# Welfare trade-offs of energy-efficient homes: poverty, environment and comfort*

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**Abstract**

Energy efficiency improvements in low-income housing are increasingly used as a policy instrument to tackle poverty. Our paper shows that targeting the poor entails lower environmental benefits. We perform a quasi-experimental evaluation of a large Dutch nationwide residential heating efficiency programme. Unlike earlier literature, we examine income-based heterogeneity in programme effects and derive formally the behavioural mechanisms behind this heterogeneity. Our empirical work follows a sample of 125,000 households over eight years, exploiting a unique conditionally random treatment assignment; the results are then combined with a computable microeconomic choice model. Our findings suggest that the poorest achieve energy and environmental savings that are one-third lower than the average. This is partly compensated by the significant comfort gains they experience. We show further that, under the high gas prices observed since 2022, the heating efficiency home upgrades may generate positive private returns, also for the poor.

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## 1 Introduction

Many countries subsidise energy-efficient home upgrades in low-income housing (e.g. insulation to diminish heat losses, solar panels, and heat pumps for renewable energy generation). These policies often hinge on two interconnected goals. One is carbon emission reduction and environmental quality improvement; see, for example, the 2012 Energy Efficiency Covenant in the Dutch social housing sector (Ministry of the Interior and Kingdom Relations, 2012). The other goal involves energy cost reduction and living comfort improvement for poor households in need.[1] This is explicit in, e.g., the Weatherization Assistance Program in the US or the UK's Warm Front Home Energy Efficiency Scheme (Fowlie et al., 2018; Sovacool, 2015). Our paper shows that the two goals are competing: prioritising energy efficiency upgrades for the poor comes at the expense of lower environmental benefits. We conclude this based on a large quasi-experimental evaluation of the Dutch nationwide residential heating efficiency programme, conducted on a sample of 125,000 households over eight years and combined with a computable microeconomic choice model. More specifically, we evaluate the (welfare) effects of the programme on energy expenditures, comfort, and environment for different income groups.

Existing economic evaluations tend to report negative private and social returns to low-income energy efficiency upgrades and document hardly any improvements in comfort. A well-known example is the seminal article by Fowlie et al. (2018), which performs a randomised experiment on a sample of 30,000 households eligible for the US Weatherization Program and finds, on average, that the benefits of Weatherization fall short of the costs. More recent literature argues that the average masks significant variation in both positive and negative returns (Christensen et al., 2024, 2023). The behavioural mechanisms behind this heterogeneity have not been sufficiently studied yet. This is unfortunate, as being able to predict the behavioural responses and the welfare gains for different population groups will help not only better target energy efficiency policies but also optimally adapt these policies to exogenous shocks, such as, for example, the peaking energy prices observed since 2022.

Our paper addresses this gap by exploring how differences in income and energy prices shape the size and type of benefits from heating efficiency upgrades. To achieve

[1] The underlying assumption is that poor households, due to severe credit constraints, may reduce their energy use to a level that is detrimental to their health and well-being (European Commission, 2023).

this, unlike earlier literature, we combine a computable microeconomic consumer choice model with a quasi-experimental evaluation of a large countrywide heating efficiency programme in the Netherlands. The consumer model formally describes how people optimise between home thermal comfort, which is produced from natural gas, and other consumption goods, and how this is affected by home heating efficiency. The model analytically derives testable hypotheses about the income heterogeneity in behavioural responses to home upgrades. Further, the model enables computation of the welfare effects of the upgrades, including the difficult-to-value comfort benefits. We use the low-income heating efficiency programme to test the predictions of, and provide the parameters for the consumer choice model. The unique features of the programme are a conditional random assignment to treatment and no possibility of opting out.

The programme began in 2012 when all Dutch housing associations - non-commercial entities owning low-income social housing - agreed in a covenant to improve the heating efficiency of over one million older dwellings they owned.[2] The home improvements were carried out in subsequent years through insulation upgrades, such as adding extra material to walls and roofs. Since a large number of houses qualified for upgrades, only a small portion could be addressed each year. Therefore, a selection rule to prioritise certain houses was introduced. As we show, housing associations prioritised dwellings based on building characteristics (e.g., construction period, energy label) and organisational factors, rather than tenant characteristics.[3] This made the treatment assignment random, conditional on observable dwelling characteristics.[4] Additionally, self-selection was prevented because tenants could not opt out of the programme.[5] Consequently, we can make use of a clean identification of programme effects and a large longitudinal sample of 125,000 qualifying houses, of which just over 10% received upgrades. The sample

[2]The social housing sector in the Netherlands is large, encompassing 2.2 million dwellings (30% of the Dutch housing stock) and around 275 housing associations. It provides housing to people earning below the median income, at regulated rent levels. In 2020, the income threshold for eligibility was approximately 40,000 euros gross annual income.

[3]For example, upgrades were coordinated with regular building maintenance, like painting, which follows a cyclical schedule planned years in advance. This regular maintenance does not affect the gas use or thermal comfort.

[4]In Section 3, we discuss the selection process in detail and provide formal tests of conditional randomness.

[5]Self-selection is a common issue in programme evaluations. We also show that tenants did not adjust their behaviour in anticipation of the upgrades.

includes significant variation in household income, which we exploit.[6]

We evaluate the effects of the programme on natural gas use by income using a two-way fixed effect panel regression (Angrist and Pischke, 2008), alongside the recent advances in staggered treatment effect estimation (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). To calculate and decompose welfare effects, we calibrate the consumer choice model parameters to match the observed pre-retrofit gas use distribution by income and the estimated quasi-experimental gas savings distribution by income. The model is then run to predict how different population groups re-optimise thermal comfort and other consumption after a home upgrade. Subsequently, compensating variation is used to value comfort increases and natural gas savings. In the welfare analysis, we consider two scenarios: (i) low gas prices (2016 level) and (ii) high gas prices (2022 level), with the latter being twice as high as the former.

There are three primary findings. First, we theoretically predict and empirically document significant income heterogeneity in the effects of home upgrades on natural gas use. Our consumer choice model shows that: (i) the poor opt for lower-than-average thermal comfort and gas use for heating, especially in homes with poor heating efficiency; (ii) they increase comfort relatively more after a home upgrade, resulting in lower gas savings (i.e., the poor experience a larger rebound effect). Empirical tests suggest that households at the very lowest end of the income distribution have 20% lower-than-average heating demand before the upgrade. After the upgrade, we find an average reduction in natural gas use of 22%, with a much smaller reduction of 16% for the poor. These estimates are robust across a range of different specifications and modelling assumptions. From a policy perspective, the results suggest that targeting the poor with heating efficiency upgrades leads to lower-than-average environmental benefits.

Second, the paper offers a variety of novel insights into the factors driving the returns from heating efficiency programmes. We begin by decomposing the private benefits into monetary savings and increased comfort. The latter accounts for up to 20% of the total private gain, but this share declines sharply with income. We then show that, while negative private and social returns prevail in the reference scenario with low gas prices, a positive private (and social) return becomes possible in the counterfactual with high

[6] Although social housing is intended for low-income individuals, income checks are only conducted when renters sign a new contract. As a result, the actual income distribution of social renters includes a notable proportion of higher-income households.

gas prices. Given that in Europe, around 20%, and in the Netherlands, nearly 50%, of the consumer price for natural gas consists of taxes and charges (Eurostat, 2024), governments seem to have effective tools to influence the private payback of heating efficiency investments and, in turn, reduce the energy efficiency gap.

Third, the computable consumer choice model allows us to derive an analytic expression for the rebound effect from microeconomic premises and document significant income heterogeneity in this rebound.[7] For example, for poor households and high gas prices, we find a rebound of 20%, while for the entire sample and low gas prices, we find 5%.

Our paper makes three primary contributions to the literature on energy efficiency. First, it provides causal evidence on income heterogeneity in the benefits of heating efficiency, based on a large field test with clean identification. There is a small quasi-experimental and non-experimental literature examining how returns vary by income and other household characteristics, see Davis et al. (2014); Aydin et al. (2017); Liang et al. (2018); McCoy and Kotsch (2021); Hammerle and Burke (2022). These studies face various identification issues, the most common of which is self-selection due to the voluntary nature of the program. Our paper, in contrast, uses a large representative sample and identification based on conditional random assignment to treatment.

Second, our paper is one of the first efforts to understand the driving factors and behavioural mechanisms behind the returns to energy efficiency investments in homes. Numerous attempts have been made to quantify the monetary savings from energy efficiency programmes, based on quasi-experimental and experimental evidence, see Gillingham et al. (2018) and Saunders et al. (2021) for reviews.[8] A recent study by Blonz et al. (2025) goes further and measures the trade-off between energy savings and indoor temperature, using experimental data from smart thermostates that regulate airconditioning. However, existing research relies largely on reduced-form econometrics and therefore cannot explicitly analyse the underlying behavioural mechanisms or predict the returns under different scenarios. Our paper combines econometrics with a computable consumer choice

[7] The analytic expression follows the definition by Gillingham et al. (2016): the difference between the actual energy savings and those forecast without any consumer or market responses to the energy efficiency improvement.

[8] Large-scale evaluations include Fowlie et al. (2018) and Allcott and Greenstone (2017) for the US; Webber et al. (2015), Peñasco and Anadón (2023), McCoy and Kotsch (2021), and Adan and Fuerst (2016) for the UK; and Davis et al. (2014) for Mexico.

model to fill this gap and derive the trade-offs consumers make from microeconomic behavioural premises. We measure the energy savings directly and develop a theory-based approach to measure and monetize comfort benefits, which is particularly applicable to the large-scale renovations of old low-income homes, for which direct temperature measurements are largely unavailable.

Third, we provide a welfare-based formula that allows us to compute the rebound effect for different income groups. Many studies measure the rebound effect as the gap between ex-ante engineering forecasts and actual savings from energy efficiency upgrades, see Sorrell and Dimitropoulos (2008); Gerarden et al. (2015); Allcott and Greenstone (2017); Aydin et al. (2017) and also a review in Peñasco and Anadón (2023). Christensen et al. (2023) uses a method based on machine learning. Our approach explicitly builds upon a simple microeconomic model. Furthermore, while income heterogeneity in the rebound was identified as early as 2000 by Milne and Boardman (2000), to our knowledge, this paper is the first to perform a large-scale empirical measurement of this heterogeneity.

The rest of the article is organised as follows. Section 2 introduces the consumer choice model, explaining why the poor have lower responses to energy efficiency upgrades. Section 3 describes the institutional background, the sample, and the data. Section 4 discusses the empirical methodology and identification and reports the main results. Section 5 derives the parameters for the computable consumer choice model and calculates welfare effects under different scenarios. Section 6 concludes.

## 2 Theoretical Framework

In this section, we develop a simple consumer choice model in which a household spends its income on consumption and heating. We solve the model and derive the optimal household consumption and gas use levels. Using the resulting indirect utility function, we compute a monetary measure of the energy efficiency upgrade: the compensating variation. To decompose this welfare gain of the household into a thermal comfort component and a consumption component, we use the Slutsky compensation.

### 2.1 Model

Household utility is given by the following constant elasticity of substitution (CES) specification:

$$u(x,\theta) \stackrel{\text{def}}{=} \left((f_1(x))^{\frac{\sigma-1}{\sigma}} + (f_2(\theta))^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $x \geq 0$ is the consumption of a composite good and $f_1(x)$ is the consumption utility component, $\theta$ is the thermal comfort measured by the indoor winter temperature and $f_2(\theta)$ is the thermal comfort utility component. The parameter $\sigma$ is the elasticity of substitution between the consumption utility and the thermal utility components.

We assume that the thermal comfort utility component $f_2(\theta)$ is increasing and concave and reaches its maximum at some temperature $\bar{\theta}$. The idea behind this assumption is that not only too low but also too high indoor temperatures negatively affect the individual well-being. As a result, the household never chooses a value of $\theta$ beyond $\bar{\theta}$. We operationalize $f_2(\theta)$ as the second degree concave polynomial as follows:

$$f_2(\theta) \stackrel{\text{def}}{=} (2\bar{\theta} - \theta)\theta.$$

For the consumption utility component $f_1(x)$, we assume

$$f_1(x) \stackrel{\text{def}}{=} x.$$

Thus, the household utility is defined for $x \geq 0$ and $\theta$ by

$$u(x,\theta) = \left(x^{\frac{\sigma-1}{\sigma}} + \left((2\bar{\theta} - \theta)\theta\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

Thermal comfort $\theta$ is produced from natural gas according to the production function:

$$\theta = \theta_0 + qg,$$

where $g > 0$ is the gas use for heating, $\theta_0$ is the natural indoor winter temperature when $g = 0$, and $q \geq 0$ is the home heating efficiency parameter. The higher is $q$, the less gas is needed to increase the indoor temperature by one degree. We use an increase in $q$ from $q = q_L$ to $q = q_H > q_L$ for modelling home heating efficiency upgrades.

The household earns income $w$ and spends it on $(x, g)$. We normalize the price for consumption to unity, $p_x = 1$, and the natural gas price is $p_g > 0$. The household budget constraint is, therefore:

$$x + \frac{p_g}{q}(\theta - \theta_0) = w. \tag{2}$$

where $\frac{1}{q}(\theta - \theta_0)$ is the annual gas use. All households face the same gas price $p_g$, and each household is characterized by parameters $(q, w, \theta_0, \bar{\theta}, \sigma)$ and chooses $x \geq 0$ and $\theta \in [\theta_0, \bar{\theta}]$ to maximize utility (1) subject to the budget constraint (2). Since we are only interested in the effects of home heating efficiency $q$ and income $w$ on household behaviour, we omit all other exogenous variables $(p_g, \theta_0, \bar{\theta})$ from the argument lists in what follows.

### 2.2 Household Optimal Behavior

The following proposition provides the solution $(x^*, \theta^*)$ to the utility maximization problem, UMP, of a household.

**Proposition 1** *Let the critical income level $\underline{w}(q)$ be defined by:*

$$\underline{w}(q) \stackrel{\text{def}}{=} (2\bar{\theta} - \theta_0)\theta_0 \left( \frac{p_g}{2q(\bar{\theta} - \theta_0)} \right)^{\sigma}. \tag{3}$$

*Then:*

1. *If $w \leq \underline{w}(q)$, then $x^*(q,w) = w$ and $\theta^*(q,w)) = \theta_0$.*

2. *If $w > \underline{w}(q)$, then $\theta^*(q,w)$ is uniquely defined by:*

$$0 = w - (2\bar{\theta} - \theta^*)\theta^* \left( \frac{p_g}{2q(\bar{\theta} - \theta^*)} \right)^{\sigma} - \frac{\theta^* - \theta_0}{q} p_g, \tag{4}$$

   *and*

$$x^*(q,w) = w - \frac{\theta^* - \theta_0}{q} p_g. \tag{5}$$

3. *For $w \geq \underline{w}(q)$, $x^*(q,w)$ and $\theta^*(q,w)$ increase in $w$.*

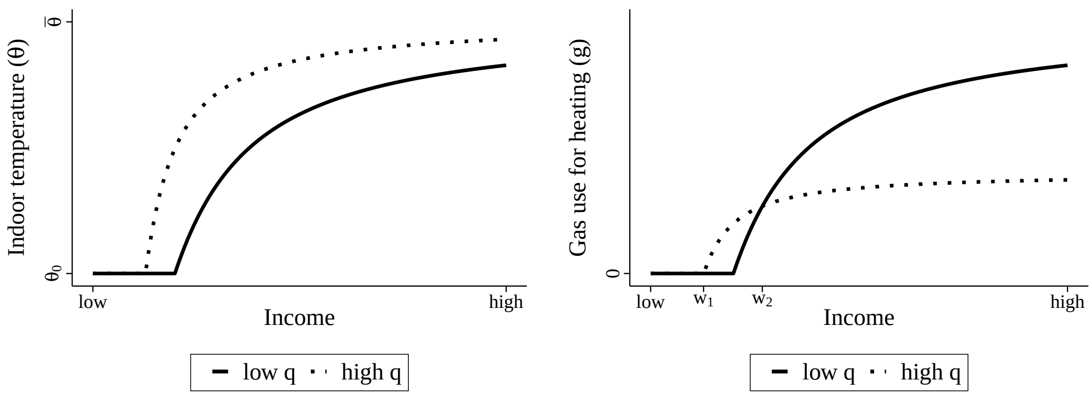
4. *The optimal thermal comfort $\theta^*(q,w)$ increases in $q$ and approaches $\bar{\theta}$ when $q$ or $w$ increase unboundedly.*

The proof of the proposition is in Appendix A. For low income levels that are below $\underline{w}(q)$, the optimal consumption is a corner solution, where the household uses no gas and stays at the natural house temperature $\theta^*(q,w) = \theta_0$. The household spends then all its income $w$ on consumption, $x^*(q,w) = w$. For higher income levels, $w > \underline{w}(q)$, the optimal thermal comfort $\theta^*$ is an interior solution satisfying $\theta^* \in (\theta_0, \bar{\theta})$. Both thermal comfort and composite good consumption are normal goods and their optimal levels increase with income $w$.

Figure 1a illustrates Proposition 1. It shows the optimal indoor temperature $\theta^*$ as a function of income $w$ for two values $q_L$ and $q_H$ of the heating efficiency parameter $q$, with $q_L < q_H$. For the lowest income levels, the optimal thermal comfort is at its natural level $\theta_0$. With rising income, the optimal thermal comfort also rises and converges in the limit to the satiety threshold $\bar{\theta}$. With the increase in $q$, the optimal thermal comfort starts to increase at lower income levels.

Figure 1: Optimal thermal comfort $\theta^*$ and gas use $g^*$.

(a) Thermal comfort (b) Gas use




*Notes*: The lines show the optimal levels of indoor temperature respectively natural gas use as a function of income ($\theta^*(w)$ respectively $g^*(w)$) as implied by the utility maximization problem Equations (1) and (2). See Appendix A for the derivations. $q \geq 0$ is the home heating efficiency parameter.

The optimal gas use $g^*(q, w)$ is determined by $\theta^*(q, w)$:

$$g^*(q, w) = \frac{1}{q}(\theta^*(q, w) - \theta_0). \tag{6}$$

The following proposition provides a characterization of $g^*(q, w)$.

**Proposition 2** *Optimal gas use $g^*(q, w)$ has the following properties:*

1. $g^*(q, w)) = 0$ *for* $w \leq \underline{w}(q)$.

2. $g^*(q, w)$ *increases in* $w$ *for* $w > \underline{w}(q)$ *and converges to* $\frac{1}{q}(\bar{\theta} - \theta_0)$ *when* $w$ *increases unboundedly.*

3. *For any* $q_L$ *and* $q_H$, $q_H > q_L > 0$, *there are two income thresholds* $w_1(q_L, q_H)$ *and*

$w_2(q_L, q_H)$ *satisfying* $w_2(q_L, q_H) \geq w_1(q_L, q_H) > \underline{w}(q_L)$ *such that:*

$$g^*(q_H, w) > g^*(q_L, w) \text{ for } w < w_1(q_L, q_H)$$
$$g^*(q_H, w) < g^*(q_L, w) \text{ for } w > w_2(q_L, q_H)$$

The proof of the proposition is in Appendix A. Figure 1b illustrates Proposition 2. It shows the optimal gas use $g^*$ as a function of income $w$ for two values $q_L$ and $q_H$ of the heating efficiency parameter $q$, with $q_L < q_H$. Since the graph of $g^*(q_H, w)$ starts to increase at a lower income level $\underline{w}(q_H)$ and converges to a lower limit $\frac{1}{q_H}(\bar{\theta} - \theta_0)$ than the graph of $g^*(q_L, w)$ does, the graphs necessarily intersect, and the income thresholds $w_1$ and $w_2$ are the lowest and the highest intersection income levels. For low income levels when $w < w_1$, the upgrade from $q_L$ to $q_H$ results in an increase of the optimal gas use, $g^*(q_H, w) > g^*(q_L, w)$. For larger income levels when $w > w_2$, the optimal gas use decreases, $g^*(q_H, w) < g^*(q_L, w)$.

Summarizing, when the heating efficiency of a house increases, all households re-optimize their consumption patterns, trading off potential natural gas savings against an increase in the level of thermal comfort. Households with a sufficiently low income increase their gas use because they are further away from the satiety threshold and, therefore, face a larger marginal benefit of a unit temperature increase. High-income households, on the contrary, decrease their gas use because for them, the marginal benefit of a unit temperature increase is low. This results in lower gas savings for the poor.

### 2.3 Household Welfare Analysis

Using the household optimal thermal comfort $\theta^*(q, w)$ and optimal consumption, we write the household indirect utility $V(q, w)$ as follows:

$$V(q, w) \stackrel{\text{def}}{=} u(x^*(q, w), \theta^*(q, w)),$$

where $u$, $\theta^*$, and $x^*$ are defined by Equations (1), (4) and (6) respectively. The exact household welfare gain for the change in heating efficiency $q$ from $q = q_L$ to $q = q_H$ is given by the compensating variation $CV$, which is implicitly defined by:

$$V(q_H, w - CV) = V(q_L, w). \tag{7}$$

Compensating variation $CV(q_L, q_H, w)$ is the household willingness to pay for the heating efficiency improvement, it is the income effect of the heating efficiency improvement. Since thermal comfort is a normal good ($\theta^*(q,w)$ increases with $w$ whenever $\theta^*(q,w) > \theta_0$), it is not surprising that high-income households which choose higher thermal comforts levels benefit more from the heating efficiency improvement than low-income households do. The following proposition states this result.

**Proposition 3** *In the interior solution, the compensating variation increases with income: if $\theta^*(q_H,w) > \theta_0$ then $\frac{\partial CV}{\partial w} > 0$.*

The proof of the proposition is in Appendix A. We compute $CV$ in Section 5 (Table 5) after fitting the model parameters from data.

Compensating variation $CV$ accounts for the changes in both thermal comfort $\theta^*$ and consumption $x^*$, for welfare analysis it is useful to value these two effects separately. $CV$ however cannot be analytically decomposed into the effect of comfort and that of consumption. To overcome this difficulty, we use two facts from micro-economic theory (see chapters 2.F and 3.I.1 in Mas-Colell et al. 1995). First, the amount negative to the compensating variation is called Hicksian compensation:

$$\Delta^H \stackrel{\text{def}}{=} -CV.$$

Second, an imprecise measure of the Hicksian compensation $\Delta^H$ is the Slutsky compensation defined by:

$$\Delta^S \stackrel{\text{def}}{=} \left(p_x x^*(q_L,w) + \frac{p_g}{q_H}(\theta^*(q_L,w) - \theta_0)\right) - w.$$

By construction, $(-\Delta^S)$ equals the income of the household that remains after the thermal upgrade from $q_L$ to $q_H$ if the household maintains the pre-upgrade consumption levels $x^*(q_L,w)$ and $\theta^*(q_L,w)$. Using Walras law

$$w = x^*(q_H,w) + \frac{p_g}{q_H}(\theta^*(q_H,w) - \theta_0),$$

we rewrite $(-\Delta^S)$ as follows:

$$(-\Delta^S) = (-\Delta^S_x) + (-\Delta^S_\theta),$$

where

$$(-\Delta^S_x) \stackrel{\text{def}}{=} x^*(q_H,w) - x^*(q_L,w), \tag{8}$$

is the effect on composite good consumption, and

$$(-\Delta^S_\theta) \stackrel{\text{def}}{=} \frac{p_g}{q_H}(\theta^*(q_H,w) - \theta^*(q_L,w)), \tag{9}$$

is the effect on thermal comfort.

The share of the thermal comfort effect in the Slutsky compensation:

$$\epsilon \stackrel{\text{def}}{=} \frac{\Delta_\theta^S}{\Delta^S}. \tag{10}$$

is the expression for the so-called *rebound effect*, defined by Gillingham et al. (2016) as the difference between the actual energy savings and those forecast without any consumer and market responses to the energy efficiency improvement.

In Section 4, we exploit quasi-experimental improvements in the heating efficiency of Dutch houses to estimate $g^*(q,w)$ as a function of income and heating efficiency. Then, in Section 5, these results are used to fit the parameters of the model Equations (1) and (2), and then to compute $CV$ and its approximation $(-\Delta^S)$.[9] Having found that the difference between $CV$ and $(-\Delta^S)$ small, we proceed with the decomposition of $(-\Delta^S)$ into $(-\Delta_x^S)$ and $(-\Delta_\theta^S)$.

## 3 Quasi-experiment, data and sample

Before discussing the empirical model, we first introduce the quasi-experiment and the data. We start by describing the institutional background of Dutch social housing as this is crucial for our identification strategy.

### 3.1 Dutch social housing: residents and dwellings

This study focuses on households living in Dutch social housing. The social housing sector in the Netherlands is large and includes 2.2 million dwellings (one third of the Dutch housing stock). It offers housing at regulated rent levels to households with an income below the median. In 2020, the threshold to be eligible for social housing was around 40,000 euros yearly gross income per household (this amounts to some 33,000 euros disposable income). However, the income check is only done once, when the renter signs a contract for a new dwelling. Therefore, although the majority of social renters are low-income people, households with incomes higher than the threshold also live in the social dwellings. Figure 2a shows the distribution of social housing residents by income;

[9] Note, that, according to theory, $\Delta^S \geq \Delta^H$. Hence, the sum of the effects $(-\Delta_x^S)$ and $(-\Delta_\theta^S)$ does not exceed $CV$:

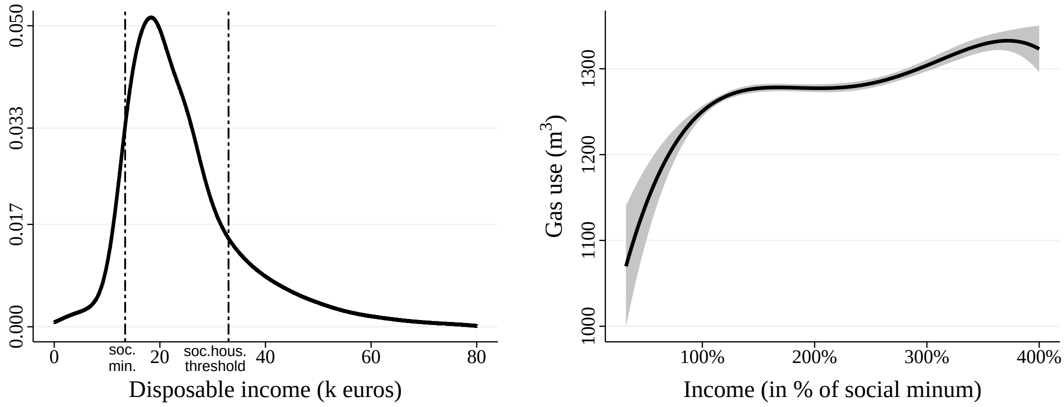
$$(-\Delta_x^S) + (-\Delta_\theta^S) = (-\Delta^S) \leq (-\Delta^H) = CV.$$

Therefore, the sum of these effects always underestimates the exact income effect $CV$.

our data offers considerable variation by income on both tails (below the social minimum and above the threshold), which we will use in our study.

Figure 2: Income and gas use in social housing 2016

(a) Distribution of disposable income (b) Gas use by income




*Notes*: Figure (a) shows the distribution of disposable income for the residents of social houses. The vertical line on the left indicates the median income of households below the social minimum (this social minimum is computed by Statistics Netherlands; its value depends on the household type). The vertical line on the right indicates the maximum income threshold to enter social housing. Figure (b) shows a polynomial fit (of degree 4) of households' gas use against income, whereby income is measured as a percentage of the social minimum in 2016.

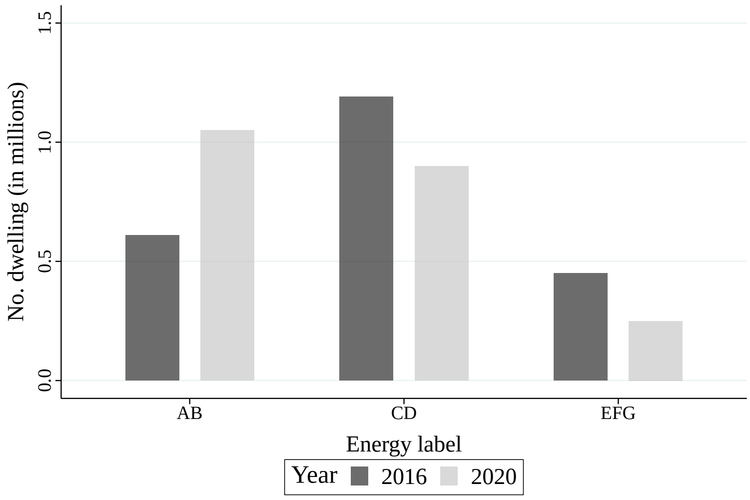
Figure 2b plots households' yearly natural gas use against their disposable incomes, for the same households as in Figure 2a. The insights from the figure are in line with the theoretical conclusions of the previous section.[10] On the one hand, gas use increases with income. On the other hand, there is a diminishing marginal effect. While the median gas use in social housing lies around 1270 $m^3$/year, the poorest consume about 20% less.

We now turn from the residents of social houses to the dwellings they live in. The potential for energy and environmental savings in the social housing sector is high. About two-thirds of the stock was built before 1993, according to the low energy efficiency building standards of that time. Social housing owners - the so-called housing associations - are required by the government to improve the energy efficiency of these properties. Home upgrades began with the 2012 Energy Efficiency Covenant, which aimed at 33% $CO_2$ savings by 2020. By 2020, half a million homes had been improved, still leaving one

[10] Note that 95% of the yearly gas used by a household is spent on thermal comfort (space heating and hot water) (Eurostat (2023)).

million homes to go.

Figure 3: Energy efficiency in social housing




*Notes*: The Figure reports the number of social houses in the Netherlands in millions, by energy efficiency label, in 2016 and 2020. Source: Aedes (2016,2020).

Figure 3 plots the distribution of social dwellings by energy efficiency in 2016 and 2020, as measured by the European energy label. This label is derived from the thermal quality of the dwelling and is assigned to dwellings by trained professionals after a technical inspection. The label takes elements such as insulation quality, heating installation, (natural) ventilation and indoor air climate, solar systems, and built-in lighting into account. The label is based on a simple universal indicator of energy use - the energy index, which reflects the engineering projection of primary energy use under average conditions. Labels 'A-B' are considered good, labels 'E-F-G' are considered bad. Figure 3 shows that the share of labels 'C' to 'G' (medium to poor energy efficiency) fell between 2016 and 2020, while the share of labels 'A' and 'B' grew. This mostly happened through heating and electricity system upgrades.[11] In this paper, we will study the effects of the heating efficiency upgrades applied to the dwellings with labels ranging from 'C' to 'G'.

### 3.2 Heating efficiency upgrades; quasi-experiment

One of the most frequent heating efficiency upgrades in social housing is *insulation of the building*, whereby materials are added to the walls and the roof to reduce heat loss and

[11] New construction was another factor that affected this shift.

the quantity of natural gas required for heating. Insulation is often seen as a prerequisite for many other energy improvements. In this and the next Sections, we study the effects of the insulation upgrades undertaken by the Dutch social housing associations between 2017-2019, on the natural gas use of the social housing residents.[12]

Two characteristics of the retrofits are important for our identification strategy and allow for a quasi-experimental approach. We highlight these here. First, the total number of dwellings that qualified for a retrofit was very large. These houses could not be improved in one go because of the financial and physical constraints. Therefore, a selection rule to prioritize certain houses was introduced. From discussions with retrofit managers from four Dutch housing associations, it appears that, during the study period, targeting was largely based on observable building characteristics (e.g. construction period, energy label) and on synchronizing the retrofit with scheduled maintenance activities (painting of exterior walls, replacement of lighting, pipes and tubes in the building).[13] Maintenance is a cyclical process where most maintenance activities are scheduled years ahead (e.g. painting is scheduled every 6 years). It is performed by *complex* - a block of adjacent houses sharing the same building year and similar technical characteristics. It is therefore plausible that the timing of regular maintenance is independent of, and uncorrelated with, the potential outcomes of insulation retrofits.[14] As a result, the assignment of qualifying houses to treatment can arguably be considered random, conditional on a few observable building characteristics such as construction year, energy efficiency and dwelling type.

The second useful feature of the social housing insulation upgrade programme is that self-selection in or out of it was impossible for individual tenants. By Dutch law, if 70% of the tenants in a complex agree to the retrofit plans (and this was usually the case in social housing), individual tenants do not have the right to opt out anymore, even if they wish to do so (see e.g. Ossokina et al. 2021). This means that we can take advantage of

[12]Insulation upgrades in our data include roof, floor, and façade insulation as well as replacing window frames and glass with energy-efficient ones. In the vast majority of cases, insulation is accompanied by the installation of a mechanical ventilation system that prevents air quality deterioration.

[13]We are grateful for these discussions to the experts of Bazalt Wonen, Elan Wonen, PreWonen and Woonbedrijf.

[14]Maintenance activities like painting, lights and pipes replacement do not affect energy efficiency of the house. The replacement of the boiler - an intervention that does affect energy-efficiency - does not fall under regular maintenance and is typically dwelling-specific.

the treated sample being representative of the social renters' population in the country.[15]

The randomness of the treatment, conditional on observed building characteristics, is an important identification assumption in the quasi-experimental evaluation we aim to perform. We will also formally test this assumption in Section 3.4.

### 3.3 Sample and data

We exploit information on insulation upgrades performed by 128 Dutch social housing associations between 2017 and 2019. The housing associations in the sample collectively own about 1 million dwellings located in all regions of the country. Our sample covers 40% of the total social housing stock and is representative of the Dutch social housing sector.

We combine two datasets. The first set includes detailed longitudinal dwelling-level data on building characteristics and energy efficiency indicators, as well as the year of retrofit, if any, for 2016-2021.[16] The second, also longitudinal, dataset contains restricted access microdata on household level made available by Statistics Netherlands. These include socio-economic characteristics of the households as well as their yearly gas and electricity use for the years 2012-2021. The two datasets are merged on address level. This yields, for one million houses, information on (1) structural house characteristics 2012-2021, (2) incidence and characteristics of insulation upgrades 2016-2021, (3) resident household characteristics 2012-2021 and (4) energy use 2012-2021.

Our main outcome variable is yearly gas use per dwelling in cubic meters. The main covariate is the binary indicator of whether a dwelling got an insulation upgrade in or before a specific year. Further, as the type and size of the insulation upgrade may differ by house, we derive a (standardized) retrofit intensity index and interact it with treatment.[17] The intensity is a continuous variable based on the engineering projections of the change in dwelling heating efficiency after the upgrade (i.e. change in the engineering-projected log gas use). Engineering projections are conventionally made under the NEN 7120 guidelines

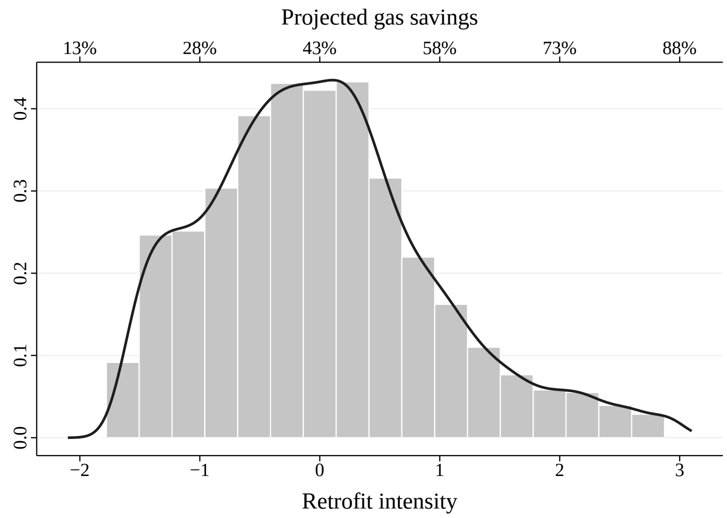
[15] We note that people could vote with their feet and relocate to another house if they did not agree with the upgrade. We will show formally that this did not happen.

[16] We thank engineering bureau Atriensis for sharing with us their Energy Monitor data, and social housing associations Bazalt Wonen, Elan Wonen, PreWonen, Woonbedrijf for sharing their expertise and additional data on retrofits.

[17] We also run regressions with retrofit intensity included as a different-order flexible polynomial and regressions without retrofit intensity, see Appendix D; this does not affect the conclusions.

by the building performance software VABI, which is used by all housing associations in our data. Figure 4 reports a histogram of the standardised retrofit intensity. Other covariates included as controls are house and household characteristics (dwelling type, construction period, surface, energy efficiency of the house, household type, number of persons, education, income, etc.).

Figure 4: Distribution of retrofit intensity




*Notes*: The figure shows the distribution of the retrofit intensity in the data sample used in this paper. We define the retrofit intensity as the standardized projected gas savings. The projected gas savings are the difference between pre- and post-retrofit projected log gas use. Projected gas use is computed by the engineering building performance model VABI.

To test the hypothesis about divergent responses of households at the left tail of the income distribution, we make use of the social minimum indicators defined by Statistics Netherlands. The definition of the social minimum is the 'minimal amount one needs in order to cover basic personal needs' (Statistics Netherlands). The amount is determined yearly and is derived from the size of the social welfare benefits. It therefore depends on the composition of the household. For example, in 2017 the social minimum equalled a monthly disposable income of €1,040 for a single person, €1,380 for a one-parent family with one child, and €1,960 for a couple with two children. We will distinguish three strata of poor households: those below (i) 100%, (ii) 130%, (iii) 150% of the social minimum.

### 3.4 Treatment and control group, balancing test

In the main analysis, we will focus on single-family dwellings that qualified for an insulation upgrade in 2016, according to two criteria: building year before 1993, energy label 'C' to 'G'.[18] We drop dwellings with missing data on energy efficiency and energy use, student condominiums, and dwellings without individual natural-gas-based heating during the study period. The resulting study sample contains 124,300 single-family dwellings, of which 13,409 belong to the treatment group and 110,891 to the control group. The treatment group is defined as houses that got an insulation upgrade between 2017 and 2019 and did not change tenants between one year before and one year after the retrofit. The control group is defined as dwellings that did not experience an energy efficiency upgrade between 2000 and 2021.

Table 1 presents the means of descriptive statistics for the treatment and the control group in 2016, the year before treatments began. As explained in Section 3.2, our identification strategy will rely on the assumption of random treatment assignment, conditional on the observed imbalance in housing characteristics. The descriptive statistics provide support for this assumption. Panel A of the table shows that household socio-economics are well-balanced. Panel B reports that dwelling characteristics are not: older and less energy-efficient homes are overrepresented in the treatment group. Panel C documents the means of gas and electricity use residuals after conditioning on the housing observables from panel B. That is, we regress baseline energy use on dwelling characteristics and report the residuals as a share of the baseline mean energy use for tractability. These residuals represent variation in energy use not explained by housing characteristics, and they are well-balanced between treatment and control groups. This supports the assumption of conditionally random assignment—i.e., treatment is as good as randomly assigned, once we control for housing characteristics. By including dwelling fixed effects and dwelling time-varying covariates in our econometric model, we will explicitly account for the imbalance in housing characteristics, allowing for identification of treatment effects based on within-dwelling variation over time.

[18] In Appendix H, the whole analysis is replicated for apartments. We did not pool the two due to sizeable differences in gas use and retrofit intensity.

Table 1: Balance between treatment and control groups at baseline

| | Mean treatment | Mean control |
|---|---|---|
| **Panel A: Socio-economics** | | |
| No. persons | 2.13 | 2.09 |
| No. children | 0.63 | 0.58 |
| No. seniors | 0.51 | 0.51 |
| Income (k euroyear) | 26.63 | 27.43 |
| Education high (0/1) | 0.10 | 0.10 |
| Migration background foreign (0/1) | 0.22 | 0.20 |
| Below 100% social min. (0/1) | 0.03 | 0.03 |
| Below 130% social min. (0/1) | 0.27 | 0.26 |
| Below 150% social min. (0/1) | 0.38 | 0.37 |
| **Panel B: House characteristics** | | |
| Surface ($m^2$) | 94.79 | 94.27 |
| Constr. Period 1906-1939 (0/1) | 0.06 | 0.07 |
| Constr. Period 1940-1965 (0/1) | 0.53 | 0.30 |
| Constr. Period 1966-1976 (0/1) | 0.38 | 0.32 |
| Constr. Period 1977-1992 (0/1) | 0.03 | 0.31 |
| Energy label EFG (0/1) | 0.45 | 0.26 |
| **Panel C: Residualized energy use** | | |
| Electricity | $-0.03$ | 0.00 |
| Gas | $-0.00$ | 0.00 |
| No. houses/households | 13409.00 | 110891.00 |

*Notes:* Panel A and B report the mean values of the covariates, at baseline (i.e. year 2016). Panel C reports the mean of the residuals after regressing energy use at baseline on house characteristics from Panel B. For tractability, residualized energy use is presented as a fraction of the mean energy use at baseline.

# 4 Gas savings from retrofits: average and poor

## 4.1 Empirical model

Our main empirical method is a two-way fixed-effect panel regression with year and household/dwelling fixed effects (Angrist and Pischke, 2008).[19] As the sample is defined to only include households that lived in the dwelling at the time of the retrofit, the dwelling and household fixed effects coincide. We will start with an event-study specification:

$$g_{i,t} = \sum_{L=-5}^{4} R_{i,t-L}\alpha_L + \delta X_{i,t} + \gamma_i + \phi T_t + u_{i,t}. \tag{11}$$

Here, $g_{i,t}$ is the (log) yearly gas use of household/dwelling $i$ in year $t$. The binary treatment variable $R_{i,t}$ takes the value 1 in the years following the retrofit and 0 otherwise; $L$ are lags that account for dynamic effects; $X_i$ controls for time-varying observable characteristics of the household (e.g. size) and dwelling (e.g. new boiler installed); $\gamma_i$ are household/dwelling time-invariant fixed effects; $T_t$ are year fixed effects, and $u_{i,t}$ is the idiosyncratic error term.

For the heterogeneity analysis, the average treatment effect in years 2 to 4 after the home upgrade will be estimated:[20]

$$g_{i,t} = R_{i,t}\left(\alpha + \beta S_i\right) + \delta X_{i,t} + \gamma_i + \phi T_t + u_{i,t}. \tag{12}$$

We include the retrofit intensity (see Section 3.3 for the definition) as a treatment-effect moderator, $S_i$. The coefficient $\alpha$ can be interpreted as the average treatment effect on the treated (ATT). When we include the retrofit intensity moderator, $\alpha$ can be interpreted as the effect of an insulation upgrade of *average intensity*, which is useful to compare treatment effects across subgroups. We estimate subgroup heterogeneity by interacting the treatment term $R_{i,t}\left(\alpha + \beta S_i\right)$ with subgroup dummies.

## 4.2 Identification

To derive a causal effect of a heating efficiency improvement on natural gas use, we exploit a treatment and a control group as defined in Section 3.4. The internal validity

[19] We will also test the robustness of the results to the recent advances in staggered treatment effect estimation (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

[20] We control separately for the retrofit year because of the noise in the data - we do not know in which month the retrofit was performed. We also control separately for year 1, based on the results of the event study.

of this approach hinges on the assumption that the treatment assignment was random, conditional on observed dwelling characteristics. Table 1 provided a formal test to support the assumption. Inclusion in the regression of dwelling fixed effects and dwelling time-varying controls accounts for the imbalance in dwelling characteristics.

Below we discuss a number of possible remaining identification concerns. The first concern is related to self-selection. We want to rule out the possibility that wealthier people self-selected to dwellings with better energy efficiency, e.g. because they qualified for these once in the past, and do not want to move out after their income increased. We also want to rule out the possible correlation between the retrofit intensity and household income. Table B1 in Appendix B shows that both, pre-retrofit energy efficiency of the house and retrofit intensity are practically the same across 10 income deciles in our data, and the F-test confirms that there are no statistically significant differences.

The second concern is attrition. As discussed in Section 3.1, by law, tenants could not opt out of the insulation retrofit program while living in the dwelling. They could, however, avoid the retrofit by moving out of the dwelling. To tackle this concern, we compare the moving rates between households in the treatment and control groups in 2016 and conclude that these are almost identical: people did not move out to avoid the insulation upgrade.[21] After the treatment, we do see a small difference in attrition. This need not be a problem, however, because the movers in the treatment and control groups do not differ in gas use: the average difference is less than 2% and is not statistically significant in both pre-retrofit and post-retrofit years (2016 and 2021). Additionally, in one of the robustness checks, we will remove the never-treated control observations from the sample and re-estimate the treatment effect using the not-yet-treated as a control group. We will show that the results are robust to this exercise; see Appendix E, Table E1.

Further, we note that pre-retrofit energy efficiency of the dwelling is negatively correlated with the retrofit intensity. Reason is that the 2012 Energy efficiency covenant prescribed an upgrade to at least a (high) energy label B.[22] Consequently, the lower the initial energy efficiency, the larger the assigned retrofit intensity would be, ceteris paribus. Equation (12) accounts for this by including the retrofit intensity in a linear way in the regression. We run various checks to ensure that the assumed functional form does not

[21] The attrition rates between households in the treatment and control groups are 3.33% and 3.30%, respectively.

[22] See Section 3.1 for an explanation of the energy label system.

affect the treatment coefficient. We will show that the results are robust to the alternative specification using a flexible higher-order polynomial in retrofit intensity, as well as a specification without retrofit intensity, Appendix F. We also regress the retrofit intensity on socio-economic characteristics and show that they are not correlated to the retrofit intensity Table B2.

Finally, we may be worried that some 40% of the treated houses received PV panels simultaneously with insulation, within the same package. PV panels do not change the price of electricity for a household, but directly affect the budget by producing 'free electricity'. This lump-sum change in income may affect the re-optimization of gas use, and thus bias the treatment coefficient. However, in the Netherlands, housing associations charge service costs of around 2.5 euro per PV panel (prices 2016) to their tenants. Subtracting this from the monthly yields–as documented by the housing associations we talked with–results in a minimal income effect of around €100 per year that is unlikely to affect the results. For this reason we decided to keep the homes with PV panels in the sample and control for the possible effect of PV by including a dummy in the econometric model. Further, we will show in a sensitivity check that the treatment effect is unaffected by the availability of solar (Appendix D, Table D5).

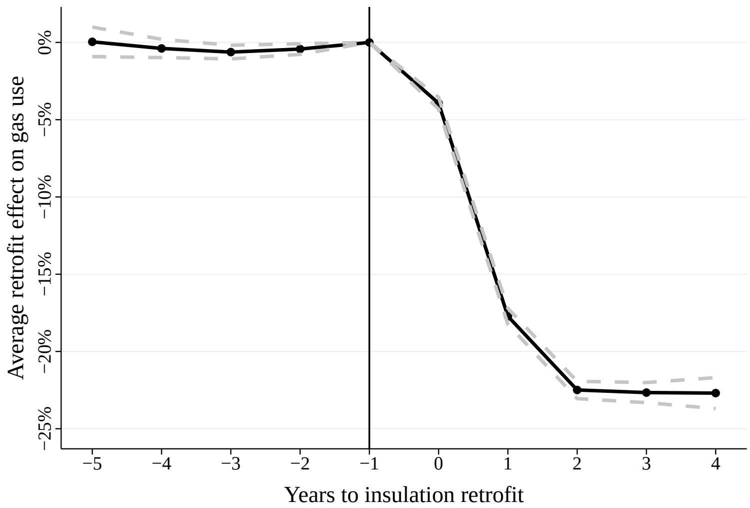
### 4.3 Empirical results

#### 4.3.1 Average treatment effect and effect for the poor

We start by reporting the yearly effects of insulation upgrades from the event study Equation (11). These are plotted in Figure 5. As expected, the figure shows point estimates close to zero in the five years before the upgrade, and a gradual increase in the absolute size of the effect after, from 19% gas savings in the first year to 22% in years two to four. Note that the effect in the year of the upgrade is not informative, because we do not know the exact month in which the retrofit was performed. In sum, it takes households two years to adjust their behaviour.

Table 2 reports the estimated average treatment effect from Equation (12) where the retrofit intensity moderator is included. To account for the adjustment process, we control for the year of retrofit and the year after with separate dummies. The results in the table should thus be interpreted as the estimated effect in the years two-four after an insulation upgrade of average intensity. Columns (1) to (4) report different specifications: with or

Figure 5: Gas savings from heating efficiency upgrade: event study by year




*Notes*: Plotted values are the coefficients of the interaction effect of the treatment indicator with the year-to-retrofit, see Equation (11). Year -1 (vertical line) is the last pre-retrofit year. The dashed lines represent the 95% confidence interval. Standard errors are clustered at household level.

without household/dwelling fixed effects and with or without controls.[23] Our preferred specification (4) includes household and year fixed effect, as well as household controls. The main finding is that an insulation of average intensity reduces natural gas use of households by about 22%. One standard deviation increase in retrofit intensity reduces gas use by another eight percentage points.[24]

We note that this table further supports our assumption that the treatment assignment is random, conditional on dwelling characteristics. Indeed, controlling explicitly for observed dwelling characteristics (Column (3)) or using dwelling fixed-effects (Columns (2) and (4)) yield an almost identical average treatment effect.

Table 3 reports the estimated average treatment effect for poor households. Here, Equation (12) was run three times, including a two-way interaction of the After retrofit indicator with each time another poverty dummy indicator, as defined in Section 3.3. In line with the theoretical model, we find that the magnitude of the gas savings falls with

[23]Table C1 in Appendix C reports the full set of coefficients for the four specifications.

[24]In Appendix F we include retrofit intensity in different functional specifications, including a flexible polynomial and a specification without the intensity variable. The average treatment effect is robust, the higher order terms are not statistically significant.

Table 2: Average effects of insulation retrofit on gas consumption

| Dependent: log of yearly natural gas use | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| After retrofit (year $\geq$ 2) | -0.149*** | -0.228*** | -0.228*** | -0.218*** |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| $\times$ Retrofit intensity | -0.058*** | -0.077*** | -0.100*** | -0.078*** |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| No. obs. | 963459 | 963459 | 959073 | 959073 |
| No. treatment houses | 13409 | 13409 | 13409 | 13409 |
| No. control houses | 110891 | 110891 | 110891 | 110891 |
| $R^2$ Adj. | 0.021 | 0.822 | 0.144 | 0.826 |
| Year fixed-effect | X | X | X | X |
| Household fixed-effect | | X | | X |
| Controls | | | X | X |

*Notes:* The table shows estimates of four separate regressions. The dependent variable is the log of gas use. Standard errors in parentheses are clustered at household level. Statistical significance: *p<0.1; **p<0.05; ***p<0.01.

income, more so at the very left tail of the income distribution. The poorest (below 100% social minimum) show one-third smaller savings than the average; those below 130% of the social minimum show one-tenth lower savings.

The above analysis provides empirical support for the hypothesis that the lowest incomes realise smaller gas savings after a heating efficiency upgrade. The underlying mechanism we hypothesised in the theoretical model is that poor households reoptimise their heating use patterns after retrofit more than others, because their pre-retrofit thermal comfort was relatively far from the satiety threshold.

### 4.4 Robustness checks

We test the results in Table 3 through several sensitivity analyses. In Appendix D, we re-estimate the model of Equation (12) for different subsamples, considering variations in: (i) the year the insulation upgrade occurred (2017, 2018, 2019), Table D1; (ii) the dwelling's energy label (C, D, E, F, G), Table D2; (iii) socio-economic characteristics, Table D3; (iv) pre-retrofit gas use, Table D4; (v) whether or not PV panels were installed simultaneously with the insulation, Table D5.

Table 3: Effects of retrofits for poor households

| | Baseline |
|---|---|
| After retrofit (year $\geq$ 2) | $-0.218$ (0.003)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.062 (0.016)$^{***}$ |
| $\times$ Below 130% soc.min. | 0.025 (0.006)$^{***}$ |
| $\times$ Below 150% soc.min. | 0.018 (0.006)$^{***}$ |

*Notes*: The table shows estimates of Equation (12) for 4 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D1 shows that the results remain consistent across all years. At first glance, Table D2 suggests that the average treatment effect is the same across pre-retrofit energy labels. This seemingly counterintuitive result can easily be explained: the pre-retrofit energy label is correlated with the retrofit intensity, which we use as treatment effect moderator. In a specification without this moderator, the retrofit effect would range from 18% for the relatively efficient label 'C' to 29% for the highly inefficient label 'G'. Table D3 shows that the treatment effect varies by household type, with singles achieving larger savings and households with a migration background saving less. Table D4 shows that pre-retrofit gas use influences the results: households with higher heating demand save more, both in absolute and relative terms. Households with low heating demand save little. Finally, Table D5 documents that the results are robust by solar panel availability. Overall, despite smaller samples reducing statistical significance, the result that poor households have lower savings remains robust across subsamples.

In Appendix E, we replicate the results of Table 3 using two state-of-the-art methods that account for possible biases due to the staggered treatment: Sun and Abraham (2021) and Callaway and Sant'Anna (2021). The results are reported in Table E1 and are robust.

Then we rerun the model using alternative model specifications, see Appendix F. These include: (i) various functional form specifications to include the retrofit intensity in the model, Table F1; (ii) including group-specific time trends, Table F2. Both the average treatment effect and the specific low-income response shown in Table 3 hold under these modeling specifications.

Finally, Appendix H shows that the above findings, which were obtained on a sample of single-family dwellings, also hold for apartments.

## 5 Welfare effects

In this section, we develop a computable version of the consumer choice model Equations (1) and (2). The model is then used to assess the welfare effects of the heating efficiency retrofits that took place in the Dutch social housing sector between 2017 and 2019, in different scenarios and for different income groups.

### 5.1 Parameters of the computable model

We begin by making some assumptions. The gas price is set to the 2016 (the year before the insulation upgrades in our data started) level of consumer gas price according to Statistics Netherlands (2024), $p_g$ = € 0.65 per cubic meter.[25] The price of other consumption is normalized to 1. We assume that the preference parameters $\bar{\theta}, \sigma$, the natural temperature $\theta_0$, and the pre-retrofit and post-retrofit heating efficiencies $q = q_L$ and $q = q_H$ take the same values for all income levels (i.e. all households). The assumption about income-independent pre-retrofit and post-retrofit energy efficiency of a home is supported by the data, see the analysis of Table B1, Appendix B. The above assumptions ensure that, conditional on $q$, any differences in the consumer choices come through variation in income.

Now we can derive the empirical values for the model parameters by fitting the consumer choice model solutions to data, using non-linear weighted least squares. More specifically, we simultaneously fit (i) the model prediction of low-heating-efficiency gas use by income, $g^*(q_L, w)$, to the observed distribution of gas use $g$ by income in 2016[26] and (ii) the model prediction of gas savings by income $[g^*(q_H, w) - g^*(q_L, w)]$ to the

[25] We use national level gas prices since we do not have house level prices.

[26] Note that in our data, there are not observations with zero gas consumption, so the model always has an interior solution.

Table 4: Computable model parameters

| Description | Parameter | Value | Confidence interval |
|---|---|---|---|
| Exogenously chosen parameters | | | |
| Price of gas (euro/$m^3$) | $p_g$ | 0.65 | |
| Price of other consumption | $p_x$ | 1 | |
| Elasticity of substitution | $\sigma$ | 1 | |
| Satiety level of thermal comfort ($^o$ C) | $\bar{\theta}$ | 24.22 | |
| Estimated parameters | | | |
| Indoor temperature at g=0 ($^o$ C) | $\theta_0$ | 10.46 | [7.75;12.28] |
| Energy efficiency before retrofit ($^o$ C/$m^3$) | $q_L$ | $\frac{1}{106}$ | $[\frac{1}{125};\frac{1}{86}]$ |
| Energy efficiency after retrofit ($^o$ C/$m^3$) | $q_H$ | $\frac{1}{85}$ | $[\frac{1}{99};\frac{1}{70}]$ |

*Notes:* Value and Confidence interval report the mean and 95% confidence interval from bootstrapping. The inverse values of $q_L$ and $q_H$ can be interpreted as the amount of gas required to gain one additional degree of indoor temperature.

quasi-experimental estimates of gas savings after retrofit $\hat{\alpha}$ from Equation (12), again by income. Standard errors for the parameters are computed by bootstrapping. Appendix G documents further details of this procedure. The results suggest we cannot reject the hypothesis that the elasticity parameter $\sigma$ equals unity, supporting a Cobb-Douglas utility function. We therefore set $\sigma = 1$. To avoid overparameterization under this functional form, we fix one additional parameter. Specifically, we set the satiety level of thermal comfort, $\bar{\theta}$, to a fixed value.[27]

Table 4 reports the resulting parameter values, including the means and the 95% confidence intervals.

### 5.2 Validation of the computable model

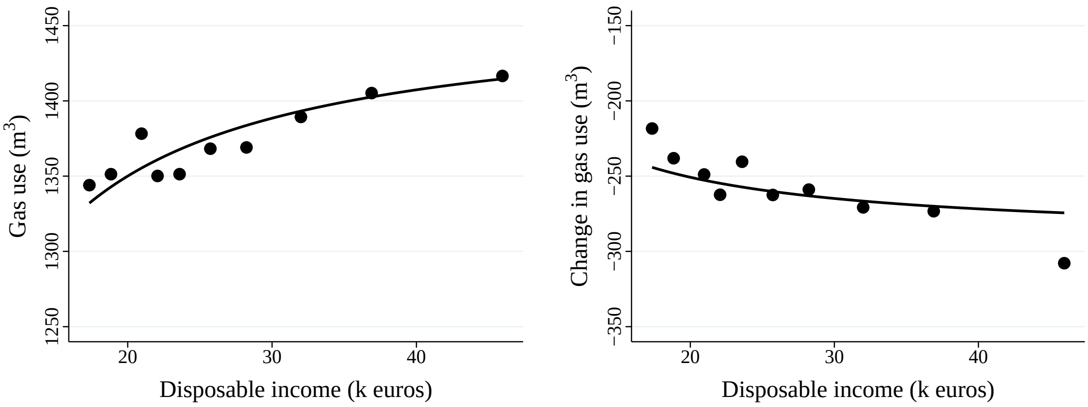
We perform a number of validation tests for the model parameters. First, Figure 6 shows that the model fits the gas use by income distribution well, both before and after the heating efficiency upgrade. If anything, we note that the model overestimates the gas savings in the lowest income decile and underestimates them in the highest income decile.

Second, we aim to assess how realistic the model's prediction of the retrofit-induced temperature change $\theta^*(q_H, w_d) - \theta^*(q_L, w_d)$ is, resulting from households adjusting their consumption for higher thermal comfort after the heating efficiency improvement. The

[27] We could have chosen any other parameter instead of $\bar{\theta}$.

Figure 6: Model fit: gas use before and after heating efficiency upgrades

(a) Pre-retrofit gas use ($m^3$) (b) Retrofit effect on gas use ($m^3$)




*Notes*: The dots represent observed values (left) and quasi-experimental estimates (right). The lines show predictions from the computable model. Panel (a) illustrates the median gas use across income deciles. Panel (b) illustrates the average effect of a heating efficiency upgrade on gas use across income deciles. Both figures use data from our research sample.

model predicts a temperature increase between 0.1 and 0.7 degrees Celsius, which decreases with income. We are aware of only a few small-scale studies measuring the effect of heating efficiency upgrades on indoor temperature, and these report similar magnitude of temperature changes, e.g., Fisk et al. (2020), Fowlie et al. (2018).

Finally, we can validate the implied price elasticity of gas use, which in our model ranges from -0.04 to -0.27. This is consistent with earlier findings, see, e.g., Asche et al. (2008). In conclusion, our computable consumer choice model provides realistic responses to exogenous shocks in heating efficiency and gas prices.

### 5.3 Welfare outcomes

Now we apply the computable consumer choice model to value the benefits from the Dutch heating efficiency programme 2017-2019 that was described in Section 3 and exploited in the quasi-experiment of Section 4.[28] Two scenarios are defined: (i) a reference scenario, for which the model parameters were calibrated (Table 4); (ii) a counterfactual, in which the gas price is set to the high level $p_g = 1.36$ euro/m$^3$ it reached in 2022, while the rest of the parameters remain unchanged. For both scenarios, we evaluate the private benefits

[28]Parameters $q_L$ (low heating efficiency, before the upgrade) and $q_H$ (high heating efficiency, after the upgrade) in Table 4 describe the upgrade homes received through the programme, on average.

from heating efficiency upgrades (i.e. following the change from $q_L$ to $q_H$). We use the Hicksian compensating variation (Equation (7)) as well as the Slutsky decomposition into the benefits of increased thermal comfort (Equation (9)) and the benefits of increased other consumption (Equation (8)).[29] All effects are calculated using a bootstrapping procedure, and the confidence intervals are reported.

Table 5 reports the welfare effects in euros as well as the underlying changes in indoor temperature, natural gas use and related $CO_2$ emissions, for three income levels: low (below the social minimum), average (median of the income distribution in our study sample) and high (75th percentile of the same income distribution).[30] Figure 7 shows the size and the Slutsky decomposition of the welfare benefits for the whole income distribution, using mean parameter values from Table 4.

We start by discussing the physical changes in gas use and thermal comfort after the home upgrade (columns 2-3 Table 5). Note first that, in the counterfactual, the indoor temperature increase is twice as large and the gas savings are 1.5 times smaller than in the reference. These differences are statistically significant. The reason is that more expensive heating services in the counterfactual make households increasingly sacrifice thermal comfort and choose uncomfortably low temperatures when $q = q_L$. The resulting high marginal utility of a one-degree temperature increase leads to larger adjustments in indoor temperature after the home upgrade. Lower natural gas savings follow. Second, fully in line with the theoretical insights from Section 2, indoor temperature improvement decreases with income, while natural gas savings rise with income. For example, for the poor, the temperature increase after retrofit reaches 0.3 degrees in the reference scenario and 0.7 degrees in the counterfactual; this is three times as much as for the higher-income households. The gas (and $CO_2$) savings of the low-income households are 13% to 30% lower than those of their more affluent peers.

Looking at the monetary valuation of the above changes (see columns (5)-(8) of Table 5 and Figure 7), we note that the private benefits of the home upgrades are distributed

[29] We note that the Slutsky and Hicksian (columns (5) and (8) in Table 5) valuations of private benefits are very similar; this allows us to use a Slutsky decomposition of the total effect into the change due to thermal comfort and other consumption.

[30] Changes in indoor temperature and natural gas use follow from the solutions of the consumer maximisation problem under $q_L$ and $q_H$, see Appendix A. $CO_2$ reduction is computed from natural gas savings under the usual assumption of 1.79kg $CO_2$ emissions per cubic metre of natural gas use (RVO, 2021).

Table 5: Program effects and private benefits, by income

| Income | Private and external effects | | | Private benefits (euro) | | | |
|---|---|---|---|---|---|---|---|
| | $\Delta$ Temp. | $\Delta$ Gas | $\Delta CO_2$ | Slutsky valuation | | | Hicksian val. |
| | $^{\circ}C$ | $m^3$ | $kg$ | $-\Delta^S$ | $-\Delta^S_\theta$ | $-\Delta^S_x$ | $CV$ |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | In prices 2016 (0.65 euro/$m^3$) | | | | | | |
| low | 0.28 | −238 | −426 | 170 | 15 | 154 | 172 |
| | [0.23; 0.34] | [−246; −229] | [−441; −411] | [166; 174] | [10; 21] | [149; 160] | [168; 176] |
| average | 0.18 | −257 | −461 | 177 | 10 | 167 | 178 |
| | [0.14; 0.21] | [−263; −252] | [−471; −451] | [172; 183] | [6; 13] | [163; 171] | [173; 184] |
| high | 0.10 | −273 | −489 | 183 | 5 | 177 | 183 |
| | [0.08; 0.12] | [−281; −265] | [−504; −474] | [176; 189] | [3; 7] | [172; 183] | [176; 190] |
| | In prices 2022 (1.36 euro/$m^3$) | | | | | | |
| low | 0.62 | −173 | −311 | 310 | 73 | 237 | 319 |
| | [0.51; 0.72] | [−202; −146] | [−361; −261] | [295; 324] | [48; 98] | [199; 275] | [306; 331] |
| average | 0.40 | −216 | −388 | 342 | 46 | 296 | 348 |
| | [0.32; 0.47] | [−231; −202] | [−413; −362] | [335; 351] | [30; 63] | [276; 315] | [341; 356] |
| high | 0.21 | −251 | −449 | 368 | 25 | 343 | 371 |
| | [0.17; 0.26] | [−257; −245] | [−460; −439] | [358; 377] | [16; 34] | [335; 351] | [360; 382] |

*Notes:* The Table reports the effects of the average retrofit in our data, as predicted by the computable choice model. Choice model parameters $\theta_0$, $q_L$ and $q_H$ are estimated, other parameters are exogenously chosen. Mean and 95% confidence interval (between brackets) from bootstrapping. This is done for two scenarios (reference with gas prices of 2016 and counterfactual with gas prices of 2022) and for three income groups (low, average and high, respectively 16keuro, 24keuro and 43keuro in disposable yearly income). Columns (2) and (3) document the changes in consumption of temperature respectively yearly gas, following the retrofits. Column (4) reports the change in annual $CO_2$ emissions, assuming 1.79$kg$ $CO_2$ per $m^3$ of natural gas. Column (5) reports the valuation of the private benefits of the retrofits using the Slutsky compensation. Column (8) reports the same valuation using the Hicksian compensation (compensating variation). Columns (6) and (7) decompose the Slutsky compensation into the parts that arise due to the change in temperature consumption respectively the change in consumption of other goods. The Table shows yearly outcomes.

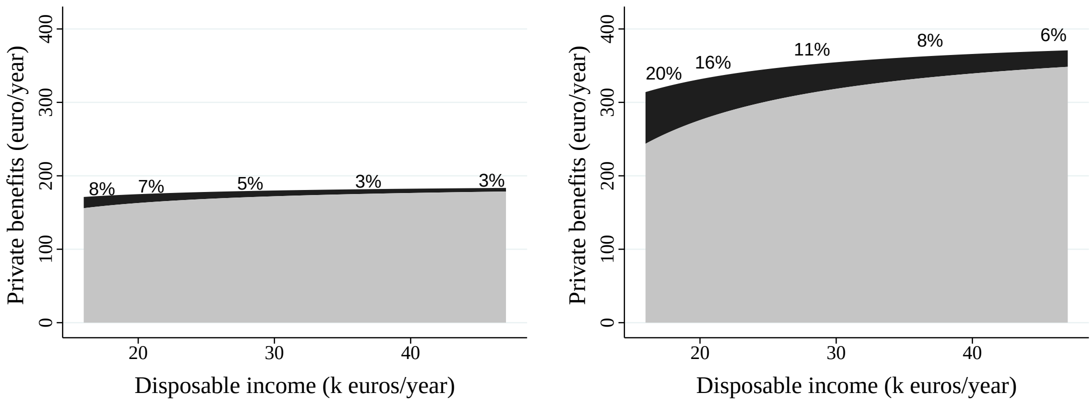
unevenly among income levels: the gains for the poor are 6 to 14% lower compared with their higher-income peers. This is again intuitive. Remember that low-income households use less gas before the upgrade (see e.g. Figure 2b). Therefore, their potential savings from heating efficiency upgrades are also smaller. However, the gains relative to disposable income are larger for the poor.

Figure 7 illustrates graphically the income heterogeneity in the distribution of the private benefits of the home upgrade between thermal comfort improvement, on the one hand, and other consumption, on the other. It is noteworthy that the comfort benefits from temperature increase make up a substantial part of the total gains, more so for the low-income households. In the reference scenario with low gas prices, the comfort benefits amount to 8% of the total utility increase for the social minima and only 3% for the richer households. In the counterfactual with high gas prices, the comfort benefits make up 20% and 6% of the total gains for the two groups, respectively. This share of thermal comfort improvement in the overall welfare benefits represents what in the literature is called *rebound effect*: the difference between the achieved reductions in energy use and those forecast without any consumer and market responses to the energy efficiency improvement (Gillingham et al. 2016 and Equation (10)). While the average rebound effect for our data equals 5% and is in line with the literature (e.g. Christensen et al. 2023; Fowlie et al. 2018), we note the large heterogeneity by income.

So far, we have valued the *private* benefits of heating efficiency upgrades. The next logical step is to extend the cost-benefit analysis by including the external effects on the environment. Two counteracting forces need to be accounted for. The first is the *positive* externality of avoided $CO_2$ emissions. Here again, income heterogeneity plays a role: smaller gas savings of the poor translate one-to-one to lower environmental ($CO_2$) benefits (Table 5). From a policy perspective, this insight points to a trade-off that accompanies policies subsidising heating efficiency improvements for low-income households. Reducing poverty and increasing living comfort for the poor comes at the expense of lower environmental benefits. There is, however, also a second - *negative* - externality that arises due to the fact that the consumer price of natural gas in the Netherlands for 50% consists of the excise duty. Lower gas consumption after the upgrade results in a decrease in tax revenues and therefore less governmental spending on public goods. The sign (positive, zero or negative) of the sum of the two externalities depends on whether the excise duty is set

Figure 7: Size and Slutsky decomposition of welfare gains, by income

(a) Reference scenario (b) Counterfactual scenario




*Notes*: The graph shows the Slutsky compensation (i.e. private benefits) over the income distribution. The black and grey ribbons are the Slutsky compensation due to increase in thermal comfort and consumption of composite good respectively. The percentage above the black ribbon is the share of thermal comfort in the private benefits (i.e. the rebound effect).

equal to, lower than, or higher than the optimal (Pigouvian) tax. Our quasi-experimental results provide some support for the assumption that the excise duty exactly internalises the negative environmental externality and can be seen as Pigouvian.[31] Then, the positive and negative externalities exactly compensate each other, and the private and the social benefits from home upgrades coincide.

To gain insight into the returns from the heating efficiency program, we compare the net present value (NPV) of the welfare gains from home upgrades reported in Table 5 to the investment cost. We use a discount rate of 2.25%, which is prescribed for Dutch cost-benefit analyses, and take a time horizon of 30 years, which is roughly half of the technically feasible lifetime for home insulation upgrades in the Netherlands. The NPV then ranges between 3.8 and 4.0 thousand euros per household in the reference scenario, and 7.1 to 8.2 thousand euros in the counterfactual (the left and right endpoints of the

[31] Take the consumer gas price of 0.65 euro/$m^3$ in the reference scenario, then the tax equals 0.33 euro/$m^3$. Based on our quasi-experimental results, the average reduction in tax revenue is 265$m^3$/year*0.33euro/$m^3$=90 euro/household/year. The corresponding reduction in $CO_2$ amounts to 474kg/household/year, implying an implicit valuation of 90/0.474=190euro per ton $CO_2$. This valuation is very close to the mean of the existing estimates for the societal benefits of $CO_2$ reduction, which range from 40 to 400 euro/ton/year (Rennert et al., 2022).

reported ranges are for low and high-income households, respectively, from Table 5). Based on various sources we consulted, the cost of an average home upgrade in our data is around 7 thousand euros, in 2016 prices, including VAT.[32] Our analysis suggests, therefore, that the private benefits from gas savings and comfort increase are comparable to the investment cost at high gas prices but fall short of these otherwise.

It is instructive to compare the costs and benefits of the insulation upgrades in the Netherlands, reported above, with the documented welfare effects of the widely studied US Weatherization program (e.g. Fowlie et al. 2018; Christensen et al. 2024, 2023). The Weatherization retrofits studied by these authors involved attic and wall insulation, infiltration reduction, and furnace replacement, and are thus comparable to the Dutch heating efficiency program. While the Weatherization program results in comparable relative gas savings of 20%,[33] its corresponding benefits are much lower due to (i) lower gas prices (0.35 dollars/$m^3$ against 0.65 euros in the reference and 1.36 euros in the counterfactual in our study) and (ii) a shorter expected life cycle of the home upgrade (16 years in the US). Furthermore, it is noteworthy that the documented investment cost in the US is around 1.5 times smaller than in the Netherlands (4600 dollars against 7000 euros).

In summary, we find a possibility of positive private returns from heating efficiency retrofits in the counterfactual, but not in the reference. The question naturally arises: which scenario is more likely to occur in the coming years? For Europe, we argue that there are reasons to expect positive returns. First, in many European countries, governments are keen to use price instruments like the excise duty to stimulate households to switch to energy-saving technologies. For instance, in the Netherlands, gas prices peaked in 2022 due to exogenous factors and remained high thereafter because of the increased excise. Second, one could expect heating efficiency upgrades to yield other private benefits as

[32]Based on Schep et al. (2022) but also talks with housing associations' employees, a full insulation upgrade costs between 12 and 14 thousand euros in 2016 prices, including VAT. A full upgrade implies that a house that did not have insulation at all gets HR+ glass in all windows; insulation of the roof, wall, and floor to the level of RC=5, RC=2, RC=3.5, respectively; and mechanical ventilation to preserve air quality. Our consumer choice model works with the insulation upgrade of average retrofit intensity, which is approximately half as effective as the full upgrade (see Figure 4). Therefore, we take 50% of the upper bound of the cost, arriving at 7 thousand euros.

[33]The absolute gas savings are larger in (Fowlie et al., 2018), as the average household there uses 80MMbtu or 2400$m^3$ gas per year, which is almost twice the average for the Netherlands.

well, besides those studied in our paper. These include, among other things: health improvement due to reduced exposure to draught and extreme temperatures (Maidment et al., 2014; Roberdel et al., 2025) and poverty alleviation gains (Banerjee et al., 2021).

## 6 Conclusion

Energy efficiency improvements in low-income housing are increasingly used as a policy tool to alleviate poverty. This paper examined the welfare trade-offs of such policies, showing that targeting the poor may come at the cost of lower environmental benefits. We evaluated a large nationwide Dutch program of heating efficiency upgrades in social housing, focusing on income heterogeneity in program effects and the behavioural mechanisms behind it. The analysis draws on a panel of 125,000 households over eight years, leveraging substantial income variation and a conditionally random treatment assignment. We combined quasi-experimental two-way fixed effects estimation with a computable microeconomic model of consumer choice between thermal comfort and other consumption.

Our study yields three main findings. First, the lowest-income households achieved substantially smaller gas savings than the average. Quasi-experimental estimates show that, following an upgrade, households on social minimum incomes reduced gas use by 16%, compared to 22% on average. Second, this heterogeneity is explained by behavioural responses: our structural model suggests that low-income households reinvest up to 20% of potential savings into higher indoor temperatures, while higher-income households reinvest only 5%, having already enjoyed higher comfort levels pre-upgrade. Third, at low gas prices, the private welfare benefits fall short of retrofit costs. But when prices reach levels observed since 2022, heating efficiency investments yield positive private returns—even for the poorest. For Europe, we argue that high energy prices may persist, making positive returns plausible.

Our analysis has strengths and limitations. The quasi-experimental design exploits a unique conditionally random assignment and rich administrative data, allowing for credible identification of causal effects. The combination of reduced-form and structural approaches enables us to quantify behavioural responses and welfare trade-offs in a way that few existing studies have done. The large sample and institutional setting support external validity, particularly within the European social housing context. At the same time, the welfare effects we computed are likely an underestimation of society's benefits due to the heating efficiency upgrades. Among other things, insulation-induced reduction in draught and mould may have a positive impact on the inhabitants' health (Maidment et al., 2014). More research into these effects is needed. Further, our structural model infers comfort preferences from consumption behaviour and income rather than from direct measurements of temperature. While our approach is particularly suitable for the large-scale renovations of old low-income homes, for which temperature measurements are mostly unavailable, it does rely on rationality assumptions and may not account for behavioural frictions. Finally, our analysis focuses on social housing; while this sector is substantial in the Netherlands and includes a range of incomes, results may not fully generalise to owner-occupied dwellings.

Concluding, our study provides novel evidence on the benefits and trade-offs of using heating efficiency upgrades as an instrument to alleviate poverty. While, specifically for the left tail of the income distribution, societal gains may be achieved through poverty alleviation (Banerjee et al., 2021), our paper shows that the environmental benefits and monetary savings from reduced gas use tend to be smaller for the poorest. Comfort gains are, on the contrary higher. Framed within broader societal debates, our insights highlight the importance of prioritizing renovations based on clearly defined policy objectives, as these objectives may conflict. Our methodology enables a comprehensive cost-benefit assessment of heating efficiency upgrades across income groups and policy scenarios.

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# A Appendix Utility maximization problem solutions

In this Appendix, we offer Proofs of Proposition 1, Proposition 2 and Proposition 3.

**Proof of Proposition 1.** We write the Lagrangian for the household utility maximization problem (UMP) as follows:

$$L = \left(x^{\frac{\sigma-1}{\sigma}} + \left((2\bar{\theta}-\theta)\theta\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} + \lambda\left(w - x - \frac{\theta-\theta_0}{q}p_g\right)$$

Due to the strict monotonicity of $u(x,\theta)$ w.r.t. $x$, it follows that $\lambda > 0$ and the F.O.C.s for an interior solution are:

$$\begin{cases} 0 = \left(x^{\frac{\sigma-1}{\sigma}} + \left((2\bar{\theta}-\theta)\theta\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} x^{-\frac{1}{\sigma}} - \lambda \\ 0 = 2\left(x^{\frac{\sigma-1}{\sigma}} + \left((2\bar{\theta}-\theta)\theta\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \left((2\bar{\theta}-\theta)\theta\right)^{-\frac{1}{\sigma}}(\bar{\theta}-\theta) - \frac{p_g}{q}\lambda \\ 0 = w - x - \frac{\theta-\theta_0}{q}p_g \end{cases} \tag{13}$$

The first two equations imply:

$$x = (2\bar{\theta}-\theta)\theta\left(\frac{p_g}{2q(\bar{\theta}-\theta)}\right)^{\sigma}. \tag{14}$$

Then, the third equation implies that $\theta^*$ satisfies Equation (4), which can be written as

$$F(\theta^*, w, q) = 0, \tag{15}$$

where

$$F(\theta, w, q) \stackrel{\text{def}}{=} w - (2\bar{\theta}-\theta)\theta\left(\frac{p_g}{2q(\bar{\theta}-\theta)}\right)^{\sigma} - \frac{\theta-\theta_0}{q}p_g. \tag{16}$$

It can be seen that for $w \geq 0$, $q > 0$, and $\theta \in [\theta_0, \bar{\theta})$, $F$ increases with $w$ and $q$ and decreases with $\theta$, because its derivatives are:

$$\begin{aligned} F_\theta &= -\left(\frac{p_g}{2q}\right)^{\sigma}\left(2(\bar{\theta}-\theta)^2 + \sigma(2\bar{\theta}-\theta)\theta\right)\left(\bar{\theta}-\theta\right)^{-\sigma-1} - \frac{p_g}{q} < 0, \\ F_w &= 1 > 0, \\ F_q &= \frac{\sigma}{q}(2\bar{\theta}-\theta)\theta\left(\frac{p_g}{2q(\bar{\theta}-\theta)}\right)^{\sigma} + \frac{\theta-\theta_0}{q^2}p_g > 0. \end{aligned}$$

Therefore, if Equation (15) has a solution $\theta^*(w,q)$, it is monotone increasing and continuous.

Since $F(\theta_0, \underline{w}, q) = 0$, where $\underline{w}$ is defined in Equation (3), it follows that for $w < \underline{w}$, Equation (15) has no solution satisfying $\theta \geq \theta_0$. For such low income levels, the UMP has a corner solution in which $\theta^* = \theta_0$ and $x^* = w$. This proves part 1 of the proposition.

For $w > \underline{w}$, Equation (15) defines a unique solution $\theta^*(w, q)$. The solution always exists because for any income $w > \underline{w}$:

$$F(\theta_0, w, q) > 0,$$
$$\lim_{\theta \uparrow \bar{\theta}} F(\theta, w, q) = -\infty,$$

and $F$ continuously decreases with $\theta$. This proves part 2 of the proposition. The monotonicity properties of $\theta^*$ follow from the monotonicity properties of $F$:

$$\theta^*_w = -\frac{F_w}{F_\theta} = -\frac{1}{F_\theta} > 0,$$
$$\theta^*_q = -\frac{F_q}{F_\theta} > 0.$$

The monotonicity of $x^*$ can be seen from:

$$x^*_w = 1 - \frac{p_g}{q}\theta^*_w > 0.$$

This proves part 3 of the proposition. Finally, since $F$ in unbounded in $w$ and $\theta$, the solution $\theta^*$ approaches $\bar{\theta}$ when $w$ increases unboundedly. Similarly, for any $\theta < \bar{\theta}$ and $w > 0$, $F(\theta, w, q)$ converges to $w > 0$ when $q$ increases unboundedly. Therefore, in the limit, it must be that the solution $\theta^*$ converges to $\bar{\theta}$. This proves part 4 of the proposition.

**Proof of Proposition 2.** The proof of the proposition is a straightforward application of the results of Proposition 1. By the construction of $\underline{w}(q)$, $g^*(q, w) = 0$ for $w \leq \underline{w}(q)$, which is part 1 of the Proposition. Since $\theta^*(q, w)$ increases with $w$ and converges to $\bar{\theta}$, eq. (6) implies $g^*(q, w)$ increases with $w$ and converges to $\frac{1}{q}(\bar{\theta} - \theta_0)$, which is part 2 of the Proposition. The existence of income thresholds $w_1(q_L, q_H)$ $w_2(q_L, q_H)$ follows from continuity of $g^*(q, w)$ and two facts:

$$g^*(q_H, \underline{w}(q_L)) > g^*(q_L, \underline{w}(q_L)) = 0,$$

and

$$\lim_{w \to \infty} g^*(q_H, w) = \frac{1}{q_H}(\bar{\theta} - \theta_0) < \frac{1}{q_L}(\bar{\theta} - \theta_0) = \lim_{w \to \infty} g^*(q_L, w),$$

which is part 3 of the Proposition.

**Proof of Proposition 3.** We omit the asterisk and consider the interior solution $(\theta, x)$ to the UMP. Differentiating Equation (7) results in:

$$\frac{\partial V}{\partial w}(q_H, w - CV)(1 - \frac{\partial CV}{\partial w}) = \frac{\partial V}{\partial w}(q_L, w),$$

so that

$$\frac{\partial CV}{\partial w} = \frac{\frac{\partial V}{\partial w}(q_H, w - CV) - \frac{\partial V}{\partial w}(q_L, w)}{\frac{\partial V}{\partial w}(q_H, w - CV)}$$

In the UMP, $\frac{\partial V}{\partial w} = \lambda > 0$ always holds. Using Equation (14), we write the first equation in 13 as follows:

$$\frac{\partial V}{\partial w} = \left(1 + \left(\frac{2q(\bar{\theta} - \theta)}{p_g}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$$

Therefore, $\frac{\partial CV}{\partial w} > 0$ if and only if $2q(\bar{\theta} - \theta)$ increases when $q = q_L$ increases to $q = q_H$ and income $w$ is compensated and decreases to $(w - CV)$, keeping utility level $u(x, \theta)$ intact. Using Equation (14) we write the indifference curve $u(x, \theta) = const$ as follows:

$$(2\bar{\theta} - \theta)\theta \left(\left(\frac{p_g}{2q(\bar{\theta} - \theta)}\right)^{\sigma-1} + 1\right)^{\frac{\sigma}{\sigma-1}} = const$$

When $q$ increases and income $w$ is compensated, thermal comfort $\theta$ always increases due to the substitution effect). The thermal comfort utility component $(2\bar{\theta} - \theta)\theta$ also increases. According to the above equation for the indifference curve, $2q(\bar{\theta} - \theta)$ also increases to keep the utility level constant. Therefore, $\frac{\partial CV}{\partial w} > 0$. This result holds as long as $\theta > \theta_0$ at $q = q_H$. When $\theta = \theta_0$ at $q = q_H$, $CV = 0$ and is independent of income $w$.

Table B1: Comparison by income group of house energy efficiency and retrofit intensity

| Income decile | Disposable income (euro/year) | Projected gas use per $m^2$ before retrofit | Retrofit intensity |
|---|---|---|---|
| 1 | 17347.28 | 23.03 | 0.03 |
| 2 | 18842.37 | 23.51 | 0.02 |
| 3 | 20957.50 | 23.11 | −0.01 |
| 4 | 22067.46 | 23.24 | 0.02 |
| 5 | 23594.01 | 23.32 | −0.00 |
| 6 | 25727.04 | 23.22 | −0.00 |
| 7 | 28227.44 | 23.61 | −0.02 |
| 8 | 31998.45 | 23.40 | −0.02 |
| 9 | 36896.39 | 23.01 | −0.03 |
| 10 | 45957.84 | 22.94 | −0.00 |
| F-value | | 1.11 | 0.60 |
| p-value | | 0.35 | 0.80 |

*Notes:* The table reports a balancing test of projected gas (scaled by house surface) and retrofit intensity between 10 income groups Income groups are income (in % of social minimum) deciles.

# B Appendix Identification

## B.1 Housing quality homogeneous by income level

In this section, we test whether wealthier people self-select to better quality dwellings. Table B1 shows, by income deciles, pre-retrofit projected gas use and retrofit intensity averages, which are proxies for house energy efficiency. Pre-retrofit projected gas use is practically the same across income deciles, with values around 23 $m^3/m^2$. The F-test confirms that the ten means are not statistically significantly different. Similarly, retrofit intensities vary around zero and show values up to 0.03, which correspond to 0.45% additional engineering projected savings - this is negligible as compared to the 43% average savings. Again, there is no statistically significant difference between the ten retrofit intensity means. Together, these two tests motivate our assumption that house efficiency parameters $q_H$, $q_L$ are homogeneous across income levels, so there is no self-selection of wealthier people into better quality homes.

### B.2 Retrofit intensity uncorrelated to socio-economics and gas use

Table B2 presents the results from an OLS regression of retrofit intensity on pre-retrofit dwelling, income, and energy use characteristics of households in 2016. The sample comprises all 13,409 retrofitted houses from our baseline dataset. The findings suggest that retrofit intensity is primarily influenced by house characteristics. Among energy use and socio-economic factors, only a few variables are statistically significant, and their effects on retrofit intensity are minimal. For instance, a one standard deviation increase in income reduces retrofit intensity by 0.035, equivalent to a 0.5 percentage point decrease in projected gas savings - this is negligible compared to the 43% average projected gas savings.

Table B2: Determinants of retrofit intensity

| | |
|---|---|
| Intercept | 0.110* (0.061) |
| **Panel A: Socio-economics** | |
| Log income (standardized) | -0.035*** (0.010) |
| No. children (standardized) | -0.050 (0.067) |
| No. persons (standardized) | 0.039 (0.074) |
| No. persons squared (standardized) | 0.052 (0.091) |
| No. senior squared (standardized) | -0.024 (0.039) |
| No. children squared (standardized) | -0.018 (0.053) |
| No. seniors (standardized) | 0.024 (0.049) |
| No. females (standardized) | 0.019 (0.021) |
| No. females squared (standardized) | -0.019 (0.021) |
| Employed 0/1 | 0.031* (0.018) |
| Household type one adult (ref) | |
| Household type nuclear family 0/1 | 0.076 (0.060) |
| Household type one senior 0/1 | 0.039 (0.046) |
| Household type single parent 0/1 | 0.149*** (0.051) |
| Household type two adults 0/1 | 0.031 (0.049) |
| Education high (ref) | |
| Education low 0/1 | 0.025 (0.024) |
| Education medium 0/1 | 0.031 (0.025) |
| Education unknown 0/1 | 0.009 (0.025) |
| **Panel B: House characteristics** | |
| Log surface (standardized) | -0.241*** (0.008) |
| Log projected gas (standardized) | 0.516*** (0.008) |
| Log construction year (standardized) | 0.214*** (0.016) |
| Solar panels 0/1 | 0.153** (0.064) |
| Boiler changed 0/1 | 0.311*** (0.025) |
| Energy label C (ref) | |
| Energy label D 0/1 | 0.207*** (0.018) |
| Energy label E 0/1 | 0.459*** (0.019) |
| Energy label F 0/1 | 0.514*** (0.026) |
| Energy label G 0/1 | 0.733*** (0.028) |
| Constr. Period 1906-1940 (ref) | |
| Constr. Period 1940-1965 0/1 | -0.616*** (0.051) |
| Constr. Period 1966-1976 0/1 | -0.418*** (0.066) |
| Constr. Period 1977-1992 0/1 | -0.794*** (0.085) |
| **Panel C: Energy use** | |
| Log gas (standardized) | -0.054*** (0.007) |
| Num.Obs. | 13401 |
| R2 | 0.443 |
| R2 Adj. | 0.442 |

*Notes*: The tables shows estimates of two separate OLS regressions. The dependent variable is the retrofit intensity. The independent variables are all pre-retrofit observed controls. Statistical significance: *p<0.1; **p<0.05; ***p<0.01.

## C Appendix Main results - full table

Table C1 reports the full set of coefficients behind Table 2.

Table C1: Average effects of insulation retrofit

| Dependent: log of yearly natural gas use | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A: Retrofit** | | | | |
| After retrofit (year $\geq$ 2) | -0.149*** | -0.228*** | -0.228*** | -0.218*** |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| After retrofit (year < 2) | -0.028*** | -0.109*** | -0.105*** | -0.100*** |
| | (0.004) | (0.002) | (0.004) | (0.002) |
| After retrofit (year $\geq$ 2) x Retrofit intensity | -0.058*** | -0.077*** | -0.100*** | -0.078*** |
| | (0.004) | (0.003) | (0.004) | (0.003) |
| After retrofit (year < 2) x Retrofit intensity | -0.024*** | -0.039*** | -0.065*** | -0.038*** |
| | (0.004) | (0.002) | (0.003) | (0.002) |
| **Panel B: Socio-economics** | | | | |
| No. children | | | -0.019** | 0.018*** |
| | | | (0.008) | (0.004) |
| No. persons | | | 0.115*** | 0.022*** |
| | | | (0.008) | (0.004) |
| No. persons squared | | | -0.014*** | -0.002** |
| | | | (0.002) | (0.001) |
| No. senior squared | | | 0.002 | -0.002 |
| | | | (0.003) | (0.002) |
| No. children squared | | | 0.011*** | 0.000 |
| | | | (0.002) | (0.001) |
| No. seniors | | | 0.020** | -0.001 |
| | | | (0.008) | (0.005) |
| No. females | | | 0.050*** | 0.061*** |
| | | | (0.008) | (0.007) |
| No. females squared | | | -0.009 | -0.024*** |
| | | | (0.006) | (0.004) |
| Household type nuclear family | | | 0.084*** | 0.059*** |
| | | | (0.007) | (0.004) |
| Household type one senior | | | 0.055*** | 0.001 |
| | | | (0.006) | (0.004) |
| Household type single parent | | | 0.094*** | 0.047*** |
| | | | (0.007) | (0.004) |
| Household type two adults | | | 0.033*** | 0.042*** |
| | | | (0.006) | (0.003) |
| Household type two seniors | | | | 0.035*** |
| | | | | (0.003) |

| | | | | |
|---|---|---|---|---|
| Employed | | | -0.013*** | -0.001 |
| | | | (0.002) | (0.001) |
| Log income | | | 0.034*** | 0.044*** |
| | | | (0.003) | (0.002) |
| Education low | | | 0.051*** | 0.016* |
| | | | (0.004) | (0.009) |
| Education medium | | | 0.035*** | 0.005 |
| | | | (0.004) | (0.008) |
| Education unknown | | | 0.050*** | 0.035*** |
| | | | (0.004) | (0.010) |
| **Panel C: House characteristics** | | | | |
| Boiler changed | | | -0.019*** | -0.042*** |
| | | | (0.005) | (0.003) |
| Solar installation | | | -0.036*** | -0.035*** |
| | | | (0.003) | (0.002) |
| Log proj. gas use | | | 0.257*** | |
| | | | (0.004) | |
| Constr. Period 1940-1965 | | | 0.017*** | |
| | | | (0.005) | |
| Constr. Period 1966-1976 | | | 0.006 | |
| | | | (0.005) | |
| Constr. Period 1977-1992 | | | -0.021*** | |
| | | | (0.005) | |
| Log surface | | | 0.215*** | |
| | | | (0.007) | |
| Energy label D | | | 0.018*** | |
| | | | (0.003) | |
| Energy label E | | | 0.034*** | |
| | | | (0.003) | |
| Energy label F | | | 0.042*** | |
| | | | (0.005) | |
| Energy label G | | | 0.049*** | |
| | | | (0.005) | |
| No. obs. | 963459 | 963459 | 959073 | 959073 |
| No. treatment houses | 13409 | 13409 | 13409 | 13409 |
| No. control houses | 110891 | 110891 | 110891 | 110891 |
| $R^2$ Adj. | 0.021 | 0.822 | 0.144 | 0.826 |
| Year fixed-effect | X | X | X | X |
| Household fixed-effect | | X | | X |
| Controls | | | X | X |

*Notes:* The table shows estimates of four separate regressions. The dependent variable is the log of gas consumption. Standard errors in parentheses are clustered at household level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

## D Appendix Sensitivity checks

In this Appendix, we subject the results of Table 3 to a series of sensitivity analyses. We re-estimate the model in Equation (12) for various subsamples, allowing the retrofit effect to vary by: (i) the year in which the insulation retrofit took place (2017, 2018, and 2019), Table D1; (ii) pre-retrofit energy efficiency, as defined by the energy label (C, D, E, F, G), Table D2; (iii) socio-economic characteristics of households, Table D3; and (iv) pre-retrofit gas use quintile, Table D4 and (v) households that did receive PV panels together with insulation and that did not, Table D5.

The results are robust across all year and energy label subsamples. However, the average effect of insulation varies by household type. For example, single households achieve larger savings, while households with a migration background reduce gas use less than average. The average effect also varies by pre-retrofit gas use: households with low gas demand achieve almost half the savings of the average, while households with high gas use save more than average. The low-income-specific response to insulation remains consistent across all subsamples, however.

The results are also robust by solar panel availability. Some households received solar panels that were coincident with the insulation treatment. Solar installation implies a lump-sum change in income, that may affect re-optimization of gas use. However, the income effect of solar panels is small (some 100 euro per year), because of the service cost of around 2.5 euro per panel that housing associations ask. As a result, the effects on natural gas are not statistically different among households that received solar or not Table D5.

Table D1: Effects of retrofits by retrofit year

| | | Retrofit year | | |
|---|---|---|---|---|
| | Baseline | 2017 | 2018 | 2019 |
| After retrofit (year $\geq$ 2) | $-0.218$ (0.003)$^{***}$ | $-0.217$ (0.005)$^{***}$ | $-0.221$ (0.004)$^{***}$ | $-0.212$ (0.005)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.062 (0.016)$^{***}$ | 0.088 (0.031)$^{***}$ | 0.046 (0.024)$^{*}$ | 0.040 (0.027) |
| $\times$ Below 130% soc.min. | 0.025 (0.006)$^{***}$ | 0.022 (0.011)$^{*}$ | 0.021 (0.010)$^{**}$ | 0.032 (0.011)$^{***}$ |
| $\times$ Below 150% soc.min. | 0.018 (0.006)$^{***}$ | 0.022 (0.010)$^{**}$ | 0.012 (0.008) | 0.017 (0.010) |

*Notes*: The table shows estimates of Equation (12) for 8 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D2: Effects of retrofits by energy label

| | | Energy label | | | | |
|---|---|---|---|---|---|---|
| | Baseline | C | D | E | F | G |
| After retrofit (year $\geq$ 2) | $-0.218^{***}$ | $-0.223^{***}$ | $-0.218^{***}$ | $-0.228^{***}$ | $-0.228^{***}$ | $-0.225^{***}$ |
| | (0.003) | (0.007) | (0.005) | (0.005) | (0.008) | (0.012) |
| $\times$ Below 100% soc.min. | $0.062^{***}$ | $0.083^{*}$ | $0.071^{**}$ | $0.050^{*}$ | 0.027 | $0.169^{*}$ |
| | (0.016) | (0.044) | (0.030) | (0.028) | (0.066) | (0.088) |
| $\times$ Below 130% soc.min. | $0.025^{***}$ | $0.035^{**}$ | $0.022^{*}$ | $0.025^{**}$ | $-0.011$ | 0.020 |
| | (0.006) | (0.017) | (0.013) | (0.012) | (0.019) | (0.031) |
| $\times$ Below 150% soc.min. | $0.018^{***}$ | 0.023 | 0.010 | $0.020^{*}$ | $-0.004$ | 0.011 |
| | (0.006) | (0.015) | (0.011) | (0.011) | (0.017) | (0.026) |

*Notes*: The table shows estimates of Equation (12) for 8 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D3: Effects of retrofits by household type

| | Mig. BG | Household type | | | | | |
|---|---|---|---|---|---|---|---|
| | Yes | one adult | nuclear family | one senior | single parent | two adults | two seniors |
| After retrofit (year $\geq$ 2) | $-0.176^{***}$ | $-0.252^{***}$ | $-0.193^{***}$ | $-0.223^{***}$ | $-0.202^{***}$ | $-0.225^{***}$ | $-0.209^{***}$ |
| | (0.006) | (0.007) | (0.006) | (0.005) | (0.007) | (0.007) | (0.005) |
| $\times$ Below 100% soc.min. | $0.090^{***}$ | $0.083^{**}$ | 0.047 | $0.064^{**}$ | 0.008 | 0.126 | $0.120^{**}$ |
| | (0.026) | (0.034) | (0.043) | (0.027) | (0.031) | (0.075) | (0.047) |
| $\times$ Below 130% soc.min. | $0.028^{**}$ | 0.005 | $0.044^{***}$ | $0.028^{**}$ | $0.028^{*}$ | 0.032 | $0.053^{***}$ |
| | (0.013) | (0.017) | (0.015) | (0.011) | (0.014) | (0.026) | (0.013) |
| $\times$ Below 150% soc.min. | $0.023^{*}$ | $-0.009$ | $0.047^{***}$ | $0.021^{*}$ | 0.019 | 0.027 | $0.033^{***}$ |
| | (0.012) | (0.015) | (0.013) | (0.011) | (0.013) | (0.022) | (0.010) |

*Notes*: The table shows estimates of Equation (12) for 8 separate regressions. Migration background (Mig. Bg) is "Yes" when all household members are born outside the Netherlands (first and second generation). Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction (e.g. below 100% soc.min. $\times$ Yes Migration background). The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D4: Effects of retrofits by pre-retrofit gas use quintiles

| | Baseline | Pre-retrofit gas use quintile: first quintile | last quintile |
|---|---|---|---|
| After retrofit (year $\geq$ 2) | $-0.218^{***}$ | $-0.128^{***}$ | $-0.265^{***}$ |
| | (0.003) | (0.010) | (0.005) |
| $\times$ Below 100% soc.min. | $0.062^{***}$ | $0.152^{***}$ | $0.047^{*}$ |
| | (0.016) | (0.049) | (0.027) |
| $\times$ Below 130% soc.min. | $0.025^{***}$ | $0.047^{**}$ | 0.014 |
| | (0.006) | (0.022) | (0.011) |
| $\times$ Below 150% soc.min. | $0.018^{***}$ | 0.031 | 0.013 |
| | (0.006) | (0.020) | (0.010) |

*Notes*: The table shows estimates of Equation (12) for 12 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction (e.g. below 100% soc.min. $\times$ first quintile). The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D5: Effects of retrofits on gas and electricity, by solar panel availability

| | Dependent: log gas | | Dependent: log electricity | |
|---|---|---|---|---|
| | No solar | Yes solar | No solar | Yes solar |
| After retrofit (year $\geq$ 2) | $-0.223$ (0.003)$^{***}$ | $-0.237$ (0.004)$^{***}$ | 0.010 (0.004)$^{***}$ | $-0.286$ (0.007)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.054 (0.019)$^{***}$ | 0.063 (0.025)$^{**}$ | 0.037 (0.022)$^{*}$ | 0.037 (0.039) |
| $\times$ Below 130% soc.min. | 0.013 (0.008)$^{*}$ | 0.041 (0.009)$^{***}$ | 0.014 (0.008)$^{*}$ | 0.006 (0.016) |
| $\times$ Below 150% soc.min. | 0.011 (0.007) | 0.027 (0.008)$^{***}$ | 0.010 (0.007) | $-0.011$ (0.015) |

*Notes*: The table shows estimates of Equation (12) for 8 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction (e.g. below 100% soc.min. $\times$ Yes solar). The dependent variable is log of gas or log of electricity. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

## E Appendix Alternative estimation techniques staggered treatment

The coefficient of the treatment effect can be biased in studies where treatment timing varies across units, as demonstrated in Callaway and Sant'Anna (2021); Sun and Abraham (2021). First, we re-estimate the results from Table 3 using the estimator from Sun and Abraham (2021), which corrects for variation in treatment timing (staggered treatment) but still relies on the never-treated control group. Next, we apply the estimator from Callaway and Sant'Anna (2021), which adjusts for variation in treatment timing and uses not-yet-treated houses as the control group (the sample then includes only houses treated between 2017 and 2019, with all other houses excluded). Table E1, columns Sunab and CS, show that in both cases, the results remain robust to the alternative estimation techniques.

Table E1: Alternative estimation techniques staggered treatment

| | TWFE | Sunab | CS |
|---|---|---|---|
| After retrofit (year $\geq$ 2) | $-0.218$ (0.003)$^{***}$ | $-0.225$ (0.003)$^{***}$ | $-0.197$ (0.007)$^{***}$ |
| Below 100% soc.min. | $-0.155$ (0.017)$^{***}$ | $-0.161$ (0.017)$^{***}$ | $-0.169$ (0.038)$^{***}$ |
| Below 130% soc.min. | $-0.209$ (0.006)$^{***}$ | $-0.224$ (0.006)$^{***}$ | $-0.205$ (0.013)$^{***}$ |
| Below 150% soc.min. | $-0.215$ (0.005)$^{***}$ | $-0.228$ (0.005)$^{***}$ | $-0.200$ (0.011)$^{***}$ |

*Notes*: The table shows estimates of Equation (12) for 12 separate regressions. "Sunab" stands for Sun and Abraham estimator (Sun and Abraham, 2021) and "CS" stands for Callaway and Sant'Anna estimator (Callaway and Sant'Anna, 2021). "TWFE" stands for two-way fixed effects, our baseline estimator. All coefficients (except "After retrofit") are estimated on the sub-samples of poor households.The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units for "Sunab" and "TWFE". The sample size is 13409 treated for "CS". Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

## F Alternative model specifications

### F.1 Functional form retrofit intensity

Table F1 presents the retrofit effect on poor households for various specifications of retrofit intensity. The first column uses the baseline specification (Equation (12)), the second column excludes the largest retrofits (retrofit intensity $> 2$), the third column accounts for non-linear effects of retrofit intensity, and the final column omits retrofit intensity entirely. The low-income response remains robust across all these specifications.

Table F1: Effects of retrofits across various retrofit intensity specifications

| | Specification of retrofit intensity | | | |
|---|---|---|---|---|
| | Baseline | Linear and $\leq$2 | Polynomial | Not controlled for |
| After retrofit (year $\geq$ 2) | $-0.218$ (0.003)$^{***}$ | $-0.222$ (0.006)$^{***}$ | $-0.223$ (0.003)$^{***}$ | $-0.217$ (0.003)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.062 (0.016)$^{***}$ | 0.064 (0.017)$^{***}$ | 0.062 (0.022)$^{***}$ | 0.063 (0.017)$^{***}$ |
| $\times$ Below 130% soc.min. | 0.025 (0.006)$^{***}$ | 0.023 (0.007)$^{***}$ | 0.013 (0.008) | 0.023 (0.006)$^{***}$ |
| $\times$ Below 150% soc.min. | 0.018 (0.006)$^{***}$ | 0.017 (0.006)$^{***}$ | 0.009 (0.007) | 0.016 (0.006)$^{***}$ |

*Notes*: The table shows estimates of Equation (12) for 16 separate regressions. In the first column, the retrofit intensity enters the model linearly. In second column, observations with the retrofit intensity larger than 2 are discarded. In the third column, the retrofit intensity and its second and third orders enter the model. In the last column, the retrofit intensity is discarded from the model. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

### F.2 Heterogeneous time trends

Table F2 shows the retrofit effect on poor households where the year-fixed effects are allowed to differ between poor and non-poor households. Low-income response is robust to this specification.

Table F2: Effects of retrofits, allowing heterogenous time trends

| | Baseline | Heterogeneous time trends |
|---|---|---|
| After retrofit (year $\geq$ 2) | $-0.218$ (0.003)$^{***}$ | $-0.218$ (0.003)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.062 (0.016)$^{***}$ | 0.054 (0.017)$^{***}$ |
| $\times$ Below 130% soc.min. | 0.025 (0.006)$^{***}$ | 0.010 (0.007) |
| $\times$ Below 150% soc.min. | 0.018 (0.006)$^{***}$ | 0.002 (0.006) |

*Notes*: The table shows estimates of Equation (12) for 8 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 13409 treated and 110891 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

## G Model parameter calibration

We calibrate the parameters of the theoretical model of Section 2.1 to ensure that the model's outputs over the income distribution align with the measured data on gas use before retrofit and estimated gas savings after retrofit. We approximate the income distribution by a set of income deciles $d = 1, \ldots, 10$, based on household income as a percentage of the social minimum. For each decile $d$, income $w_d$ and pre-retrofit gas use $g_d$ are set to the mean values of the treated in that decile. We also assign to each decile the quasi-experimental estimate of the retrofit effect $\alpha_d$ from Equation (12), measured as the change in cubic meters of gas use following the heating efficiency upgrade.[34] Table G1 shows these mean pre-retrofit gas use and quasi-experimental estimates across income levels. Then, we derive the values of the parameters ($\bar{\theta}$, $\sigma$, $\theta_0$, $q_L$ and $q_H$) by minimizing the error between our empirical outcomes and the CES model outcomes for gas use and gas savings. For this, we solve the following optimization problem:

$$\min D = \sum_d v_d^T \Sigma^{-1} v_d \tag{17}$$

$$\text{subject to}: q_L > 0, q_H > 0, \theta_0 \geq 0, \bar{\theta} \in [18, 25], \sigma \geq 0,$$

where

$$v_d = \begin{bmatrix} g_d - g^*(q_L, w_d) \\ \alpha_d - (g^*(q_H, w_9) - g^*(q_L, w_9)) \end{bmatrix}$$

are vectors with two components, pre-retrofit gas use error and retrofit effect error respectively. The variance-covariance matrix $\Sigma$ is a two-by-two matrix calculated as $\frac{1}{9}\sum_d v_d v_d^T$.

To obtain a confidence interval for each calibrated parameter, we use bootstrapping. We repeatedly (380 times) solve the minimization problem Equation (17) on new samples that are generated by resampling with replacement from the baseline study sample (Efron, 1992). The resampling is done in a stratified manner, ensuring that each income decile is represented proportionally.

Table G2 shows the resulting mean values of the parameters and the 95% confidence intervals. Table G3 shows the resulting Program effects and benefits, by income.

We note that the confidence interval of $\sigma$ includes the value 1. So we cannot reject the hypothesis that $\sigma$ equals unity, and the CES utility Section 2.1 reduces to the Cobb-Douglas specification:

[34] So we re-estimate Equation (12) in levels for 10 deciles of gas use.

Table G1: Calibration data

| Income decile | Disposable income (euro/year) | Income (% of soc. min.) | Gas use before retrofit ($m^3$/year) | Retrofit effect ($m^3$/year) | Standard error ($m^3$/year) |
|---|---|---|---|---|---|
| 1 | 17347 | 99 | 1344 | −218 | 9 |
| 2 | 18842 | 111 | 1351 | −238 | 9 |
| 3 | 20957 | 126 | 1378 | −249 | 9 |
| 4 | 22067 | 144 | 1350 | −262 | 8 |
| 5 | 23594 | 165 | 1351 | −240 | 8 |
| 6 | 25727 | 189 | 1368 | −263 | 9 |
| 7 | 28227 | 217 | 1369 | −259 | 8 |
| 8 | 31998 | 250 | 1389 | −271 | 9 |
| 9 | 36896 | 295 | 1405 | −273 | 9 |
| 10 | 45958 | 398 | 1417 | −308 | 9 |

*Notes:* Statistics across income (in % of social minimum) deciles of our research sample. Income and gas use are samples mean, retrofit effect and standard error estimated from Equation (12), where the dependent variable is gas use in cubic meter per year.

$$u(x, \theta) = x(2\bar{\theta} - \theta)\theta \tag{18}$$

We set $\sigma = 1$ and, to prevent overparametrization, need to normalize one more parameter.[35] We choose to normalize $\bar{\theta}$ to its mean value, $24.2^oC$ . Then we repeat the bootstrapping procedure. Table 5 shows the resulting Program effects and benefits, by income. Table 4 shows the resulting parameters. Fixing the two parameters $\bar{\theta}$ and $\sigma$ reduces the variation in the bootstrapping distributions of the Slutsky and Hicksian compensations, compare Table G3 with **??**.

[35]Indeed, the expressions (3)-(5) in Proposition 1 are homogeneous in $(\bar{\theta}, \theta_0, \theta^*, q)$, implying that for $\sigma = 1$, one of the parameters can be freely chosen (to be strictly positive), and the values of the other parameters will follow from the minimization problem.

Table G2: Computable model parameters

| Description | Parameter | Value | Confidence interval |
|---|---|---|---|
| Exogenously chosen parameters | | | |
| Price of gas (euro/$m^3$) | $p_g$ | 0.65 | |
| Price of other consumption | $p_x$ | 1 | |
| Estimated parameters | | | |
| Elasticity of substitution | $\sigma$ | 1.61 | [0.8;2.09] |
| Satiety level of thermal comfort ($^o$ C) | $\bar{\theta}$ | 24.22 | [18.54;25] |
| Indoor temperature at g=0 ($^o$ C) | $\theta_0$ | 2.17 | [1;11.86] |
| Energy efficiency before retrofit ($^o$ C/$m^3$) | $q_L$ | $\frac{1}{69}$ | $[\frac{1}{211};\frac{1}{62}]$ |
| Energy efficiency after retrofit ($^o$ C/$m^3$) | $q_H$ | $\frac{1}{55}$ | $[\frac{1}{170};\frac{1}{50}]$ |

*Notes:* Value and Confidence interval report the mean and 95% confidence interval from bootstrapping. The inverse values of $q_L$ and $q_H$ can be interpreted as the amount of gas required to gain one additional degree of indoor temperature.

Table G3: Program effects and private benefits, by income

| Income | Private and external effects | | | Private benefits (euro) | | | |
|---|---|---|---|---|---|---|---|
| | $\Delta$ Temp. | $\Delta$ Gas | $\Delta CO_2$ | Slutsky valuation | | | Hicksian val. |
| | $°C$ | $m^3$ | $kg$ | $-\Delta^S$ | $-\Delta^S_\theta$ | $-\Delta^S_x$ | $CV$ |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | In prices 2016 (0.65 euro/$m^3$) | | | | | | |
| low | 0.63 | −239 | −428 | 177 | 22 | 155 | 180 |
| | [0.13; 1.04] | [−246; −231] | [−441; −414] | [167; 187] | [11; 35] | [150; 160] | [169; 192] |
| average | 0.48 | −257 | −460 | 184 | 16 | 167 | 186 |
| | [0.07; 0.85] | [−262; −252] | [−469; −451] | [174; 196] | [7; 29] | [163; 170] | [175; 200] |
| high | 0.34 | −274 | −491 | 190 | 11 | 178 | 191 |
| | [0.03; 0.64] | [−283; −266] | [−506; −477] | [178; 205] | [3; 22] | [173; 184] | [178; 209] |
| | In prices 2022 (1.36 euro/$m^3$) | | | | | | |
| low | 1.25 | −159 | −285 | 310 | 92 | 217 | 321 |
| | [0.29; 1.93] | [−198; −113] | [−355; −203] | [293; 324] | [54; 139] | [155; 270] | [311; 332] |
| average | 0.98 | −194 | −348 | 338 | 72 | 265 | 347 |
| | [0.16; 1.65] | [−226; −153] | [−404; −275] | [328; 347] | [36; 119] | [209; 308] | [339; 354] |
| high | 0.70 | −230 | −412 | 365 | 51 | 314 | 372 |
| | [0.07; 1.30] | [−256; −199] | [−459; −357] | [357; 373] | [16; 93] | [272; 350] | [361; 382] |

*Notes:* The Table reports the effects of the average retrofit in our data, as predicted by the computable choice model. Choice model parameters $\sigma$, $\theta_0$, $\bar{\theta}$, $q_L$ and $q_H$ are estimated, other parameters are exogenously chosen. Mean and 95% confidence interval (between brackets) from bootstrapping. This is done for two scenarios (reference with gas prices of 2016 and counterfactual with gas prices of 2022) and for three income groups (low, average and high, respectively 16keuro, 24keuro and 43keuro in disposable yearly income). Columns (2) and (3) document the changes in consumption of temperature respectively yearly gas, following the retrofits. Column (4) reports the change in annual $CO_2$ emissions, assuming 1.79$kg$ $CO_2$ per $m^3$ of natural gas. Column (5) reports the valuation of the private benefits of the retrofits using the Slutsky compensation. Column (8) reports the same valuation using the Hicksian compensation (compensating variation). Columns (6) and (7) decompose the Slutsky compensation into the parts that arise due to the change in temperature consumption respectively the change in consumption of other goods. The Table shows yearly outcomes.

# H Replication of the analysis for the apartments

In this section, we replicate our main analysis for apartments.

## H.1 Treatment and control group

Table H1 shows mean values of selected covariates, for the treatment and control group. As expected, house characteristics are not balanced: treated houses are older and have a lower energy efficiency. Various socio-economics covariates are well balanced: poverty status, education, number of seniors and income.

## H.2 Gas savings

Table H2 reports the treatment effect, average and for the three low-income groups.

## H.3 Computable model: parameters and validation

Figure H1 shows how well the model fits the data. Left the model predictions and the observed data for gas use are plotted, right the model predictions and the quasi-experimental estimates of the treatment effect is plotted, by income decile. Table H3 shows the underlying calibration data and Table H4 shows the resulting parameters of the computable consumer model.

## H.4 Welfare outcomes

Table H5 reports the (welfare) effects as predicted by the computable consumer choice model for the apartments. Columns (2)-(3) of Table H5 describe the effects of the retrofits on the households' optimal indoor temperature and natural gas use. Columns (4)-(7) of Table H5 report the private welfare gains from the upgrade: total and decomposed into the benefits of increased temperature respectively of other consumption, as derived in Equations (7) to (9). Figure H2 shows the welfare effects for the whole income distribution. It is noteworthy that the benefits from home upgrades are of similar magnitude in apartments as in the single-family dwellings; the costs are however smaller. In the case of apartments, positive returns to the heating efficiency retrofits are easier to achieve.

Table H1: Comparison of treatment and control groups

| | Mean treatment | Mean control |
|---|---|---|
| **Panel A: Socio-economics** | | |
| No. persons | 1.85 | 1.55 |
| No. children | 0.55 | 0.30 |
| No. seniors | 0.36 | 0.43 |
| Income (k euroyear) | 23.12 | 22.08 |
| Education high (0/1) | 0.15 | 0.14 |
| Migration background foreign (0/1) | 0.46 | 0.35 |
| Below 100% social min. (0/1) | 0.05 | 0.05 |
| Below 130% social min. (0/1) | 0.34 | 0.36 |
| Below 150% social min. (0/1) | 0.44 | 0.46 |
| **Panel B: House characteristics** | | |
| Surface ($m^2$) | 73.69 | 71.57 |
| Constr. Period 1906-1939 (0/1) | 0.04 | 0.03 |
| Constr. Period 1940-1965 (0/1) | 0.33 | 0.24 |
| Constr. Period 1966-1976 (0/1) | 0.48 | 0.28 |
| Constr. Period 1977-1992 (0/1) | 0.16 | 0.45 |
| Energy label EFG (0/1) | 0.48 | 0.31 |
| **Panel C: Energy use** | | |
| Electricity relative residuals | 0.05 | $-0.00$ |
| Gas relative residuals | 0.06 | $-0.01$ |
| No. dwellings | 5049 | 62720 |
| No. complexes | 228 | 4770 |

*Notes:* The table reports the mean values of selected covariates, at baseline (i.e. year 2016). Residuals obtained by regressing, at baseline, on projected gas use, construction year, dwelling surface and energy label. Relative residuals are defined as the group mean residual divided by that group's baseline mean outcome.

Table H2: Effects of retrofits for energy poor (apartments)

| | baseline |
|---|---|
| After retrofit (year $\geq$ 2) | $-0.257$ (0.008)$^{***}$ |
| $\times$ Below 100% soc.min. | 0.095 (0.038)$^{**}$ |
| $\times$ Below 130% soc.min. | 0.029 (0.015)$^{*}$ |
| $\times$ Below 150% soc.min. | 0.036 (0.015)$^{**}$ |

*Notes*: The table shows estimates of Equation (12) for 4 separate regressions. Coefficients reported are two- and three-way interactions. The symbol $\times$ indicates an effect as compared to the reference level (non-poor). The combination of the column and row name indicates the interaction. The dependent variable is log of gas. Each regression includes controls, household fixed-effects and year fixed-effects. The sample size is 5049 treated and 62720 control units. Standard errors in parentheses are clustered at household level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H3: Calibration data

| Income decile | Disposable income (euro/year) | Income (% of soc. min.) | Gas use before retrofit ($m^3$/year) | Retrofit effect ($m^3$/year) | Standard error ($m^3$/year) |
|---|---|---|---|---|---|
| 1 | 15770 | 98 | 1111 | $-216$ | 17 |
| 2 | 17047 | 103 | 1134 | $-254$ | 23 |
| 3 | 18245 | 111 | 1174 | $-247$ | 17 |
| 4 | 20154 | 126 | 1178 | $-250$ | 19 |
| 5 | 20838 | 143 | 1159 | $-246$ | 19 |
| 6 | 21756 | 163 | 1147 | $-261$ | 17 |
| 7 | 23975 | 188 | 1146 | $-245$ | 18 |
| 8 | 26372 | 218 | 1204 | $-287$ | 18 |
| 9 | 29741 | 259 | 1163 | $-258$ | 17 |
| 10 | 37010 | 383 | 1170 | $-288$ | 17 |

*Notes:* Statistics across income (in % of social minimum) deciles of our research sample. Income and gas use are samples mean, retrofit effect and standard error estimated from Equation (12), where the dependent variable is gas use in cubic meter per year.

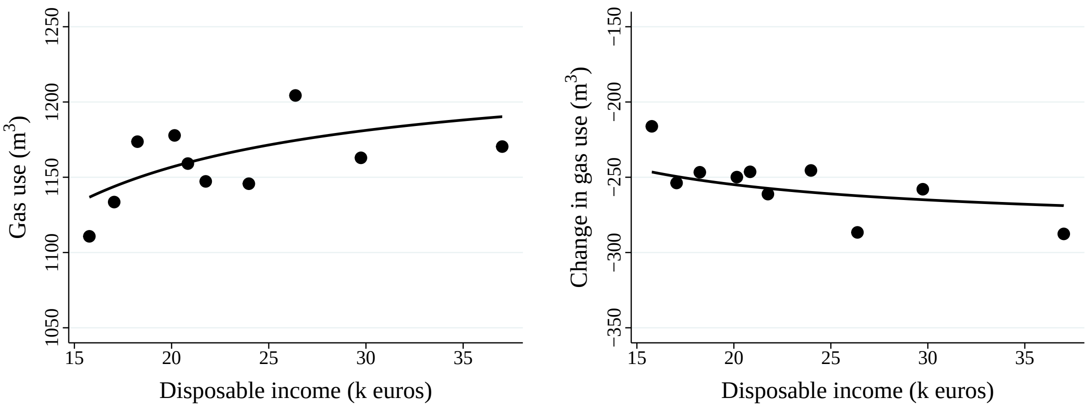
Table H4: Computable model parameters

| Description | Parameter | Value | Confidence interval |
|---|---|---|---|
| Exogenously chosen parameters | | | |
| Price of gas (euro/$m^3$) | $p_g$ | 0.65 | |
| Price of other consumption | $p_x$ | 1 | |
| Elasticity of substitution | $\sigma$ | 1 | |
| Satiety level of thermal comfort ($^o$ C) | $\bar{\theta}$ | 19.54 | |
| Estimated parameters | | | |
| Indoor temperature at g=0 ($^o$ C) | $\theta_0$ | 7.89 | [1;11.15] |
| Energy efficiency before retrofit ($^o$ C/$m^3$) | $q_L$ | $\frac{1}{105}$ | $[\frac{1}{155};\frac{1}{64}]$ |
| Energy efficiency after retrofit ($^o$ C/$m^3$) | $q_H$ | $\frac{1}{81}$ | $[\frac{1}{118};\frac{1}{49}]$ |

*Notes:* Value and Confidence interval report the mean and 95% confidence interval from bootstrapping. The inverse values of $q_L$ and $q_H$ can be interpreted as the amount of gas required to gain one additional degree of indoor temperature.

Figure H1: Model fit: gas use before and after heating efficiency upgrades

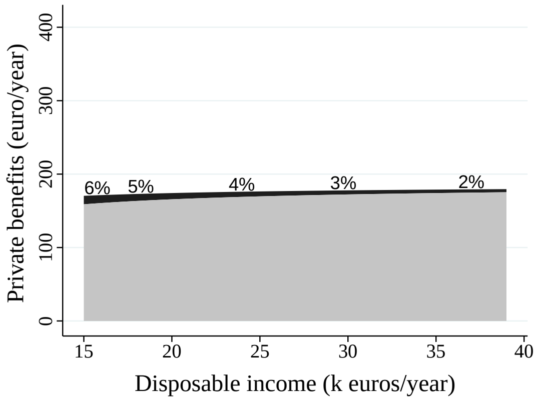
(a) Pre-retrofit gas use ($m^3$) (b) Retrofit effect on gas use ($m^3$)



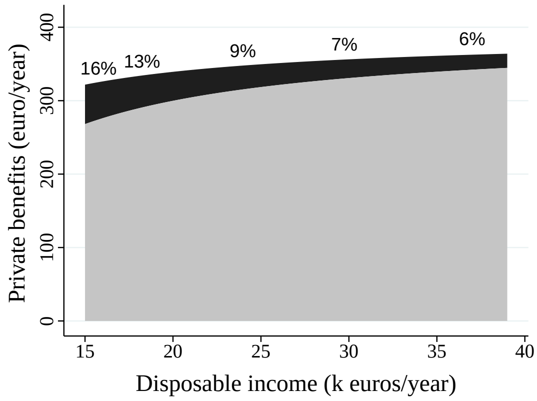

*Notes*: The dots represent observed values (left) and quasi-experimental estimates (right). The lines show predictions from the computable model. Panel (a) illustrates the median gas use across income deciles. Panel (b) illustrates the average effect of a heating efficiency upgrade on gas use across income deciles. Both figures use data from the apartment sample of 67,769 households (treatment + control).

Figure H2: Size and Slutsky decomposition of welfare gains, by income

(a) Reference scenario




(b) Counterfactual scenario




*Notes*: The graph shows the Slutsky compensation (i.e. private benefits) over the income distribution. The black and grey ribbons are the Slutsky compensation due to increase in thermal comfort and consumption of composite good respectively. The percentage above the black ribbon is the share of thermal comfort in the private benefits (i.e. the rebound effect).

Table H5: Program effects and private benefits, by income

| Income | Private and external effects | | | Private benefits (euro) | | | |
|---|---|---|---|---|---|---|---|
| | $\Delta$ Temp. | $\Delta$ Gas | $\Delta CO_2$ | Slutsky valuation | | | Hicksian val. |
| | $^\circ C$ | $m^3$ | $kg$ | $-\Delta^S$ | $-\Delta^S_\theta$ | $-\Delta^S_x$ | $CV$ |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | In prices 2016 (0.65 euro/$m^3$) | | | | | | |
| low | 0.22 | −242 | −433 | 170 | 13 | 157 | 172 |
| | [0.12; 0.32] | [−257; −227] | [−460; −407] | [162; 179] | [4; 24] | [147; 167] | [162; 182] |
| average | 0.14 | −258 | −463 | 176 | 8 | 168 | 177 |
| | [0.08; 0.21] | [−270; −247] | [−484; −443] | [165; 188] | [2; 15] | [160; 175] | [165; 190] |
| high | 0.08 | −272 | −486 | 181 | 4 | 176 | 182 |
| | [0.04; 0.11] | [−291; −253] | [−521; −454] | [166; 196] | [1; 8] | [165; 189] | [166; 197] |
| | In prices 2022 (1.36 euro/$m^3$) | | | | | | |
| low | 0.49 | −188 | −337 | 317 | 60 | 257 | 326 |
| | [0.28; 0.68] | [−239; −132] | [−428; −237] | [289; 346] | [19; 108] | [181; 327] | [303; 349] |
| average | 0.31 | −224 | −402 | 344 | 38 | 306 | 350 |
| | [0.17; 0.44] | [−251; −196] | [−449; −351] | [330; 359] | [11; 70] | [268; 343] | [335; 365] |
| high | 0.17 | −253 | −453 | 366 | 20 | 345 | 369 |
| | [0.09; 0.24] | [−264; −242] | [−472; −434] | [344; 389] | [6; 38] | [331; 360] | [345; 394] |

*Notes:* The Table reports the effects of the average retrofit in our data, as predicted by the computable choice model. Choice model parameters $\theta_0$, $q_L$ and $q_H$ are estimated, other parameters are exogenously chosen. Mean and 95% confidence interval (between brackets) from bootstrapping. This is done for two scenarios (reference with gas prices of 2016 and counterfactual with gas prices of 2022) and for three income groups (low, average and high, respectively 16keuro, 24keuro and 43keuro in disposable yearly income). Columns (2) and (3) document the changes in consumption of temperature respectively yearly gas, following the retrofits. Column (4) reports the change in annual $CO_2$ emissions, assuming 1.79$kg$ $CO_2$ per $m^3$ of natural gas. Column (5) reports the valuation of the private benefits of the retrofits using the Slutsky compensation. Column (8) reports the same valuation using the Hicksian compensation (compensating variation). Columns (6) and (7) decompose the Slutsky compensation into the parts that arise due to the change in temperature consumption respectively the change in consumption of other goods. The Table shows yearly outcomes.