relative economic importance for the household, captured here by the amount of the voucher and the level of income. Column 4 of Table 2 presents that income and voucher amount have opposite effects on take-up. The logarithm of the voucher amount is positively and significantly associated with its use in all specifications. The magnitude of the effect remains stable when individual, housing, and spatial controls are introduced (coefficients between 0.079 and 0.120, all significant at the 1% level). This result indicates that a higher voucher increases the probability of use: a one-unit increase in the logarithm of the voucher amount — corresponding to multiplying the original amount by

Table 2: Factors influencing the use of energy voucher

	Eligible households sample			
	No controls	**Ind. controls**	**Dwell. controls**	**All**
	(1)	(2)	(3)	(4)
Log amount of energy voucher	0.120***	0.079***	0.117***	0.082***
	(0.01)	(0.01)	(0.01)	(0.01)
Log total gross income per CU	-0.155***	-0.303***	-0.152***	-0.304***
	(0.01)	(0.02)	(0.02)	(0.02)
Having received the 2021 voucher	0.345***	0.270***	0.306***	0.245***
	(0.02)	(0.02)	(0.02)	(0.02)
Application for social benefits	0.137***	0.085***	0.141***	0.094***
	(0.02)	(0.02)	(0.02)	(0.02)
Individual controls	No	Yes	No	Yes
Dwelling controls	No	No	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes
N	4,210	4,207	3,711	3,709
Pseudo-R^2	0.205	0.245	0.224	0.258
Log-likelihood	-2,269.251	-2153.691	-1,952.682	-1,866.050

Note: Standard errors, reported in parentheses, are clustered at the regional level and are robust to heteroskedasticity. Coefficients for the control variables are reported in Table 13 in Appendix D. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

approximately 2.7 — increases the probability of use by about 8.2 percentage points. In contrast, the logarithm of gross income per consumption unit is negatively and significantly associated with voucher use in all specifications (coefficients between -0.152 and -0.304). Wealthier households therefore use the benefit less frequently: a one-unit increase reduces the probability of using the voucher by 30.4 percentage points, all else equal. This substantial effect well illustrates that the marginal value of the energy voucher declines rapidly with households' income.

Taken together, these results indicate that take-up increases with the size of the transfer and decreases with households' resources, consistent with theoretical Prediction 1 and its Implication 1a. Empirically, the voucher amount and income capture two complementary dimensions of financial incentive to participate. On one hand, a higher voucher directly increases the utility gain from using it. On the other hand, since the voucher amount decreases with income by policy design, higher-income households receive smaller amounts relative to their resources and face lower financial pressure, reducing the perceived benefit of using the voucher. The estimated coefficients thus reflect both the direct effect of the subsidy value and the decreasing marginal utility of additional financial aid as income rises.

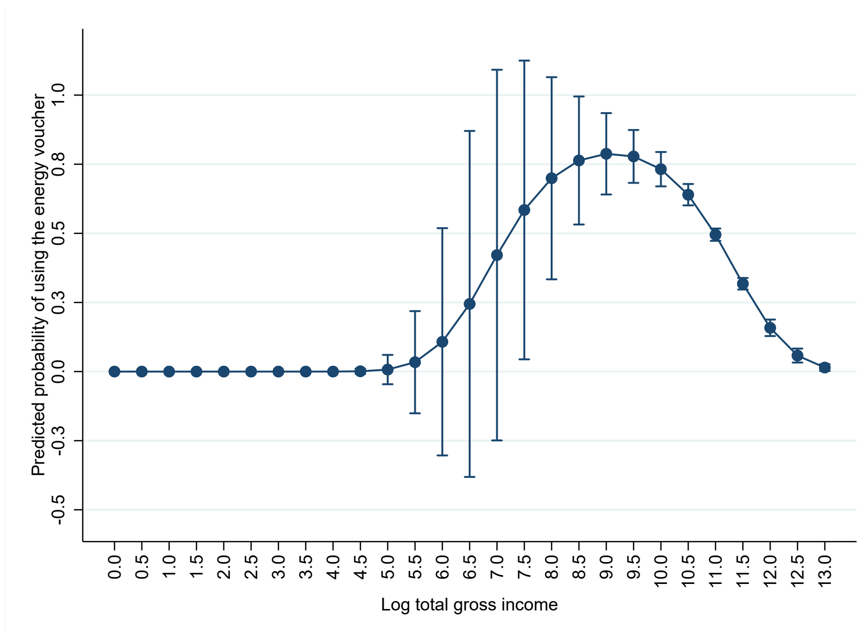
4.1.2 Learning Effect

Beyond the monetary incentive, the results emphasize the role of administrative experience and familiarity with social programs, reflecting the learning effect in explaining take-up. Prior receipt of the energy voucher is strongly and positively associated with current use: households that received the voucher in the previous year have a 24.5 percentage-point higher probability of using it in 2022 than otherwise similar households, with this effect remaining substantial even after introducing the full set of controls. This suggests a program-specific learning effect: households previously exposed to the voucher are more familiar with its procedures, better understand its benefits, and face lower administrative costs — particularly due to the possibility of automating future voucher deductions on energy bills. Past participation thus reduces informational and administrative frictions that may reduce initial use. Having previously applied for social benefits is also positively associated with voucher take-up, with coefficients between 0.085 and 0.141. Although smaller than the effect of prior voucher receipt, this effect remains stable and significant across all specifications, likely reflecting higher administrative skills and familiarity with social programs. Such households may be better informed about their rights, more comfortable with procedures, or less affected by the psychological costs of claiming public assistance

Overall, these two variables capture complementary dimensions of institutional learning: program-specific learning through direct experience with the energy voucher, and general administrative learning through broader social benefit claiming. As predicted in Implication 2a from the Prediction 2, reducing administrative burdens substantially increases usage. Prior experience with the voucher and with social benefits more generally decreases cognitive and procedural barriers. Furthermore, the energy voucher allows beneficiaries to request full automation for future bills, effectively eliminating remaining administrative effort. This policy design helps explain the particularly strong effect of prior voucher receipt on the likelihood of using the subsequent year's benefit. The positive effects of these variables indicate that non-use is not only driven by economic factors but also by cognitive, informational, and administrative costs. Consequently, participation partly depends on households' familiarity with its procedures.

Figure 1 shows that the marginal effect of the log of total gross income on take-up is non-linear and follows an inverted U-shaped pattern, consistent with Implication 1b from theoretical Prediction 1. The marginal effect is close to zero and statistically insignificant for households with log income below 6.5 (corresponding to annual gross income below €1,000). The effect then increases sharply, reaching its maximum at around log income 8.0 - 8.5 (approximately €1,700 – €2,600 annually), where an additional unit increase in log income is associated with an 8 percentage point increase in the probability of take-up. Beyond this threshold, the marginal effect declines progressively, becoming negative and approaching zero again for the highest income levels (log income above 11.5, or approximately €49,500). This pattern provides empirical support for the theoretical mechanism outlined above. At very low income levels, despite the potentially large monetary value of the voucher relative to household resources, administrative costs appear to constitute a barrier to participation. The near-zero marginal effect in this region suggests that small income increases do little to overcome these fixed costs. As income rises into the middle range of the eligible distribution, administrative costs decline while the voucher amount remains substantial enough to generate meaningful utility gains. Then, the subsequent decline in marginal effects at higher income levels reflects the diminishing relative value of the voucher. For households with log income above 9.0 (approximately €4,500 annually), each additional increase in income reduces the importance of the voucher benefit, both because the absolute amount decreases and because the marginal utility of the additional income provided by the voucher declines. For households approaching the upper eligibility threshold, the remaining voucher amount becomes too small to justify even the reduced administrative effort required to claim it.

Figure 1: Marginal effect of the log total gross income



4.2 Effects Across Income Deciles

This section examines how size and learning effects varies across income levels. The French energy support policy was extended in 2021 and 2022 to protect as many vulnerable households as possible from the energy crisis. As a result, in addition to the poorest 30% of households — who are eligible for the regular energy voucher — middle-income households were also supported through an exceptional voucher covering up to the sixth income decile. Beneficiaries of energy assistance are therefore highly heterogeneous, and the determinants of take-up may differ substantially across income groups. To account for this heterogeneity, the effects of size and learning on the probability of take-up are estimated separately for two income groups: low-income households (those in the first to third deciles, who received higher voucher amounts) and middle-income households (those in the fourth to sixth deciles, who received only the exceptional voucher).

Table 3 reports the marginal effects of the estimated coefficients β. For each group, three specifications are estimated: the baseline model in Equation 5 (Columns 1 and 2), and two alternative specifications in which the log amount of the energy voucher is replaced, first, by the voucher share of energy expenditures (Columns 3 and 4), and second, by the voucher share of income (Columns 5 and 6). All specifications include the individual and dwelling characteristics, as well as the fixed effects, used in the first specification reported in Table 2.

Table 3: Determinants of non-take across income deciles

	Voucher amount		*Voucher share of energy expenditures*		*Voucher share of income*	
	Standard D1-D3	**Exceptional D4-D6**	**Standard D1-D3**	**Exceptional D4-D6**	**Standard D1-D3**	**Exceptional D4-D6**
	(1)	(2)	(3)	(4)	(5)	(6)
Log amount of energy voucher	0.073					
	(0.05)					
Voucher share of energy spending (%)			-0.001*	-0.001*		
			(0.00)	(0.00)		
Voucher share of income (%)					0.044**	0.937***
					(0.02)	(0.16)
Log total gross income per CU	-0.237***	-0.459***	-0.243***	-0.432***		
	(0.03)	(0.05)	(0.03)	(0.04)		
Having received the 2021 voucher	0.270***	0.210***	0.273***	0.213***	0.301***	0.225***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
Application for social benefits	0.119***	0.054*	0.115***	0.050	0.132***	0.066**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling controls	Yes	Yes	Yes	Yes	Yes	Yes
Spatial FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1937	1772	1985	1810	1937	1772
Pseudo-R^2	0.226	0.170	0.220	0.172	0.207	0.145
Log-likelihood	-1023.175	-807.376	-1058.846	-821.770	-1049.046	-831.628

Note: In the third specification (Columns 5 and 6), the income variable is excluded from the set of controls because the voucher-to-income ratio already captures variation in individual income. Standard errors, reported in parentheses, are clustered at the regional level and are robust to heteroskedasticity. Coefficients for the control variables are reported in Table 13 in Appendix D. * / ** / *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2.1 Size Effect

Results from Table 2 show that both the value of the energy voucher and household income strongly influence the decision to use the voucher. Columns 1 and 2 focus on the baseline specification, which aims to compare the magnitude of the size effect across low- and middle-income households.

For both groups, the logarithm of gross income per consumption unit is negatively and significantly associated with voucher use. The magnitude of this effect is substantially larger for middle-income households (-45.9 percentage points) than for low-income households (-23.7 percentage points). Wealthier households are therefore significantly less likely to use the energy voucher, a finding consistent with the results in Table 2 and with the existing literature. In contrast, the energy voucher amount is no longer a significant determinant of take-up for either group. Among the poorest 30% of households, doubling the initial voucher amount has no statistically significant effect, indicating that increases in benefit levels do not meaningfully influence their take-up decisions. For middle-income households, the voucher amount cannot explain take-up behavior because all beneficiaries received the same fixed payment of 100 euros, leaving no within-group variation in benefit size. Taken together, these results suggest that take-up decisions are not driven by the absolute value of the benefit, but rather by how households perceive and evaluate the benefit — an assessment that may differ across income groups.

Share of energy expenditures covered by the energy voucher

One way to assess the value of the energy voucher is to consider the share of household energy expenditures that it covers. A higher coverage rate may increase the attractiveness of the voucher and generate a larger perceived utility gain, thereby encouraging its use. The voucher share of energy spending is calculated by dividing the total voucher amount received by total annual energy and heating expenditures. For half of the sample, the energy voucher covers less than 16% of total energy expenditures, which is consistent with official estimates.[12] Columns 3 and 4 present results for both income groups. The estimated effect of this variable is only weakly significant and very close to zero (-0.001). This suggests that the share of energy expenditures covered by the voucher does not meaningfully influence households' decisions to use it and another way to asses the energy voucher value is likely to to exist.

Share of gross income covered by the energy voucher

A second way to assess the value of the energy voucher is to consider the share of household gross income that it represents. Low- and middle-income households often experience financial stress and may be particularly attentive to variations in available income. A higher coverage rate may increase disposable income available for other expenditures (a potential rebound effect), thereby raising utility in two ways: by reducing the energy bill and by increasing the resources available for other consumption. The voucher share of gross income is calculated by dividing the total voucher amount received by total annual gross income. For households in income deciles D4 to D6, variation in this share reflects only differences in income, as all households in this group receive the same voucher amount (100 euros). On average, the voucher represents a very small share of income, with a mean of 1.27%. By contrast, among the poorest households, the voucher can represent up to 20% of annual income in extreme cases. Columns 5 and 6 present the results for both income groups. The estimated effect of this variable is statistically significant at the 5% level for low-income households and highly significant at the 1% level for middle-income households. A one-percentage-point increase

[12] In 2019, housing energy expenditures represented a larger share of the budget for lower-income households: on average, 11% for the poorest decile, compared with less than 2% for the richest decile. In the same year, the energy voucher covered approximately 12% of annual household energy expenses, excluding the exceptional voucher (French Ministry for the Ecological Transition, 2021).

in the voucher ratio raises the probability of using the energy voucher by about 4 percentage points among low-income households, but by approximately 93 percentage points among middle-income households. These results indicate that the share of income covered by the voucher meaningfully influences take-up decisions, particularly among less vulnerable households.

Overall, the benefit size effect appears to be much stronger for middle-income households than for poorer households. The negative effect of income on the probability of use, together with the differing sensitivity to the voucher share in gross income, suggests that middle-income households give greater weight on the perceived monetary value of the voucher. For low-income households, other barriers or constraints likely play a more important role in explaining non-take-up.

4.2.2 Learning Effect

The estimates of the three specifications provide strong and consistent evidence of a learning effect on the energy voucher use. First, prior receipt of the energy voucher is systematically and strongly associated with subsequent program use across all specifications and income groups. The estimated coefficients range from 0.210 to 0.301 and are statistically significant at the 1% level in every model. This magnitude indicates a large persistence effect: households previously exposed to the public policy are more likely to use it again. The strength and robustness of this variable suggest that initial participation reduces informational uncertainty, procedural complexity, and perceived administrative burden. Familiarity with eligibility rules, payment modalities, and especially the possibility of automating voucher deductions for future energy bills likely lowers the effective cost of participation. This pattern is consistent with a dynamic learning process in which past use reduces future cognitive and procedural barriers. The effect is observed across both lower-income households (D1 to D3) and middle-income eligible households (D4 to D6), although it is larger for the lowest-income group in several specifications. This suggests that administrative learning may be particularly valuable where financial constraints and cognitive scarcity are more important. For these households, overcoming initial administrative frictions appears to generate strong persistence in usage.

Second, prior application for social benefits is also positively and significantly associated with voucher use in most specifications, despite the magnitude is smaller than that of prior voucher receipt. The estimated coefficients range from 0.050 to 0.132, and while consistently positive, statistical significance is weaker in some middle-income specifications. This pattern indicates a more general form of administrative learning: households familiar with the welfare system may possess better information about eligibility rules, greater procedural confidence, or lower psychological costs of interacting with public institutions. Such households may also have developed practical skills in document preparation, online or in-person application processes, and bureaucratic skills.

Comparing the two learning channels reveals an important distinction. Program-specific experience generates the largest and most robust effects, suggesting that direct exposure to the energy voucher substantially reduces the fixed and variable administrative costs of use. In contrast, general administrative experience produces smaller but still meaningful effects, reflecting transferable knowledge and familiarity with institutional procedures. These findings support the interpretation that participation decisions are shaped not only by financial incentives but also by reductions in administrative and cognitive barriers. Households do not face a constant cost of using benefits: the administrative costs decline with experience. Overall, the evidence is consistent with the theoretical Predictions 4 and 5 that higher administrative costs reduce participation, while learning processes mitigate these costs over time.

Beyond size and leaning effects, it is relevant to examine the socio-demographic factors that may influence voucher utilization. Figure 4 in Appendix D presents the marginal effects of the control variables included in the logistic model, allowing estimation of the probability of 2022 energy voucher use across social categories.

5 Additional Findings: Welfare Impact

This section examines whether the Energy Voucher policy achieves its intended objective, in light of the substantial non-take-up. A doubly robust difference-in-differences estimator is employed, with further details on the methodology, validity tests, and robustness checks provided in Appendix E.

A secondary objective of the empirical strategy is to estimate the causal effect of the 2022 French Energy Voucher on households that actually used it. Treated households are those that are eligible and effectively used the voucher, while eligible non-users serve as the control group.[13] However, logit results indicate systematic differences between users and non-users, implying that treatment assignment is not exogenous but reflects socio-economic choices and constraints. To address this issue, the analysis employs the doubly robust difference-in-differences (DR-DID) estimator proposed by Sant'Anna and Zhao (2020).

The DR-DID combines propensity score weighting with outcome regression to provide consistent estimates of the average treatment effect on the treated (ATT), even if either the propensity score or the outcome model is misspecified. In a two-period DID framework, it compares changes in outcomes for treated households with changes observed for control households, accounting for observable characteristics to support the parallel trends assumption. Formally, the estimator is given by:

$$\hat{\tau}^{DR} = \frac{1}{N_T} \sum_{i \in T} \left[\big(Y_{i,post} - Y_{i,pre}\big) - \big(\hat{m}_0(1, \mathbf{X}_i) - \hat{m}_0(0, \mathbf{X}_i)\big) \right] \cdot \frac{T_i}{\hat{e}(\mathbf{X}_i)} \tag{6}$$

Here, $Y_{i,t}$ is the outcome vector for household i at time t, T_i indicates treatment status, $\hat{e}(\mathbf{X}_i)$ is the estimated propensity score conditional on covariates $\mathbf{X}_i$ (household and dwelling characteristics),

[13] To avoid bias and simplify identification, households that received the energy voucher in 2021 are excluded from the analysis.

$\hat{m}_0(t, \mathbf{X}_i)$ is the predicted outcome from the control regression model, and N_T is the number of treated households. Outcome variables, as well as household and dwelling characteristics, are presented in Appendix E with summary statistics.

The French Energy Voucher policy is designed to alleviate household energy expenditures. If this form of energy assistance exerts a significant welfare effect, it can be expected to produce observable improvements across three dimensions: total energy consumption, energy poverty, and financial stress. Because the voucher directly reduces the energy bill and is non-transferable, households are expected to maintain their energy consumption, implying that expenditures on energy not covered by the aid should remain stable. Households may also enhance their ability to adequately heat their homes and experience fewer arrears on electricity bills. Finally, if the energy voucher generates a rebound effect, households could experience an increase in disposable income, thereby reducing the share of income allocated to energy, alleviating financial pressure, potentially exiting poverty, or perceiving an improvement in their overall financial situation. Figure 5 presents the evolution of the eight outcomes for both groups from 2020 to 2023. On average, the untreated group exhibits a better financial situation, with greater ability to keep their homes warm (7-e), higher log disposable income (7-g), and a more favorable perception of their financial situation (7-h). With the onset of the energy crisis, households in both groups report increased difficulties, reflected in higher total energy costs per m^2 (7-a) and total heating expenditures (7-b). For most indicators, pre-treatment trends and magnitudes are highly similar across groups, supporting the parallel trends assumption necessary for causal identification (see Appendix E for further tests). Post-treatment trends remain largely parallel. Graphical evidence suggests that the Energy Voucher does not generate substantial improvements in household outcomes; a significant effect would be observed as reduced energy costs or improved ability to pay electricity bills after 2022, which is not apparent.

The causal effects of the 2022 Energy Voucher on household outcomes are estimated using the doubly robust difference-in-differences (DR-DID) approach described in Equation 6. Table 4 reports the estimated average treatment effects on the treated (ATT) for each outcome variable. Estimates account for observable household and dwelling characteristics, ensuring comparability between treated and control households. Standard errors are robust to heteroskedasticity. The results indicate the magnitude and direction of the voucher's impact, allowing assessment of whether actual use of the policy translates into measurable improvements in financial well-being, energy expenditures, and household comfort.

Overall, the results point to no statistically significant impact of the voucher on most outcomes. The estimated coefficients for total energy and heating costs per square meter (Columns 1 and 2) are negative, suggesting a reduction in expenditures among treated households, but these effects are small in magnitude and not statistically significant. Similarly, no significant effects are found for total housing costs, arrears on electricity bills, the ability to keep the home adequately warm, or the poverty indicator (Columns 3 to 6). The only statistically significant effect concerns log disposable

Table 4: Results of the double-robust difference-in-differences

	Total energy cost per m^2	Total heating cost per m^2	Total housing cost per m^2	Arrears on electricity bills	Ability to keep home adequately warm	Poverty indicator	Log disposable income	Perceived financial situation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATET	-1.559	-0.973	0.093	-0.014	0.066	0.038	-0.138*	0.005
	(1.031)	(1.059)	(0.457)	(0.013)	(0.056)	(0.025)	(0.076)	(0.078)
Observations	6,202	6,004	5,694	6,490	6,464	6,496	6,474	6,464

Note: Table 26 reports the distribution of inverse probability weights estimated in the first step of the model. The mean weight is 2.1, and 99% of the weights are below 11, which is consistent with values commonly reported in the literature. Overall, the weights are well behaved, with most observations receiving moderate weights. This indicates that the DR-DiD estimates are not driven by a small number of highly influential observations. Distribution of IPW are showing in Figure 6. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

income (Column 7), with a small negative coefficient significant at the 10% level, indicating that voucher users experienced a slightly less favorable income evolution than eligible non-users, likely reflecting greater underlying socio-economic vulnerability. Finally, there is no detectable effect on households' perceived financial situation (Column 8). Results are robust to several robustness checks described in Appendix E.

Taken together, these findings are consistent with the descriptive and graphical evidence and suggest that, despite being targeted at more vulnerable households, actual use of the 2022 Energy Voucher did not translate into measurable improvements in energy expenditures, thermal comfort, or overall financial well-being.

6 Conclusion

Using microdata from the European Union Statistics on Income and Living Conditions (EU-SILC), which provides household-level information on income and living conditions, this paper analyzes the determinants of non-take-up of the French Energy Voucher program and quantifies their effects on households' take-up decisions across the income distribution. The empirical strategy relies on a logistic model to identify barriers to take-up by estimating the probability of voucher use after receipt. The model compares users and non-users among recipient households, conditional on socio-economic characteristics and prior behavior regarding social benefit claims. The analysis is conducted on a split sample to capture heterogeneity in behavior across income groups.

The results show marked differences in the drivers of non-take-up across the income distribution. Among modest households, the benefit size effect emerges as the primary barrier to take-up. A one-unit increase in log income per consumption unit reduces the probability of voucher use by 40 percentage points, indicating that the financial benefit becomes insufficient to offset the perceived effort of use. In contrast, take-up decisions among poor households are more strongly influenced by learning effects. While the benefit size does not significantly explain non-take-up in this group, severely poor households that had claimed the 2021 energy voucher are 7.6 percentage points more likely to use the 2022 voucher than moderately poor households, highlighting the role of familiarity with administrative procedures.

Low-income households face particularly high administrative costs, which constrain take-up despite substantial need. At the bottom of the income distribution, the utility gain from the energy voucher is potentially large, given both the voucher amount and the high marginal utility of income. However, these households also experience the highest administrative burdens, reflecting cognitive constraints, procedural complexity, and limited administrative capacity. As a result, take-up remains relatively low because administrative costs offset the expected utility gains. At higher income levels, take-up declines as the voucher amount becomes too small to compensate for the remaining administrative effort, even when such costs are lower. Overall, the findings align with the predictions of a simple utility-maximization framework inspired by Moffitt (1983), in which households decide to use the voucher by weighing expected benefits against a fixed administrative cost and a variable administrative cost — or hassle cost.

In addition, the paper assesses whether the Energy Voucher policy achieves its intended objectives in the presence of substantial non-take-up. The results indicate no statistically significant impact of voucher use on most outcomes related to financial well-being, energy expenditures, or household comfort.

This paper contributes to the literature on social benefit take-up by highlighting the heterogeneity of constraints faced by low-income households compared to middle-incomes. The findings suggest that effective energy policies require a combination of well-targeted short-term financial assistance and long-term structural interventions, with careful consideration of eligibility rules, incentive structures, and households' behavioral responses. These insights provide a natural basis for assessing the design and effectiveness of the French Energy Voucher policy.

From a policy perspective, the findings indicate that the French Energy Voucher, in its current design, is unwell suited to effectively address energy poverty. The relatively low voucher benefit amount limits its capacity to offset rising energy costs, while persistent administrative and cognitive burdens continue to exclude the poorest households, despite automatic allocation. These results are consistent with the literature showing that take-up is highly sensitive to participation costs and administrative complexity (Currie, 2004). Consequently, increasing the voucher amount alone is unlikely to substantially improve take-up or household outcomes unless administrative barriers are simultaneously reduced. Generally, the analysis suggests that policies aimed at alleviating energy poverty should move beyond short-term bill assistance and address its structural determinants, particularly housing quality and tenure status. Low-income households, who are disproportionately renters, tend to occupy energy-inefficient dwellings, while landlords face weak incentives to invest in energy-saving renovations. Existing studies show that targeted public support for energy renovation programs can significantly reduce energy expenditures, especially for vulnerable households (Kröger et al., 2023; Chaton, 2025). Overall, the results highlight the need for differentiated policy instruments that account for heterogeneity in constraints across the income distribution. Effective policy design should combine sufficiently generous and well-targeted financial support with simplified or fully automatic delivery mechanisms for the poorest households, while complementing income-based transfers with structural housing interventions. Such an approach is more likely to ensure that energy assistance policies reach their intended beneficiaries and generate lasting improvements in welfare (Charlier and Kahouli, 2019).

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A The French Energy Voucher Policy

Table 5: Energy voucher amounts by household size (CU) and income (RTI per CU), 2022

(5a) Regular energy voucher

	<€5,600	**€5,600 – €6,699**	**€6,700 – €7,699**	**€7,700 – €10,799**
1 CU	194	146	98	48
1.25 CU to 1.9 CU	240	176	113	63
2 CU or more	277	202	126	76

Note: For example, a household composed of two adults and two children under 14 (2.1 consumption units) with a reference tax income of €10,500 per CU (based on the 2020 tax declaration) would receive an energy voucher of €76 in 2022 (French Court of Audit, 2022).

(5b) Regular and exceptional energy voucher

	<€5,600	**€5,600 – €6,699**	**€6,700 – €7,699**	**€7,700 – €10,799**	**€10,800 – €17,399**
1 CU	394	346	298	248	100
1.25 CU to 1.9 CU	440	376	313	263	100
2 CU or more	477	402	326	276	100

Table 6: Energy voucher recipients by income and household size, 2022

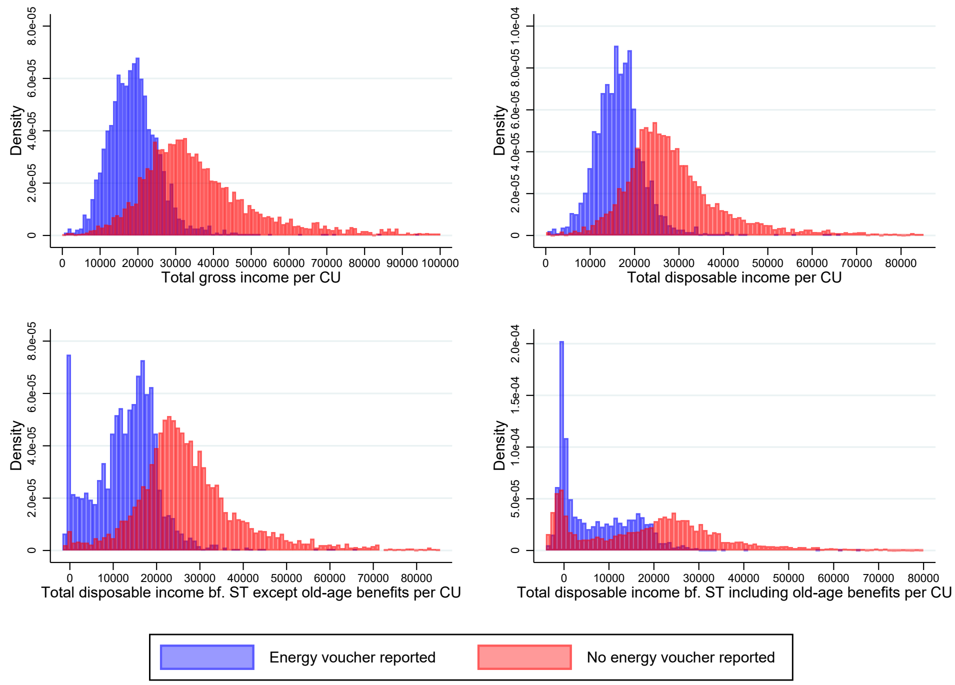
	Regular energy voucher	**Exceptional energy voucher**
Number of consumption units (CU) in the household		
1 CU	47%	37%
1.25 CU to less than 2 CU	34%	46%
2 CU or more	19%	17%
Reference tax income per consumption unit (CU)		
Less than €5 600	46%	9%
€5 600 to less than €6 700	9%	2%
€6 700 to less than €7 700	9%	2%
€7 700 to less than €10 800	36%	8%
€10 800 or more	–	79%
Number of households	5 773 000	28 965 200

Note: For example, 37% of the 2022 regular energy vouchers were allocated to households of 1 consumption unit (lone adult households), while 37% of exceptional vouchers were also issued to 1-CU households. Based on reference tax income per CU, 46% of recipients of the regular energy voucher had less than €5,000 per CU (DREES, 2023).

B Identifying Non-Take-Up: Eligibility versus Actual Use

This appendix provides detailed steps and methodological considerations for estimating which households used their 2022 energy voucher, based on their income declarations and reported receipt of state energy aid.

Figure 2: Income distribution of households by energy voucher receipt declaration across four income measures



Note: This figure shows the income distribution for four different income variables used for the reference tax income variable construction — total gross income per CU, total disposable income per CU, total disposable income before social transfers other than old-age and survivor's benefits per CU, and total disposable income before social transfers including old-age and survivor's benefits per CU. The graph compares households reporting the energy voucher (blue group) with those not (red group). These distributions illustrate a paradox: some low-income households, who are automatically eligible for the voucher, report not having received it, highlighting the difference between eligibility and actual use.

B.1 Estimation of Reference Tax Income

The reference tax income (RTI) is calculated by tax authorities based on declared income. The RTI allows to obtain social benefits or tax exemptions. It takes into account all household income (taxable or not), adds tax-exempt income (e.g., certain tips, foreign income), and accounts for deductible allowances from net taxable income. Thus, the RTI can highly differ from earned income amount. The reference tax income is calculated in four steps.

First step — Total gross income

The EU-SILC variable total household gross income (*hy010*) does not match the French fiscal definition of total gross income. Based on Methodological Guidelines and Description of EU-SILC Target Variables, total household gross income (*hy010*) includes several components that are exempt from taxation or already included elsewhere : company car (already counted in net salaries) ; inimum old-age pension benefit (exempt) ; disability benefits (exempt) ; sickness benefits (exempt or counted) ; family/children-related allowances (exempt) ; social exclusion not elsewhere classified (exempt) ;

housing allowances (exempt) ; income received by people aged under 16 (non-taxable).

Thus, the total gross income can be calculated from the total disposable household income before social transfers including old-age and survivor's benefits (*hy022*) minus the sum of regular inter-household cash transfer received (*hy080n*), income received by people aged under 16 (*hy110n*), the 10% reduction on wages (Table 7), the 10% reduction on retirement pensions (Table 8), and the 30% reduction on minimum old-age pension benefit (Table 9).

The reduction of 10% for professional expenses is applied automatically. The minimum amount of this allowance is 472 euros per working individual in 2023 on income declared in 2022, unless the declared income is lower. In that case, the allowance is equal to the amount of the declared gross salary. The maximum allowance is capped at a revalued amount each year. Thus, if net taxable income is below 4 720 euros, the allowance will be 472 euros, representing 10% of income. For instance, with an income of 4 000 euros, the 10% allowance would equal 400 euros, but the administration applies the minimum of 472 euros. Conversely, if income exceeds 144 260 euros, the allowance is limited to 13 522 euros. The same mechanism is applied for retirement pensions.

Table 7: Thresholds for the 10% wages reduction

	2020	**2021**	**2022**	**2023**
Cap per working individual	€12 502	€12 652	€12 839	€13 522
Min. amount per working individual	€437	€443	€448	€472

Table 8: Thresholds for the 10% retirement pension reduction

	2020	**2021**	**2022**	**2023**
Max. amount per tax residence	€3 850	€3 858	€3 912	€4 123
Min. amount per retired	€393	€394	€400	€422

The ASPA — a French solidarity allowance for elderly people — is a non-contributory benefit, provided without prior contributions, designed to guarantee a minimum income for individuals aged 65 or older (or younger in the case of disability) who are permanent residents of France. ASPA supplements existing income up to a defined limit. For example, a single person receiving a annual retirement pension of 7 200 euros would be eligible for approximately 4 241.49 euros in ASPA, bringing their total monthly income to 11 441.49 euros in 2023.

Table 9: Thresholds for the 30% minimum old-age pension benefit reduction

	2020	**2021**	**2022**	**2023**
Max. amount for a single individual	€11 441.49	€10 881.72	€10 838.40	€10 418.40
Max. amount for a couple	€17 762.96	€16 893.84	€16 826.64	€16 174.59

Second step — Total net income

From the total gross income, deductible expenses are subtracted to obtain total net income. These include child support payments (*hy131n*), retirement saving contributions (part of *hy140n*, only available in the French EU-SILC survey), and certain tax deductions from financial investments. Here, business and property losses cannot be accounted.

Third step — Taxable net income

Once total net income is calculated, for certain specific households special tax deductions are applied to estimate taxable net income. These concern in particular elderly people, disabled people, and families. Only elderly and disabled deductions can be estimated (Table 10). The amount of the elderly/disabled person allowance depends on total net income. If both members of a couple meet the age or disability requirements, the allowance is doubled. Eligibility requirements: 1) be at least 65 years old on December 31 of the tax year ; 2) hold a disability card (more than 40%, or classified as second or third category disability).

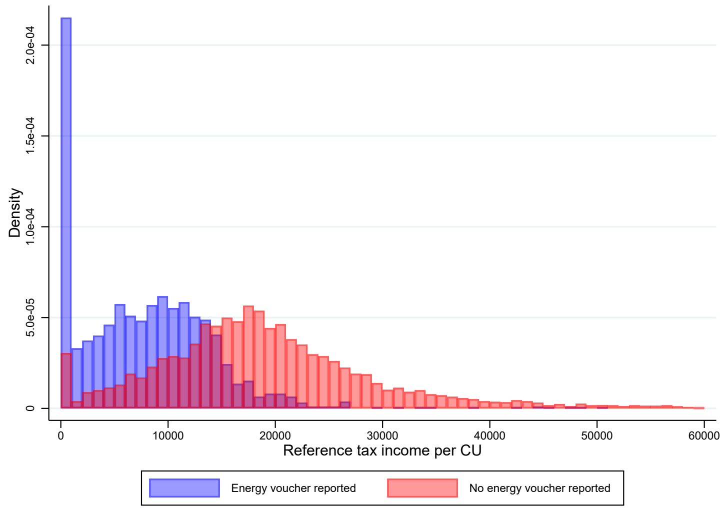
Table 10: Deduction for elderly or disabled persons

	Taxable household income	**Amount of deduction**
Income 2023 on 2022	Up to €16 410	€2 620
	Between €16 411 and €26 400	€1 310
	Above €26 400	No deduction
Income 2022 on 2021	Up to €15 560	€2 484
	Between €15 561 and €25 040	€1 242
	Above €25 040	No deduction
Income 2021 on 2020	Up to €15 340	€2 448
	Between €15 341 and €24 690	€1 224
	Above €24 690	No deduction
Income 2020 on 2019	Up to €15 300	€2 442
	Between €15 301 and €24 640	€1 221
	Above €24 690	No deduction

Fourth step — Reference tax income

The reference taxable income is calculated based on net taxable income. To obtain the RTI, the following components must be added: certain tax-exempt income (financial investment), income from movable capital (part of *hy140n*, only available in the French EU-SILC survey), deductible allowances on dividends (40%), certain expenses deductible from income (e.g., retirement saving contribution), and interest, dividends, profits from capital investments in business (*hy090*).

Figure 3: 2020 Reference tax income per CU distribution by 2022 energy voucher receipt declaration



B.2 Robustness of the reference tax income estimation

Table 11 presents summary statistics of the estimated reference tax income per consumption unit in 2020 and 2022, compared with official figures from General Directorate of Public Finances (2022, 2024). Overall, the estimates closely match the official values, with a slight tendency to underestimate. Deviations are small for most percentiles but increase for the highest ones (99th and 99.9th). Correlation between estimated and official values is extremely high for both years (0.99).

Table 11: Estimated and actual RTI by decile

(11a) 2020

Decile	Estimated RFR (€)	Actual RFR (€)	Difference (€)
7%	0	0	0
10%	2,131	1,575	556
20%	6,758	6,358	400
30%	9,805	9,388	417
40%	12,691	11,770	921
50%	14,920	14,089	831
60%	17,339	16,333	1,006
70%	19,991	19,075	916
80%	23,583	22,983	600
90%	30,052	30,508	-456
99%	69,698	74,880	-5,182
99.9%	181,873	226,800	-44,927
Mean	16,909	16,891	18

(11b) 2022

Decile	Estimated RFR (€)	Actual RFR (€)	Difference (€)
7%	0	0	0
10%	1,953	1,973	-20
20%	7,099	7,010	89
30%	10,525	10,203	322
40%	13,632	12,771	861
50%	16,053	15,313	740
60%	18,930	17,775	1,205
70%	22,037	20,686	1,351
80%	26,376	24,831	1,545
90%	34,130	32,911	1,219
99%	80,694	82,800	-2,106
99.9%	254,478	271,200	-16,722
Mean	18,955	18,559	396

C Summary Statistics

Table 12: Descriptive statistics for the true positive and false negative groups

	True positives			**False negatives**		
	Mean	Min.	Max.	Mean	Min.	Max.
Households' characteristics						
Age	57.56	20.00	98.00	57.93	22.00	102.00
Sex						
Female	0.52	0.00	1.00	0.42	0.00	1.00
Male	0.48	0.00	1.00	0.58	0.00	1.00
Education						
Master's degree or higher	0.04	0.00	1.00	0.07	0.00	1.00
Bachelor's degree	0.14	0.00	1.00	0.23	0.00	1.00
High school diploma	0.46	0.00	1.00	0.45	0.00	1.00
No diploma	0.36	0.00	1.00	0.24	0.00	1.00
Occupation						
Employed	0.47	0.00	1.00	0.55	0.00	1.00
Unemployed	0.08	0.00	1.00	0.02	0.00	1.00
Retired	0.38	0.00	1.00	0.40	0.00	1.00
Other	0.08	0.00	1.00	0.02	0.00	1.00
Household type						
One-person household	0.42	0.00	1.00	0.38	0.00	1.00
Lone parent with at least one child	0.16	0.00	1.00	0.08	0.00	1.00
Couple without any children	0.16	0.00	1.00	0.26	0.00	1.00
Couple with at least one child	0.24	0.00	1.00	0.27	0.00	1.00
Other type of household	0.02	0.00	1.00	0.01	0.00	1.00
Total gross income per CU (€)	20,857.51	1,232.10	91,440.63	30,397.57	193.89	109,940.00
Dwelling's characteristics						
Tenure status						
Owner	0.49	0.00	1.00	0.70	0.00	1.00
Tenant, with a rent	0.50	0.00	1.00	0.28	0.00	1.00
Tenant, rent free	0.01	0.00	1.00	0.02	0.00	1.00
Dwelling surface (m^2)	84.29	2.00	360.00	97.10	2.00	1,960.00
Total energy cost per m^2 (€)	15.91	0.00	381.33	15.19	0.00	325.00
Arrears on electricity bills						
No	0.91	0.00	1.00	0.96	0.00	1.00
Yes, once or more	0.09	0.00	1.00	0.04	0.00	1.00
Energy voucher's characteristics						
Reference tax income per CU (€)	8,203.47	0.00	93,950.61	14,219.67	0.00	124,473.70
2021 energy voucher reported						
No	0.61	0.00	1.00	0.94	1.00	1.00
Yes	0.39	0.00	1.00	0.06	1.00	0.00
Amount of energy voucher received (€)	124.00	0.00	277.00	54.81	0.00	277.00
Amount of the exceptional energy voucher received (€)	173.50	100.00	200.00	139.68	100.00	200.00
Total amount of energy vouchers received (€)	297.51	100.00	477.00	194.49	100.00	477.00
Observations	1,789			2,563		

Note: The true positives sample corresponds to eligible households that used the 2022 energy voucher, while the false negatives sample consists of eligible households that did not use the voucher. Summary statistics are reported for household characteristics in 2022.

D Logistic model: Additional Results and Robustness Checks

D.1 Coefficient estimates for control variables

Table 13: Coefficients of control variables from logistic models, dwelling characteristics

	Logit Table 2		*Logit Table 3*					
	Column 2	**Column 4**	**Column 1**	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual characteristics								
Sex: Male	-0.035*	-0.043**	-0.088***	0.003	-0.091***	-0.004	-0.090***	0.000
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age	0.000	-0.000	-0.001	0.000	-0.001	-0.000	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education: Bachelor's degree	-0.028	-0.012	-0.064	0.047	-0.067	0.052	-0.037	0.053
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Education: High school diploma	0.022	0.035	0.005	0.072	0.003	0.070	0.053	0.087**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Education: No diploma	0.060	0.070	0.031	0.121**	0.022	0.118**	0.087*	0.141***
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Occupation: Unemployed	-0.006	-0.031	0.022	-0.146***	0.047	-0.143**	0.056	-0.137**
	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
Occupation: Retired	-0.038	-0.020	0.024	-0.090***	0.024	-0.086**	0.073*	-0.051
	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Occupation: Other	0.019	0.032	0.047	0.172	0.055	0.158	0.085*	0.153
	(0.04)	(0.04)	(0.05)	(0.11)	(0.04)	(0.11)	(0.05)	(0.12)
Citizenship: Other	0.006	0.003	0.004	0.018	0.006	0.024	0.014	0.025
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Household size	0.091***	0.090***	0.073***	0.134***	0.077***	0.132***	0.042**	0.054***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Household type: Lone parent with at least one child	0.062*	0.039	0.027	0.068	0.034	0.064	-0.009	-0.008
	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.06)
Household type: Couple without any children	0.002	0.013	0.006	0.035	0.006	0.031	-0.055	-0.060
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Household type: Couple with at least one child	0.022	0.017	0.037	-0.010	0.025	-0.018	-0.052	-0.146**
	(0.04)	(0.04)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Household type: Other type of household	0.087	0.075	0.084	0.080	0.105	0.065	0.019	-0.059
	(0.07)	(0.07)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
Having a computer: Yes	-0.033	-0.025	-0.026	-0.022	-0.025	-0.032	-0.040	-0.025
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
N	4,207	3,709	1937	1772	1985	1810	1937	1772

Note: The coefficients of control variables from result Table 2 and Table 3 are presented in marginal effect. For the dummy variables sex, education, occupation, citizenship, household type, and computer ownership, the reference categories are respectively female, master's degree or higher, employed, French citizenship, one-person household, and no computer. Standard errors in parentheses are clustered by region. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 14: Coefficients of control variables from logistic models, dwelling characteristics

	Logit Table 2		*Logit Table 3*					
	Column 3	**Column 4**	**Column 1**	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dwelling characteristics								
Region: Paris Basin	0.068*	0.083**	0.090**	0.094**	0.076*	0.093**	0.108**	0.090**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Region: North	0.056	0.062	0.044	0.105**	0.039	0.102**	0.067	0.111**
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Region: East	0.053	0.057	0.044	0.080*	0.054	0.083*	0.061	0.083*
	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Region: West	0.025	0.044	0.031	0.079**	0.024	0.078*	0.051	0.081**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Region: South-West	0.032	0.051	0.042	0.074*	0.034	0.075*	0.070	0.081*
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Region: Centre-East	0.078*	0.088**	0.082*	0.107**	0.073	0.106**	0.101**	0.112***
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Region: Mediterranean	0.109***	0.121***	0.091*	0.178***	0.069	0.177***	0.112**	0.176***
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Energy poverty: yes	0.064***	0.037*	0.039	0.022	0.042*	0.024	0.043*	0.026
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Share of income spent on energy expenses (%)	0.003	-0.001	-0.000	-0.007			0.005	-0.008
	(0.00)	(0.00)	(0.00)	(0.01)			(0.00)	(0.01)
Housing construction: 1919 - 1945	-0.001	-0.028	-0.083**	0.043	-0.066**	0.037	-0.073**	0.042
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Housing construction: 1946 - 1970	-0.013	-0.028	-0.032	-0.014	-0.017	-0.014	-0.025	-0.019
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Housing construction: 1971 - 1990	-0.002	-0.016	-0.046	0.022	-0.028	0.023	-0.036	0.026
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Housing construction: 1991 - 2005	0.013	0.005	0.016	0.017	0.025	0.013	0.025	0.003
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Housing construction: After 2006	0.018	-0.012	-0.022	0.013	-0.005	0.015	-0.010	0.005
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Dwelling surface	-0.000	-0.001**	-0.001**	-0.001*	-0.001**	-0.001*	-0.001***	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tenure status: Tenant, with a rent	0.077***	0.035	0.036	0.032	0.043	0.033	0.052*	0.041
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Tenure status: Tenant, rent free	-0.013	-0.048	-0.065	-0.008	-0.039	0.026	-0.040	-0.012
	(0.06)	(0.06)	(0.07)	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)
Housing type: Apartment	-0.034	-0.016	-0.018	-0.011	-0.012	0.000	-0.009	-0.014
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Housing type: Some other kind of accommodation	-0.117	-0.128	-0.188*	0.078	-0.154	0.156	-0.162	0.057
	(0.09)	(0.09)	(0.11)	(0.18)	(0.10)	(0.22)	(0.12)	(0.18)
Energy source: Gas	0.018	0.014	0.011	0.020	0.011	0.025	0.010	0.018
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Energy source: Oil	0.014	0.007	0.029	-0.027	0.022	-0.013	0.045	-0.027
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Energy source: Wood logs	0.060*	0.035	0.033	0.028	0.042	0.045	0.055	0.023
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Energy source: Other	0.074**	0.054*	0.010	0.091**	0.020	0.100***	0.015	0.091**
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)		
City size: Small towns < 20 000 inhabitants	-0.068**	-0.067***	-0.084***	-0.062**	-0.078***	-0.062**	-0.097***	-0.062**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
City size: Medium towns < 200 000 inhabitants	-0.041	-0.038	-0.023	-0.066**	-0.020	-0.067**	-0.036	-0.069**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
City size: Big cities	-0.094***	-0.084***	-0.091***	-0.087***	-0.078**	-0.084**	-0.103***	-0.093***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
N	3,711	3,709	1937	1772	1985	1810	1937	1772

Note: The coefficients of control variables from result Table 2 and Table 3 are presented in marginal effect. For the dummy variables region, housing construction, tenure status, housing type, energy source, and city size are respectively Paris, before 1919, owner, house, electricity, and rural area. Standard errors in parentheses are clustered by region. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

D.2 Robustness checks

Robustness checks were performed by alternatively controlling for total disposable income per CU, using three specifications: (i) log of total disposable income, (ii) log of disposable income before social transfers except old-age and survivor benefits, and (iii) log of standard of living. For social benefit, alternative measures are: (i) total number of administrative procedures undertaken (completed or not), (ii) procedure undertaken (completed or not): enrollment in an educational/training institution, (iii) procedure undertaken (completed or not): other application. Across all specifications, the results remain statistically significant. Results are presented in 15 and 16.

Table 15: Robustness tests of the income variable

	Log total disposable income			Log disposable income before social transferts			Log standard of living		
	Full	Poor class	Middle class	Full	Poor class	Middle class	Full	Poor class	Middle class
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log amount of energy voucher received	0.089***	0.082*		0.097***	0.075		0.089***	0.097**	
	(0.01)	(0.05)		(0.01)	(0.06)		(0.01)	(0.05)	
Log income variable	-0.275***	-0.205***	-0.417***	-0.095***	-0.064***	-0.307***	-0.289***	-0.020***	-0.040***
	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)	(0.05)	(0.03)	(0.01)	(0.01)
Having received the 2021 voucher	0.255***	0.279***	0.216***	0.271***	0.296***	0.219***	0.258***	0.303***	0.251***
	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.05)	(0.02)	(0.02)	(0.05)
Application for social benefits	0.101***	0.123***	0.069**	0.108***	0.130***	0.049	0.098***	0.134***	0.078**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
N	3,700	1,930	1,770	3,698	1,479	2,219	3,700	1,912	1,747
Pseudo-R^2	0.250	0.219	0.155	0.236	0.213	0.147	0.251	0.207	0.127
Log-likelihood	-1,881.300	-1,028.858	-819.9938	-1,914.088	-1036.7418	-829.491	-1,875.959	-1033.701	-841.149

Note: Columns 1, 4, and 7 are robustness checks for the Column 4 of Table 2's coefficients. Others Columns (2, 3, 5, 6, 8 and 9) are robustness checks for the first specification of Table 3's coefficients. Standard errors in parentheses are clustered by region. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 16: Robustness tests of the social benefits application variable

	Number of administrative procedures undertaken			Enrollment in a vocational training institution			Various administrative procedures		
	Full	Poor class	Middle class	Full	Poor class	Middle class	Full	Poor class	Middle class
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log amount of energy voucher received	0.083***	0.075	0.091***	0.083***	0.072	0.090***	0.084***	0.076	0.090***
	(0.01)	(0.06)	(0.02)	(0.01)	(0.06)	(0.02)	(0.01)	(0.06)	(0.02)
Log total gross income	-0.317***	-0.232***	-0.414***	-0.314***	-0.230***	-0.413***	-0.315***	-0.230***	-0.415***
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
Having received the 2021 voucher	0.248***	0.282***	0.206***	0.250***	0.284***	0.205***	0.250***	0.284***	0.206***
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
Application for social benefits variable	0.025***	0.019*	0.026***	0.061**	0.076*	0.033	0.067**	0.073*	0.059
	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
N	3,709	1,487	2,222	3,709	1,487	2,222	3,709	1,487	2,222
Pseudo-R^2	0.256	0.237	0.181	0.255	0.238	0.178	0.255	0.237	0.179
Log-likelihood	-1,870.394	-758.667	-1,081.067	-1,874.031	-758.563	-1,084.265	-1,873.393	-758.7193	-1,083.305

Note: Standard errors in parentheses are clustered by region. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 17: Correlation matrix of variables

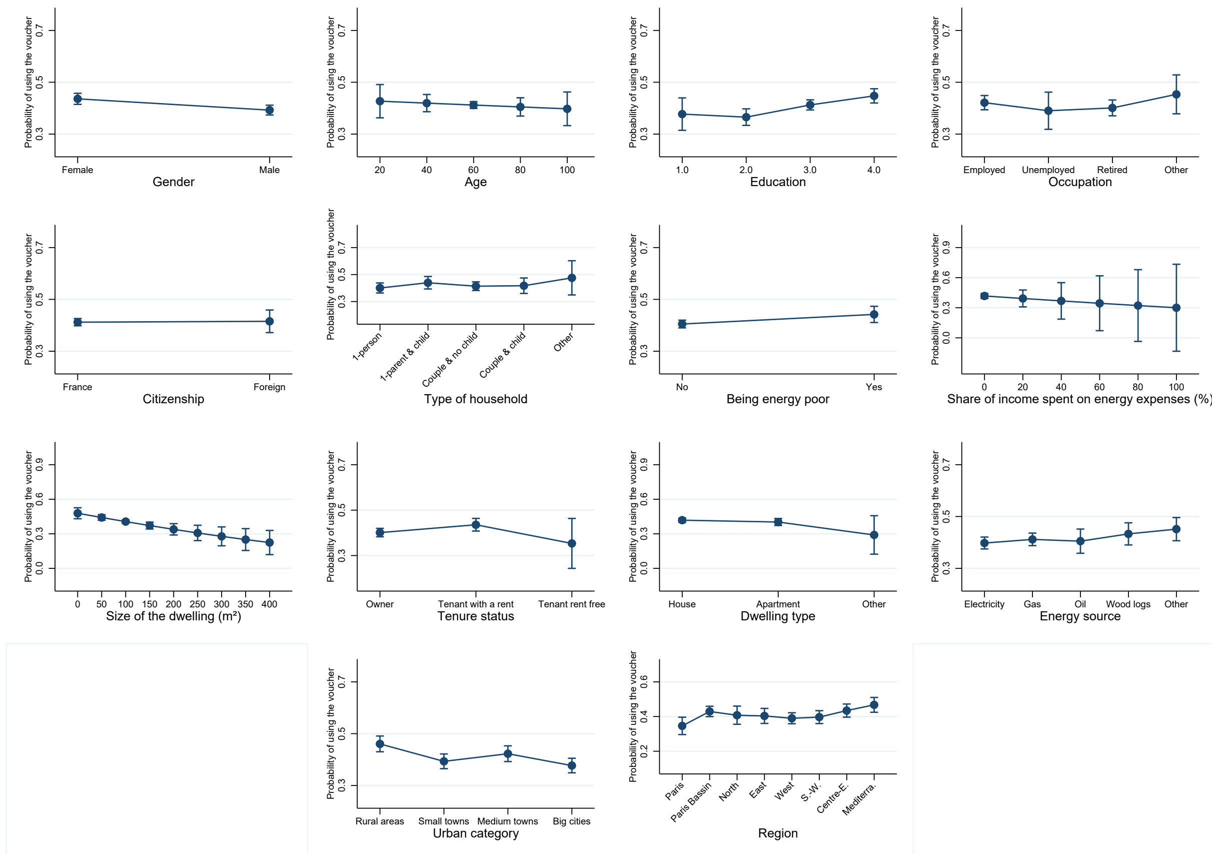
	Having 2022 EV	Log amount of EV	Log gross income	Having 2021 EV	App for social benefits	Sex	Age	Education	Occupation	Citizenship	HH size	HH type	Having a computer	Energy poverty	Energy share	Housing construction	Dw. size	Tenure status	Energy source	City size	Region	
Having 2022 EV	1.000																					
Log amount of EV	0.365	1.000																				
Log gross income	-0.337	-0.372	1.000																			
Having 2021 EV	0.392	0.378	-0.265	1.000																		
App. for social benefits	0.166	0.119	0.019	0.159	1.000																	
Sex	-0.101	-0.122	0.233	-0.076	-0.013	1.000																
Age	-0.024	0.003	-0.359	-0.090	-0.264	-0.094	1.000															
Education	0.171	0.102	-0.321	0.096	-0.070	0.033	0.365	1.000														
Occupation	0.083	0.133	-0.488	0.023	-0.158	-0.072	0.697	0.338	1.000													
Citizenship	0.076	0.120	-0.062	0.112	0.028	0.039	0.011	0.012	0.004	1.000												
HH size	0.021	-0.025	0.624	0.074	0.188	0.221	-0.476	-0.171	-0.455	0.090	1.000											
HH type	-0.080	-0.159	0.669	-0.038	0.122	0.347	-0.352	-0.132	-0.371	0.051	0.829	1.000										
Having computer	-0.143	-0.135	0.377	-0.116	0.065	0.090	-0.304	-0.305	-0.273	-0.036	0.280	0.307	1.000									
Energy poverty	0.136	0.133	-0.040	0.140	0.125	-0.015	-0.145	0.015	-0.057	0.049	0.115	0.058	-0.005	1.000								
Energy share	0.192	0.223	-0.549	0.160	0.003	-0.098	0.205	0.169	0.255	0.026	-0.214	-0.230	-0.197	0.046	1.000							
Housing construction	-0.016	-0.038	0.093	-0.006	0.041	-0.015	-0.126	-0.048	-0.110	0.003	0.097	0.085	0.101	-0.104	-0.098	1.000						
Dw. size	-0.127	-0.136	0.302	-0.108	-0.018	0.112	-0.014	-0.089	-0.082	-0.042	0.262	0.295	0.151	-0.057	-0.028	-0.038	1.000					
Tenure status	0.203	0.212	-0.249	0.248	0.125	-0.114	-0.159	0.045	-0.026	0.123	-0.073	-0.171	-0.094	0.199	-0.007	0.085	-0.330	1.000				
Dw. type	0.090	0.146	-0.242	0.124	0.056	-0.152	-0.070	-0.025	0.018	0.181	-0.204	-0.281	-0.087	0.067	-0.090	0.080	-0.389	0.516	1.000			
Energy source	0.015	-0.033	0.079	-0.025	-0.017	0.078	0.019	0.033	-0.026	-0.052	0.102	0.131	0.037	-0.065	-0.114	-0.084	0.172	-0.226	-0.229	1.000		
City size	-0.030	0.066	-0.032	0.046	0.017	-0.089	-0.046	-0.092	-0.001	0.189	-0.059	-0.110	0.007	0.065	-0.057	0.069	-0.237	0.263	0.479	-0.275	1.000	
Region	0.044	0.042	-0.052	0.022	-0.001	-0.044	0.049	-0.019	0.031	0.021	-0.049	-0.030	-0.012	-0.032	-0.005	0.074	0.019	0.009	0.035	-0.034	-0.005	1.000

D.2.1 Socio-demographic determinants of non-take-up

D.3 Additional Determinants: Socio-Demographic Characteristics

Women are slightly more likely than men to use the energy voucher, consistent with literature indicating that women disproportionately bear cognitive and household management labor — the planning, organizing, and administrative tasks required to run a household — relative to men (Ciciolla and Luthar, 2019; Ervin et al., 2022). The probability of use decreases slightly with age, with larger disparities observed among young adults (around 20) and the elderly (around 100), two groups that are often more economically vulnerable. A negative relationship is observed between educational attainment and voucher use: lower levels of education are associated with higher likelihoods of utilization. A similar pattern emerges regarding household composition: households with children or more complex structures exhibit higher probabilities of voucher use, whereas couples without children show lower probabilities. Households reporting energy poverty are more likely to utilize the voucher. The share of income spent on energy shows a downward trend: as this share increases, the probability of voucher use decreases, although estimates are less precise at higher levels. Housing size is negatively associated with voucher use, with larger dwellings corresponding to lower probabilities. Tenure status also plays a role: tenants who pay rent exhibit the highest probability of using the voucher, while tenants not paying rent have the lowest. Comparable patterns are observed across urban categories, with higher probabilities in rural areas and lower probabilities in large cities.

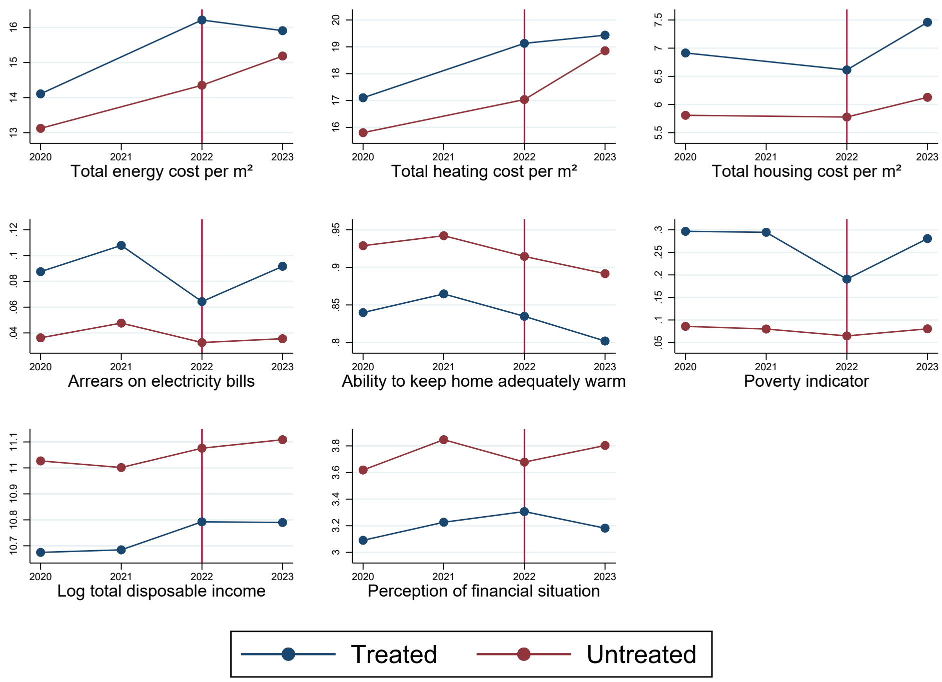
Figure 4: Marginal effects of economic and socio-demographic characteristics of households, 2023



E Double robust DID: Additional results and robustness checks

The baseline doubly robust difference-in-differences model aims to estimate the impact of the 2022 Energy Voucher Policy using outcome variables that reflect the policy's intended objectives, such as reducing financial stress related to energy expenditures and improving energy well-being. Eight outcomes are considered: (1) total energy cost per m^2 (annual electricity and gas consumption), (2) total heating cost per m^2 (annual amount of energy and heating expenses), (3) total housing cost per m^2 (monthly housing costs including rent, mortgage interest, utilities, electricity, water, gas, heating, and property taxes), (4) arrears on energy bills (inability to pay electricity, gas, or water bills on time in the past 12 months due to financial difficulties), (5) ability to keep the home adequately warm, (6) a poverty indicator, (7) the log of total disposable income, and (8) perceived financial situation (ranging from very difficult to very easy). Table 18 presents summary statistics of each outcome variables for treated and control groups after treatment.

Figure 5: Trends in economic and energy indicators by group, 2020–2023



Note: The figure shows average values for eight variables from 2020 to 2023 by group. Three variables are not observed in the 2021 survey: total energy cost per m² (7-a), total heating cost per m² (7-b), and total housing cost per m² (7-c). Arrears on electricity bills, ability to keep the home adequately warm, the poverty indicator, and perceived financial situation are binary variables coded as follows: 0 = no and 1 = yes for arrears and heating adequacy, 0 = non-poor and 1 = poor for the poverty indicator, and a scale from 1 (very difficult) to 6 (very easy) for perceived financial situation. The red vertical line indicates the treatment year.

Table 18: Descriptive statistics of DID outcome variables for treated and control groups after treatment (2023)

	Untreated			Treated		
	Mean	Min.	Max.	Mean	Min.	Max.
Total energy cost per m² (€)	15.19	0.00	325.00	15.91	0.00	381.33
Total heating cost per m² (€)	18.85	0.00	1462.00	19.43	0.00	514.80
Total housing cost per m² (€)	6.13	0.00	203.67	7.46	0.24	386.67
Arrears on electricity bills	0.04	0.00	1.00	0.09	0.00	1.00
Ability to keep home adequately warm	0.89	0.00	1.00	0.80	0.00	1.00
Poverty indicator (at the 60% threshold)	0.08	0.00	1.00	0.28	0.00	1.00
Log total disposable income (€)	11.11	5.07	12.52	10.79	8.37	12.40
Perception of financial situation	3.80	1.00	6.00	3.18	1.00	6.00
Observations	2563			1789		

To be robust and unbiased, the DR-DID should be implemented on outcomes for which no anticipation of the treatment can be occur. Based on the fact that energy voucher value is relatively low and the calendar allocation of the state aid vary a lot between year, it can be assume that new first beneficiaries of the voucher do not anticipate their voucher receive on their energy consumption or other financial expenditure. Moreover, Table 19 presents results from naive differences-in-difference, showing almost zero and non-significant effect of the treatment for the years before the treatment year for most outcomes (except for the perceived financial situation, for which according to naive check result could decrease with the energy voucher, even though the effect is close to zero). Table 20 shows t-tests of outcomes on the difference between treated and untreated groups.

Table 19: Naive difference-in-differences

	Total energy cost per m^2	Total heating cost per m^2	Total housing cost per m^2	Arrears on electricity bills	Ability to keep home adequately warm	Poverty indicator	Log disposable income	Perceived financial situation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year 2023 × treated = 1	-1.002	-0.860	0.141	-0.005	0.009	-0.029***	0.016	-0.095***
	(0.883)	(0.977)	(0.431)	(0.010)	(0.013)	(0.011)	(0.011)	(0.037)
Year 2021 × treated = 1				-0.001	0.021*	-0.015	0.019	-0.096***
				(0.010)	(0.012)	(0.011)	(0.012)	(0.036)
Year 2020 × treated = 1	-0.698	0.369	0.225	0.005	0.010	-0.010	-0.015	-0.098**
	(0.780)	(1.128)	(0.354)	(0.012)	(0.016)	(0.015)	(0.017)	(0.046)
Constant	15.148***	18.049***	6.242***	0.056***	0.874***	0.155***	10.937***	3.458***
	(0.220)	(0.231)	(0.105)	(0.003)	(0.004)	(0.003)	(0.004)	(0.011)
Observations	9,280	9,121	8,764	14,326	14,290	14,335	14,305	14,287
R^2	0.009	0.008	0.002	0.001	0.012	0.001	0.040	0.013

Note: Estimates are obtained using a fixed-effects panel model without additional covariates. The specification includes year indicators and their interaction with the treatment variable, with 2022 as the reference year. Standard errors are clustered at the individual level. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 20: T-test of outcomes on the difference between treated and untreated groups

	Untreated	**Treated**	**Difference**	**Pr(|T| >|t|)**
Total energy cost per m^2	14.35	16.21	-1.86**	0.025
Total heating cost per m^2	17.03	19.13	-2.10**	0.014
Total housing cost per m^2	5.78	6.61	0.08**	0.004
Total heating and water cost per m^2	0.03	0.06	0.03***	0.000
Arrears on electricity bills	0.91	0.83	-0.08***	0.000
Poverty indicator	0.06	0.19	-0.13***	0.000
Log total disposable income	11.08	10.79	0.29***	0.000
Perception of financial situation	3.68	3.31	0.37***	0.000
Observations	2,336	1,075		

The choice of control covariates is crucial for the correct specification of both the propensity score and outcome regression models. Only observable characteristics that explain pre-treatment differences between treated and control households should be included; these variables must not be affected by the energy voucher allocation and must be related to the likelihood of treatment. At the same time, the number of covariates is deliberately limited to avoid over-parameterisation. The selected covariates are informed by the logit model and are reported in Table 21.

Table 21: T-tests of differences in covariates between treated and untreated groups

	Untreated	**Treated**	**Difference**	**Pr(|T| >|t|)**
Log total gross income	11.29	10.93	0.36***	0.000
Application for social benefits	0.03	0.05	-0.02***	0.000
Sex	0.59	0.51	0.08***	0.000
Age	56.96	58.37	-1.41	0.018
Education	2.85	3.13	-0.28***	0.000
Occupation	1.86	2.07	-0.21***	0.000
Household size	2.21	2.15	0.06	0.230
Dwelling size	97.45	88.29	9.17***	0.000
Tenure status	1.32	1.43	-0.11***	0.000
Dwelling type	1.32	1.36	-0.04	0.064
City size	2.62	2.47	0.15***	0.001
Region	4.74	4.89	-0.15	0.132
Observations	2,336	1,075		

Note: The results indicate whether the differences between the treated and control groups are statistically significant for each covariate. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Results are robust to several robustness checks. First, estimates remain stable when the set of control variables is reduced (Table 22). Second, results are robust to alternative specifications of the treatment model, using a probit instead of a logit to estimate the propensity score (Table 23). Third, estimates are unchanged when applying severe trimming of the inverse probability weights, excluding observations in the bottom and top 10 percent of the weight distribution to mitigate the influence of extreme propensity scores (Table 24). Finally, results are robust to the use of an alternative weighting scheme based on Inverse Probability Tilting (DRIMP), which rebalances the weights to reduce the impact of observations with extreme propensity scores (Table 25).

Table 22: DR-DID robustness check — restricted covariates

	Total energy cost per m^2 (1)	**Total heating cost per m^2** (2)	**Total housing cost per m^2** (3)	**Arrears on electricity bills** (4)	**Ability to keep home adequately warm** (5)	**Poverty indicator** (6)	**Log disposable income** (7)	**Perceived financial situation** (8)
ATET	-0.867	-0.550	0.115	-0.008	0.007	0.008	-0.027**	-0.080*
	(1.095)	(1.157)	(0.476)	(0.012)	(0.016)	(0.015)	(0.013)	(0.046)
Observations	5,428	5,276	5,006	5,694	5,668	5,698	5,680	5,670

Note: In these specifications, covariates are restricted to log disposable income, sex, age, education, and occupation. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 23: DR-DID robustness check — Probit model

	Total energy cost per m^2	Total heating cost per m^2	Total housing cost per m^2	Arrears on electricity bills	Ability to keep home adequately warm	Poverty indicator	Log disposable income	Perceived financial situation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATET	-1.572	-0.972	0.106	-0.016	0.070	0.037	-0.146*	0.010
	(1.036)	(1.063)	(0.459)	(0.013)	(0.059)	(0.025)	(0.081)	(0.081)
Observations	6,176	5,980	5,670	6,464	6,438	6,470	6,448	6,438

Note: In these specifications, the probit is use as alternative specification of the treatment model, instead of a logit to estimate the propensity score. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 24: DR-DID robustness check — Severe trimming

	Total energy cost per m^2	Total heating cost per m^2	Total housing cost per m^2	Arrears on electricity bills	Ability to keep home adequately warm	Poverty indicator	Log disposable income	Perceived financial situation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATET	-1.002	-0.816	0.079	-0.015	0.003	0.034*	-0.041**	-0.078
	(1.040)	(1.105)	(0.473)	(0.014)	(0.021)	(0.019)	(0.017)	(0.054)
Observations	5,428	5,276	5,006	5,694	5,668	5,698	5,680	5,670

Note: In these specifications, severe trimming of the inverse probability weights is applying, excluding observations in the bottom and top 10 percent of the weight distribution. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Table 26: Summary statistics of inverse probability weights

	Percentiles		
1%	1.029		
5%	1.071		
10%	1.110		
25%	1.215	**Obs.**	7,370
50%	1.465	**Mean**	2.077
75%	2.072	**Std. dev.**	2.855
90%	3.202	**Variance**	8.149
95%	4.486	**Skewness**	13.689
99%	10.148	**Kurtosis**	250.464

Table 25: DR-DID robustness check — Alternative ponderation

	Total energy cost per m^2 (1)	Total heating cost per m^2 (2)	Total housing cost per m^2 (3)	Arrears on electricity bills (4)	Ability to keep home adequately warm (5)	Poverty indicator (6)	Log disposable income (7)	Perceived financial situation (8)
ATET	-1.145	-0.973	0.101	-0.014	0.002	0.024	-0.038***	-0.098*
	(1.023)	(1.115)	(0.473)	(0.013)	(0.019)	(0.018)	(0.014)	(0.050)
Observations	5,428	5,276	5,006	5,694	5,668	5,698	5,680	5,670

Note: In these specifications, use of an alternative weighting scheme based on Inverse Probability Tilting (DRIMP), which rebalances the weights to reduce the impact of observations with extreme propensity scores. * / ** / *** represent significance at the 0.10 / 0.05 / 0.01 levels, respectively.

Figure 6: Distribution of the inverse probability weights