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Distributional Impacts of Climate Policy in Belgium: Carbon Pricing Under Household Heterogeneity

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General Introduction

I started this thesis torn between the idea of directly contributing to public policy development and the conviction that a doctorate would help me better understand contemporary economic issues. By choosing to conduct my research in applied public economics, I hoped to inform policymaking. Guided by the same spirit and the urgency of tackling climate change, it seemed logical to pursue this endeavour in the field of environmental taxation. Although technical, I discovered an intriguing subject at the intersection of economics, political science, law, sociology... all addressing similar issues from different perspectives. Broadly speaking, my interest in this subject could be summed up as follows: how should climate policy address greenhouse-gas emissions in a way that is both effective and politically sustainable?. Specifically, when it comes to taxing households' emissions: how can this be done in a *fair* way? Among concrete policy proposals, carbon pricing has long occupied a central place in economic analysis because it "simply" prices CO_2 emissions in proportion to the damage caused, which is *efficient* from an economic standpoint. But economists' dreams are sometimes other social scientists' nightmares: whether due to legal complexity, political cleavage, or public opposition (see, e.g., the so-called *Yellow Vests* protests in France), carbon pricing is likely to encounter obstacles to its implementation. This is particularly the case when the chosen design is perceived as unfair, ineffective, or too complex. Therefore, this thesis quantifies the distributional impacts of different carbon pricing schemes to provide a better understanding of its incidence on household welfare. In particular, attention is devoted to redistribution, energy poverty, and consumers' reaction to energy prices, all central to the public acceptability of environmental taxation. Considering concrete policy designs, I voluntarily abstract from resolving an optimal tax problem and conduct empirical research grounded in an applied-public-economics approach. Thanks to ex ante microsimulation based on household survey data, I "predict" the impact carbon pricing would have on different types of individuals, using information on energy bills, housing conditions, and sociodemographic characteristics. The results are reported in separate chapters with specific conclusions about revenue-recycling (Chapter 1), energy vulnerability and behaviours (Chapter 2), and investment profitability in residential buildings (Chapter 3). The remaining of this general introduction sets the stage by discussing the current context of carbon pricing and implementation options. The second part addresses distributional concerns more precisely. Finally, I detail the main concepts underlying my approach, explain the methodological choices, and highlight the contribution to the existing literature.

Climate Policy and Carbon Pricing

Carbon pricing has become an increasingly important instrument in climate policy. As of now, about 40 national and 25 sub-national jurisdictions have implemented carbon pricing schemes, collectively covering 28% of worldwide greenhouse gas (GHG) emissions (Bank, 2026; United Nations Climate Change, 2026). And coverage will expand as the EU *Fit for 55* agenda includes the introduction of a new Emissions Trading System for road transport and buildings (ETS 2).[1] With ETS 2 set to take effect in 2028, carbon pricing will be applied for the first time on these sectors in Belgium, where price signal are otherwise distorted by other fiscal instruments not aligned with carbon content (FPS Health, 2025). Along with the ETS 2, the European Commission has planned to introduce the Social Climate Fund (SCF) for a fair and inclusive transition by supporting people vulnerable to higher energy prices. Set to enter into effect as from 2027, Member States must provide the Commission with their Social Climate Plans detailing their intended use of the Fund. This juncture presents an opportunity, and necessity, to examine how carbon pricing can be implemented in a socially balanced way. Anticipating the country's trajectory can contribute to a just transition in Europe, ensuring that climate policy aligns with both environmental and social objectives.

Because of direct incidence and (perceived) equity concerns, carbon taxes can face strong public resistance if not designed with distributional impacts in mind. Policymakers have learned this the hard way. A notable example is the 2018 *Yellow Vests* protests in France, where a planned fuel tax increase based on carbon content sparked widespread backlash. Indeed, public opinion often turns negative when climate policies seem to disproportionately hurt low-income households; behind the normative concern for distributional justice lies the practical issue of social acceptability. It is also widely acknowledged that people worry about how a carbon tax will affect their budgets, and wonder whether the policy is effective in reducing emissions (Dechezleprêtre et al., 2025). The Belgian context is no exception: support for carbon pricing is likely to hinge on assurances that low- and middle-income families, in particular energy-vulnerable households, are protected. In response to these concerns, attention has turned to the design of climate policies and how it can be tweaked to bolster fairness and public trust.

Increasing energy prices is politically sensitive as people need fossil fuels to meet basic needs, to heat and move around; some of them to go working at places and hours where public transport does not run, others to heat poorly insulated dwellings. And, unless they

[1] ETS 2 is the EU's new "cap-and-trade" system for emissions from road transport and buildings (suppliers must buy tradable allowances for the transport and heating fuels they sell). It relates to a carbon tax because both put a price on CO_2 emissions, which increases the prices of fossil fuels, notably for households' transport and heating uses.

are given alternatives, low-income households who cannot invest in cleaner durable goods (electric vehicle or heat pump) risk to be pushed further into (energy) poverty. However, an advantage of carbon pricing over certain regulations (e.g., energy performance standards) is that it generates public revenue. This creates an opportunity to address equity concerns by redistributing the proceeds. In fact, the way revenue-recycling occurs (or not) determines whether such a reform ends up being progressive or regressive (Fremstad & Paul, 2019; Klenert et al., 2018). Many economists and stakeholders have suggested giving the money back to citizens directly (i.e., cash transfers). For example, the 'Economists' Statement on Carbon Dividends' (2019) argues that returning all carbon revenues as equal lump-sum rebates would "maximize fairness and political viability". The appeal of a universal dividend resides in its simplicity and visibility: every household gets an identical rebate, which for most low-income households would exceed their extra fuel costs, thus leaving them better off on balance. In the Belgian setting, such redistribution is indeed sufficient to overturn the initial regressive impact of carbon pricing (see Chapter 1).

Nevertheless, uniform dividends are no silver bullet and some vulnerable households might still be heavily impacted under a tax-and-rebate framework. Hence, alternatives for redistributing carbon revenues include targeted transfers. When taking the form of subsidies, it provides the possibility to support investments in non-fossil equipments. Rather than acting as a punitive taxation, carbon pricing can thus be used as a lever for energy transition. And, if targeted towards households unable to invest, such transfers concentrate the financial help where it is needed most (Berry, 2019). Some countries have even adopted hybrid strategies: British Columbia uses carbon tax revenue for both broad-based tax cuts and targeted household credits, Switzerland splits its emissions revenues between green investment programs and lowering health insurance costs, and Austria had introduced a "climate bonus": higher lump-sum payments for residents of rural areas (Linden et al., 2025). The upcoming EU's SCF will also use a portion of carbon permit auction revenues to support vulnerable households with energy expenses and retrofit investments (European Union, 2023a, 2023c). The former examples highlight that there is no one-size-fits-all solution: the choice of revenue recycling mechanism should be tailored to national circumstances and policy priorities.[2] No matter what, the intent is to cushion consumers from price shocks and to bolster the political acceptability of carbon pricing. Overall, redistribution must balance efficiency with fairness, mitigating hardship for the most vulnerable and securing broad public buy-in, while preserving the incentive to reduce emissions.

[2]Hence, the SCF will be accessible to Members States specifying in their Social Climate Plans (SCP) how they plan to use these revenues, and actively participating to its funding (to at least 25% of the estimated total costs of their national SCP).

Distributional Impacts of Carbon Pricing

A core challenge with carbon pricing is its uneven impact across households. Pricing carbon raises the cost of transport and heating fuels, which tend to represents a larger share of income for the poorer households. Consequently, a uniform carbon tax often weighs more heavily on the budget of poorer households, exhibiting a regressive pattern (see Chapter 1 for Belgium, and Maier et al. (2024) for an EU-wide cross-comparison). The underlying reason is that many carbon-intensive goods are necessities: even when incomes are small, people must spend on heat and electricity, leaving less room to cut back without sacrificing well-being (see welfare measures computed in Chapter 2). Beyond income-based disparities (vertical equity), there are also important horizontal inequities (potentially exceeding vertical ones, Cronin et al. (2019) and Tovar Reaños and Lynch (2023)): households with similar incomes might experience very different burdens depending on their circumstances and consumption patterns. For instance, a rural worker commuting by car or a pensioner living in an old oil-heated home could face much higher carbon costs than an urban dweller in a well-insulated apartment with direct access to public transport. These differences in profiles mean that the impact of carbon taxation is not monolithic: it creates distinct "winners" and "losers". A growing body of literature has documented these distributional outcomes and emphasized that any serious climate policy must account for them (for a review, see Linden et al. (2026)). In sum, understanding who bears the cost of carbon pricing is crucial. Not only is it a matter of social fairness, but it also sets the stage for how the public will respond to such policies.

Energy vulnerability adds a crucial layer to the distributional debate. It measures the affordability of domestic energy, and whether households can meet their heating/electricity needs required for health and a decent standard of living. In the context of ETS 2, energy poverty is explicitly part of the EU policy rationale for accompanying measures under the SCF. In Belgium, recent evidence suggests that energy vulnerability is widespread: it reached 21.8% of households in 2022 (Fondation Roi Baudouin, 2024). Importantly, this phenomenon is multidimensional: some households appear highly exposed because they spend a large share of their income on domestic energy, others are less impacted simply because they already restrict heavily on energy consumption (e.g., by under-heating their home). This motivates treating energy vulnerability not only as an outcome of the distributional analysis (as the changes in energy poverty rates from Chapter 1), but also as a lens for identifying different types of households whose capacity to adjust is constrained (Chapter 2).

What I (don't) do in this thesis: Modelling choices and study focus

A first clarification concerns the link between carbon pricing and optimal taxation. In the canonical public-finance perspective associated with the Atkinson-Stiglitz theorem (Atkinson & Stiglitz, 1976), redistribution is primarily achieved through the design of the direct tax-and-transfer system (notably labor income taxation), while indirect taxes are mainly justified to correct for externalities. This thesis does not attempt to solve that optimal-tax problem, nor to derive a globally optimal mix of labor and commodity taxes. Instead, it evaluates realistic and implementable policy mixes that are compatible with the EU policy trajectory in the household sector, in particular ETS 2 and the accompanying compensation logic embedded in the Social Climate Fund.

That said, the broader literature has long emphasised that carbon pricing can positively interact with the wider fiscal system. The "double dividend" hypothesis highlights that recycling carbon-pricing revenues through cuts in distortionary taxes may yield both environmental gains and efficiency benefits (Goulder, 1995). In principle, shifting part of the tax base from labor towards CO_2 emissions could therefore be closer to an optimal-tax benchmark than relying exclusively on lump-sum compensation. In practice, however, the policy debate surrounding ETS 2 is largely organised around cost-of-living protection and the targeting of vulnerable households. Reflecting this institutional constraint, the thesis prioritises distributional performance and political feasibility within the SCF architecture, while keeping in mind that alternative recycling options, including reductions in distortionary taxes, remain an important reference point for welfare-improving environmental tax reforms.

Methodologically, this thesis relies on economic microsimulation (i.e., simulation on microdata). It is particularly well suited to study distributional concerns because it can capture heterogeneity in incidence at the individual level (Montenegro et al., 2021). Therefore, microsimulation has also become a standard tool for evaluating carbon pricing, precisely as it creates dispersed and uneven impacts between households, driven by differences in income, household composition, housing characteristics, heating technologies, and mobility needs. Microsimulation makes it possible to map these differences directly using granular data, and to quantify outcomes not only "on average", but also across the income distribution and within socio-demographic groups. This is especially useful when assessing revenue recycling designs, since small changes in targeting rules (per capita vs. per household) can shift who is protected from large losses.

In the scope of microsimulation, I had to make several modelling choices regarding

(i) data and geographical coverage, (ii) tax coverage, (iii) the treatment of behavioural responses, (iv) revenue recycling, and (v) the use of specific metrics for distributional comparisons.[3] Concretely, the entire analysis is built on rich microdata, with the aim of informing policy debates under the forthcoming EU carbon-pricing context. In terms of tax coverage, the focus is deliberately aligned with the ETS 2 perimeter: direct CO_2-related price increases on household heating and road-transport fuels, rather than economy-wide footprint taxation; in particular, the thesis does not attempt to model indirect emissions embodied in non-energy goods using environmentally extended input–output tables. Regarding behaviors, the thesis combines three complementary perspectives that mirror different timings at which carbon pricing can be investigated. Yet, this work does not embed the microsimulation in a full general-equilibrium framework with endogenous wages, factor returns, and firm responses, nor does it implement a macro–micro linkage. Instead, it prioritises household heterogeneity and policy-design detail for compensation schemes, vulnerable households identification, and instrument comparison. Lastly, this thesis makes use of specific metrics well suited to a comprehensive distributional analysis (compensation gap, equivalent variation, and life-cycle cost).

Belgium provides a policy-relevant case study because it combines (i) high income levels in a small open economy (ii) high population density and widespread car ownership (two characteristics closely tied to mobility-related emissions) and (iii) relatively small households (about 2.25 persons per household), a scale that limits within-household sharing and can raise per-capita domestic energy demand (Statbel, 2026a). These patterns interact with a housing context that is particularly informative for carbon-pricing analysis: Belgian dwelling stock is old (e.g., more than 2/3 of dwellings were built before 1981, see Chapter 1), and home-ownership is high (± 70% of Belgium households, see Chapter 2), which matters for renovation incentives and take-up. Space-heating is still largely fossil-based and dominated by natural gas. Finally, Belgium's moderate income inequality (Gini of ± 0.25 in recent years) provides an insightfull setting to study distributional trade-offs and acceptance constraints that are central in the carbon-tax literature, especially as the country prepares for the EU-wide extension of carbon pricing under ETS 2. Taken together, these features make Belgian evidence externally relevant for other high-income, car-reliant, densely populated countries with fossil-oriented heating and aging owner-occupied housing stocks; most of these characteristics are shared by other Western-European countries also concerned by the upcoming EU-ETS 2.

[3] See Linden et al. (2026) for a discussion about all possible modelling choices

Research Objectives and Outline

In the light of the above, the objective of this thesis is academic and applied: to advance the literature on carbon tax incidence by integrating revenue recycling and behavioural responses, and to inform policymakers seeking to implement carbon pricing in a way that is politically feasible and publicly acceptable. A distinctive feature of this work is its temporal scope. It considers three time horizons, each raising different questions and methodological challenges. Consequently, the way behaviors are treated throughout time is central and structures the argument. In Chapter 1, the key issue is the immediate burden of carbon pricing and how recycling schemes can be used for compensating highly impacted individuals; it stands as a good starting point for following chapters by drawing a comprehensive distributional picture of the day-after effect, telling who would be capable (or not) of coping with carbon pricing. In Chapter 2, households may adjust their consumption in the short run, which changes the incidence of carbon pricing, particularly for energy-vulnerable households whose characteristics are studied thoroughly; econometric analysis is used to distinguish behavioural adaptation and related welfare costs between specific groups all facing higher energy prices. In Chapter 3, price signals can stimulate larger structural changes, such as investments in energy efficiency (dwelling insulation) and low-carbon technologies (heat pumps); engineering-economic simulations are leveraged to reflect medium-run decision-making. A common thread across all chapters is the evaluation of carbon pricing distributional impacts under different policy designs, with particular focus on ensuring ambitious reforms of environmental taxation can transition from theory to reality. The following chapters delve into each time frame in detail, offering evidence and insight to support climate policies that are not only effective in reducing emissions but also socially inclusive and publicly acceptable.

Chapter 1

Carbon Pricing and Redistribution: A Microsimulation Analysis for Belgium

Joint work with Gilles Grandjean

Abstract

In this chapter, we simulate the distributional effects of a €45/tCO_2 carbon price on Belgian households' heating and transport fuels using microdata from the 2016 Household Budget Survey. Without compensation, the policy is regressive and increases energy poverty, with especially large burdens for singles, seniors, and households heating with oil. To tackle these distributional impacts, we compare three revenue-recycling designs: equal transfers per household, equal transfers per capita, and a fuel-type-differentiated scheme that provides larger transfers to fossil-heated households. It appears that per-household recycling protects vulnerable households better than per-capita recycling, which tends to undercompensate small households. Additionally, differentiating transfers by heating fuel further reduces large losses and within-income-group dispersion; it prevents an increase in energy poverty while preserving overall progressivity of the reform.

1.1 Introduction

The European Union is committed to reducing its greenhouse gas emissions by 55% between 1990 and 2030, and to achieving climate neutrality by 2050. As part of the Fit for 55 package, the EU will introduce a new Emissions Trading Scheme for road transport and buildings (hereafter, ETS 2). In 2021, both sectors accounted for 23% and 14% of CO_2 emissions in the EU, respectively (European Environment Agency, 2023). Under ETS 2, fuel suppliers will be required to acquire emission permits for the CO_2 released through the combustion of the fuels they sell on the market. As a result, end-user fuel prices are expected to increase to reflect the cost of carbon allowances. Aware of distributional concerns, the EU has embedded two notable safeguards in ETS 2: (i) a price-stability mechanism intended to limit excessive allowance-price increases in the initial years through the release of additional allowances, and (ii) the creation of the Social Climate Fund (SCF), financed in part by ETS 2 revenues, to support households facing energy and transport poverty (European Union, 2023a, 2023c).

Like any policy that raises fuel prices, carbon pricing risks facing public resistance. The Yellow Vests movement in France was precisely triggered by an increase in transport fuel prices (Douenne & Fabre, 2022). And if environmental policy is shaped by public sentiment (B. Anderson et al., 2017; Ewald et al., 2022; Schaffer et al., 2022), insufficient support can lead to incomplete implementation, low adoption, or policy stagnation (Ohlendorf et al., 2021; Parry, 2015). Yet, there are ways to foster public acceptability: in the case of carbon pricing, the substantial fiscal revenues it raises can be recycled to that effect. To enhance political feasibility, numerous proposals advocate for redistributing carbon revenues back to households. Among them, the 'Economists' Statement on Carbon Dividends' (2019) argues that "to maximize the fairness and political viability of a rising carbon tax, all the revenue should be returned directly to citizens through equal lump-sum rebates", claiming that most households would benefit on net.[4] Besides, public support is also shaped by beliefs about effectiveness and fairness, and by loss aversion (Bergquist et al., 2022; Dabla-Norris et al., 2023; Dechezleprêtre et al., 2025; Douenne & Fabre, 2022; Ewald et al., 2022; Kahneman & Tversky, 1979). Therefore, this study aims to inform policy debates on the expected distributional impacts and ways of compensating vulnerable households with particular attention to the individuals most affected by carbon pricing, across income groups and within sociodemographic subgroups.

To replicate the introduction of ETS 2, this paper quantifies the impacts of a €45/tCO_2 price on heating and transport fuel use among Belgian housholds. Using a microsimulation model calibrated on microdata from the Household Budget Survey, we predict "day-after"

[4]See also Klenert et al. (2018) and Carattini et al. (2017) on design principles for acceptability.

effects and compare alternative revenue-recycling options: equal lump-sum transfers per household, equal lump-sum transfers per capita, and a fuel-type-differentiated design with targeted supplements for households heating with natural gas or heating oil. We evaluate these designs using standard distributional indicators (average net burden, share of winners, high-loss incidence, energy poverty) and a new metric, the compensation gap, which measures the targeting efficiency of compensation schemes by summarising the average amount needed to bring losing households back to their pre-reform income.

Four main results emerge. First, consistent with the literature (Bursens et al., 2026; Callan et al., 2009; Douenne, 2020; Feindt et al., 2021; Flues & Thomas, 2015; Grainger & Kolstad, 2010; Linden et al., 2024; Mathur & Morris, 2014; Pizer & Sexton, 2019; Vandyck & Van Regemorter, 2014), carbon pricing is regressive in static incidence because lower-income households devote a larger share of income to energy. With equal lump-sum recycling, the reform becomes progressive on average: lower-income deciles record net gains and higher shares of winners since they consume less fuel in absolute terms (Douenne, 2020; Fremstad & Paul, 2019; Williams et al., 2014). Second, we corroborate the concern that per-capita recycling can result in a higher concentration of large losses among poorer households (Rausch et al., 2011); by contrast, per-household recycling lowers high-loss rates in bottom deciles and yields a flatter distribution of net burdens. Third, we document pronounced horizontal dispersion within income groups (as Cronin et al. (2019), Douenne (2020), Linden et al. (2024), Missbach and Steckel (2025), Missbach et al. (2024), Pizer and Sexton (2019) and Többen et al. (2023)) and show that heating technology emerges as the main observable driver of gross payments as oil-heated households face substantially higher burdens. Moreover, singles (Shim & Song, 2025) and seniors (Tian et al., 2023; Zhang et al., 2025) are disproportionately exposed, while being at elevated risks of energy poverty (Cartagena-Farias et al., 2025).[5] Crucially, a fuel-type component reduces large losses and within-decile dispersion, improving protection for the most exposed groups without sacrificing overall progressivity. To our knowledge, this is the first paper to show that differentiation by heating fuel can meaningfully reduce horizontal disparities; prior work has generally found little scope for revenue recycling to mitigate horizontal impacts. Fourth, our conclusions are robust across several dimensions. We show that the relative ranking of per-household versus per-capita recycling can depend on whether outcomes are computed at the household or individual level, but the fuel-type-differentiated design dominates under both perspectives. When assessing sensitivity to the wealth measure (income vs. expenditures) and to behavioural responses, we find that the qualitative policy ranking remains unchanged.

[5] Because a substantial share of energy costs arises at the dwelling level, smaller households do not benefit from economies of scale as much as larger ones.

The remainder of the paper is organised as follows. Section 1.2 presents the data, methodology, and the simulated reform. Section 1.3 analyses the distributive impacts of carbon pricing, documenting both vertical and horizontal incidence. Section 1.4 compares revenue-recycling strategies and introduces the compensation-gap metric. We conduct robustness checks and discuss the main results in Section 1.5. Section 1.6 concludes with policy implications and external validation considerations.

1.2 Methodology

1.2.1 Data

We use the Household Budget Survey (HBS) conducted in 2016[6] for which 4,500 households representative of the Belgian population reported their expenditures over a month. The data include expenditures for transport fuels (gasoline and diesel) purchased during the survey period. We divide them by the corresponding monthly price index from 2016 to obtain transport fuel quantities. Expenditures for heating fuels (natural gas and heating oil) come from the last annual energy bill reported by the households. Consequently, we use lagged prices to obtain the corresponding quantities of domestic energy consumed and report them on a monthly basis.[7] The dataset also incorporates socio-demographic characteristics of the households, including the income, age and employment status of each member; family composition; region; the type of housing occupied (house/apartment and owner/renter); and the ownership of durable goods (cars, appliances).

1.2.2 The reform

We consider the introduction of a uniform carbon price of €45 per ton of CO_2 on heating (natural gas and heating oil) and transport fuels (diesel and gasoline), which, calibrated on 2016 prices,[8] corresponds to the benchmark level discussed for the initial phase of ETS 2 (European Union, 2023a). We assume that the emission permits are subject to a 21% VAT, and that the full carbon price is passed on to consumers.[9] The related increases in energy

[6] We do not use more recent waves as the reporting period shrank from one month to two weeks after the 2016 survey. For transport fuel expenditures, this leads to bias in reporting and poor measurement of consumption patterns at the individual level. Nevertheless, we compared our aggregate results for 2016 with 2022 and did not find significant changes in population-level expenditure patterns.

[7] All prices come from the Consumer Price Indices computed by the National Statistics Agency in Belgium, Statbel (2026b). We used the social rate to compute the quantities of natural gas consumed by social rate beneficiaries. Poor households purchasing heating oil are eligible for a fixed, *ex-post*, rebate, which does not influence the computation of quantities.

[8] All price increases are computed relative to 2016 observed consumer prices, holding pre-existing fuel taxes and excise duties constant.

[9] Andersson (2019) provides empirical evidence supporting this assumption.

Table 1.1: Impact of a €45/tCO_2 carbon price on energy prices (2016 price baseline)

	Price increase	Relative price increase
Gasoline	0.13 €/litre	+8.7 %
Diesel	0.14 €/litre	+9.5 %
Heating Oil	0.14 €/litre	+20.2 %
Natural Gas	9.5 €/MWh	+15.6 %

prices are presented in Table 1.1. In relative terms, transport fuels are less affected than heating fuels, as their nominal prices are already much higher due to substantial excise duties.

1.2.3 Assumptions

We assume that fuel consumption remains unchanged, which is relevant to the study of immediate distributional impacts. Moreover, the meta-analysis by Labandeira et al. (2017) reports low price elasticities in the short run, ranging from -0.017 to -0.293 for the energy sources studied here. Given that we assume no changes in consumption, we also overlook the environmental benefits associated with reduced fossil energy consumption.[10] We discuss the sensitivity of our results to this assumption in Section 1.5.1. Other recent partial-equilibrium microsimulation studies explicitly incorporate consumer responses when simulating household carbon pricing, providing a useful benchmark for sensitivity to behavioural adjustments (Bursens et al., 2026; Immervoll et al., 2025).

Another limitation of our analysis lies in its focus on the direct effects on households' energy bills.[11] In practice, the reform also affects firms' production costs, which can be passed through to consumer prices, and can feed back into factor incomes (wages, returns to capital) via changes in activity and input use. Such indirect effects are typically substantial when carbon pricing primarily targets firms (as under the EU's original ETS) because cost pass-through raises downstream prices.[12] By contrast, ETS 2 covers end-use fuels consumed by households: direct impacts on energy bills are likely to dominate, although some indirect channels (e.g., goods transport, services) may remain (Immervoll et al., 2025; OECD, 2024). In our simulations, we recycle only the carbon payments made by households; those paid by companies are assumed to fund firm-oriented measures, which

[10] Tovar Reaños and Lynch (2023) show that the carbon burden decreases considerably when accounting for these environmental benefits.

[11] For a quantification of indirect emissions, recent EU-wide work extends EUROMOD with household global GHG footprints, enabling harmonised cross-country carbon tax simulations (Maier et al., 2024).

[12] The macro-distributional literature distinguishes use-side (consumption) from source-side (income) channels in CGE models; source-side effects are often progressive and partly offset consumption-side regressivity (see, e.g., Rausch et al. (2011) and Vandyck and Van Regemorter (2014)).

would tend to limit pass-through pressures on consumer prices and factor incomes.

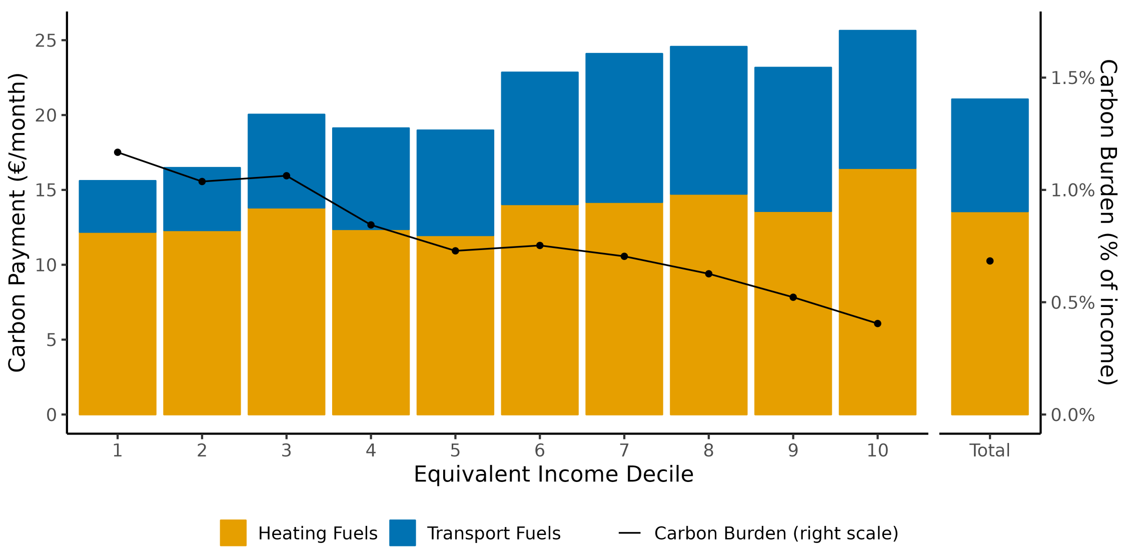
1.3 Carbon Pricing

In this section, we assess the incidence of a €45/tCO_2 carbon price on household expenditures in the absence of revenue recycling. We document how carbon payments vary across the income distribution, identify the main determinants, and report impacts by household types.

1.3.1 Vertical distributive impact

Figure 1.1 reports average monthly carbon payments per household for heating and transport fuels, together with the carbon burden (the ratio of a household's total carbon payment to its disposable income), by equivalent income deciles.[13] On average, households face a monthly carbon payment of €21, split between €7.5 for transport fuels and €13.5 for heating fuels. The average payment is slightly lower in the bottom income deciles and somewhat higher in the upper ones. Notably, heating-related carbon payments are relatively flat across the distribution, whereas transport-related payments rise across the income distribution, a pattern consistent with evidence for Belgium and other European countries (Bursens et al., 2026; Feindt et al., 2021; Jacobs et al., 2022).

Figure 1.1: Carbon Payment per Type of Fuels and Carbon Burden, by decile



[13]Equivalent income is obtained by summing the incomes of all household members and dividing by the number of consumption units (CU) as defined by the modified OECD equivalence scale: $1 + 0.5 \times$ (additional adults) $+ 0.3 \times$ (children).

The reform is regressive: lower-income households devote a larger share of their income to carbon payments than higher-income households. The average carbon burden declines from more than 1% of income in the first income decile to less than 0.5% in the tenth.[14]

1.3.2 Main determinants

We estimate Ordinary Least Squares (OLS) regressions to identify the main determinants of the monetary impact of carbon pricing. The dependent variable is the monthly household carbon payment (in €). We control for household size and income using linear and quadratic terms across three specifications. Model 1 does not include additional explanatory variables; Model 2 adds heating-system type and an indicator for high-efficiency heating; Model 3 further includes transport and housing characteristics (number of cars, building construction year, dwelling type, ownership status), as well as basic sociodemographics. The results are presented in Table 1.2.

We lack data on several important drivers of energy demand such as dwelling floor area, insulation quality, and commuting distances.[15] Nevertheless, the covariates in Model 3 explain a sizeable fraction of the variation in carbon payments ($R^2 = 0.41$).[16] Several regressors are categorical; coefficients are interpreted relative to the omitted categories: households with "other" heating (electricity or solid fuels), no private car, living in a flat, and residing in Flanders. "Attached house" refers to semi-detached and terraced houses. "Owner" and "Social-tariff eligible" are indicators equal to one if the household owns (vs. rents) its dwelling, and is eligible for the social tariff, respectively; remaining controls are counts.

Heating technology is the strongest predictor of carbon payments. The explanatory power rises sharply when heating variables are added (from $R^2 = 0.09$ in Model 1 to $R^2 = 0.32$ in Model 2), and the associated coefficients remain large once additional controls are included in Model 3. Looking at this last specification, we observe that, relative to "other" heating, households heating with gas pay €10.4 more per month, while those heating with oil pay €22.3 more (all else equal). A first-order driver is carbon intensity: heating oil emits about 0.26 kg CO_2/kWh versus 0.20 kg CO_2/kWh for natural gas, roughly a 30% difference in emissions per kWh. This alone cannot explain a twofold increase in coefficient size. The residual difference likely reflects unobserved correlates of heating

[14] Equivalent deciles can be constructed from income or total expenditures. As in most studies, regressivity appears stronger when using income-based deciles rather than expenditure-based deciles (see Section A.3)

[15] The latter may be partially proxied by region, with Brussels being the largest urban area and Wallonia being more rural.

[16] In closely related specifications, Douenne (2020) report R^2 values between 0.36 and 0.38, Farrell (2017) values between 0.15 and 0.36, and Missbach and Steckel (2025) find an average value of 0.23 in a cross-country comparison (ranging from 0.03 to 0.59).

Table 1.2: Determinants of monthly carbon payments (OLS)

Variable	Model 1: Income & Size	Model 2: + Heating	Model 3: + Controls
(Intercept)	9.548***	-0.727	-5.772***
	(0.814)	(0.987)	(2.061)
Income (k€)	1.813***	1.720***	1.153***
	(0.152)	(0.133)	(0.131)
Income squared	-0.012***	-0.012***	-0.008***
	(0.001)	(0.001)	(0.001)
Household size	4.124***	3.177***	0.765
	(0.661)	(0.572)	(0.555)
Household size squared	-0.483***	-0.346***	-0.052
	(0.105)	(0.091)	(0.087)
Heating: Gas		7.735***	10.438***
		(0.801)	(0.770)
Heating: Oil		23.777***	22.318***
		(0.833)	(0.790)
High-efficiency heating system		1.706***	0.365
		(0.432)	(0.426)
Private cars: 1			3.961***
			(0.518)
Private cars: 2+			10.517***
			(0.685)
Building year (decade)			-0.011
			(0.015)
Dwelling type: Detached House			7.366***
			(0.605)
Dwelling type: Attached House			4.048***
			(0.527)
Owner			-2.310
			(1.617)
Region: Brussels			1.653**
			(0.669)
Region: Wallonia			3.424***
			(0.426)
Age (reference person)			0.041***
			(0.013)
Social tariff eligibility			1.878***
			(0.683)
N	4439	4439	4439
R^2	0.09	0.32	0.41

technology that are not fully captured by our controls. Examples include larger heated floor areas, poorer insulation, thermostat set points, and occupancy patterns. Because we lack direct measures for these features, the estimated coefficients should be interpreted as conditional correlations rather than purely causal effects.

Transport and housing characteristics also matter: relative to households without a car, owning one private car is associated with €4 higher monthly payments, and owning two or more cars is associated with €10.5 higher monthly payments. Relative to living in a flat, residing in an attached house is associated with €4 higher monthly payments, and in a detached house with €7.4, all else equal. These transport patterns are consistent with Douenne (2020), who find that households relying on private vehicles incur substantially larger losses on average, helping to explain the higher incidence in rural and peri-urban areas. Regional differences persist after controlling for observables: carbon payments are higher in Brussels (by €1.7) and especially in Wallonia (by €3.4) relative to Flanders. Finally, households eligible for the social tariff exhibit slightly higher carbon payments (€1.9), consistent with the notion that lower effective energy prices are associated with higher consumption, all else equal.

1.3.3 Impact on categories of individuals

We examine the impact of carbon pricing across sociodemographic groups using four metrics: (i) the average carbon burden (Avg. CB, in % of disposable income), (ii) the share of households whose total expenditures rise by more than 0.5% of disposable income (hereafter, the share experiencing a high loss), (iii) the energy poverty rate[17] (in % of the population), and (iv) the change in energy poverty (in percentage points). Results are summarised in Table 1.3.

In most cases, impacts are more pronounced among groups that already exhibit higher energy poverty rates. Households with a head aged 65 or older, singles, and those heating with oil appear particularly vulnerable. Relative to the population average, these groups display a higher energy poverty rate, a higher average carbon burden, and a greater likelihood of experiencing a high loss. For example, singles' energy poverty rate rises to 23.1% due to carbon pricing, their average carbon burden amounts to 0.97% of income, and 66.9% of them experience an expenditure increase exceeding 0.5% of income.[18]

By contrast, Brussels residents, couples, and households using "other" heating systems (electricity or solid fuels) face smaller adverse effects on average. This pattern is consistent

[17] Our measure of energy poverty follows the King Baudouin Foundation (Fondation Roi Baudouin, 2024) definition: households in the bottom five income deciles are classified as energy poor when their energy expenditures exceed twice the median ratio of energy spending to disposable income (net of housing costs).

[18] These findings are in line with other studies (see, e.g., Többen et al. (2023) and Tovar Reaños (2021)).

Table 1.3: Carbon Pricing Impact per Groups

Group	Avg. CB	High Loss	EPoverty	Δ EPoverty
Total Population	0.83 %	62.7 %	14.5 %	+ 3.4 p.p.
Age				
>=65	0.99 %	72.7 %	22.2 %	+ 4.6 p.p.
<65	0.79 %	59.8 %	12.2 %	+ 3 p.p.
Heating System				
Other	0.26 %	18.7 %	7.4 %	+ 1.2 p.p.
Gas	0.77 %	62.6 %	12.4 %	+ 2.8 p.p.
Oil	1.34 %	91.6 %	23.7 %	+ 6.2 p.p.
Dwelling Type				
Flat	0.71 %	53.4 %	14.4 %	+ 3.7 p.p.
House	0.88 %	66.3 %	14.3 %	+ 3.3 p.p.
Dwelling Ownership				
Owner	0.83 %	62.5 %	14.4 %	+ 3.4 p.p.
Renter	1.19 %	74.9 %	24.6 %	+ 2.5 p.p.
Household Composition				
Single	0.97 %	66.9 %	23.1 %	+ 4.4 p.p.
Couple	0.74 %	60 %	8.89 %	+ 2.8 p.p.
Car Ownership				
None	0.76 %	50.1 %	22.8 %	+ 3.5 p.p.
At least one car	0.85 %	65.7 %	12.5 %	+ 3.4 p.p.
Region				
Brussels	0.66 %	50.8 %	6.99 %	+ 3 p.p.
Not Brussels	0.85 %	64.2 %	15.4 %	+ 3.4 p.p.
Energy Poverty				
Not Energy-poor	0.7 %	59.1 %	3.82 %	+ 3.8 p.p.
Energy-poor	1.9 %	91.9 %	100 %	0 p.p.

with evidence that carbon-pricing impacts are stronger in rural areas, where households are more likely to live in houses, travel longer distances, and rely more on private vehicles. Our data cannot fully recover the urban–rural gradient, as we only observe the region of residence; yet, since Brussels' region is also the country's largest urban area, the lower incidence in urban settings is most likely in Belgium as well.

To explain these differences in carbon burden, one must look both at the numerator (heating and transport carbon payments) and the denominator (disposable income) of the measure. Heating oil users face structurally higher payments because oil is more carbon intensive than gas, and oil systems are more often found in older, less efficient houses (Table A.2); our regressions confirm the result. Higher burdens among seniors and singles largely reflect lower disposable incomes, whereas couples benefit from household economies of scale that spread fixed energy requirements over greater combined income (see Table A.1). Moreover, greater home occupancy among seniors increases heating needs, further amplifying the impact.[19] Households with more cars face higher transport payments, whereas carless households have lower transport exposure but often low incomes and elevated baseline energy poverty risks. Finally, Brussels residents experience smaller adverse effects on average, consistent with more flats and better access to public transport, while renters' higher burdens reflect lower incomes and potentially older, less efficient dwellings due to split-incentive barriers to efficiency upgrades.

1.4 Carbon Dividend

In this section, we compare redistribution rules along complementary fairness dimensions: (i) vertical equity (distribution of impacts across the income distribution), (ii) horizontal equity (the dispersion of monetary impacts among households with similar incomes), (iii) the incidence on vulnerable groups, and (iv) targeting performance—i.e., the ability of a given scheme to compensate those most adversely affected. We assume that the carbon payments collected from households are fully returned to households (a "carbon dividend"). We define the net carbon burden as the difference between the carbon payment and the transfer received, divided by disposable income; a negative net burden indicates a net gain.

Three revenue-recycling designs are considered here. First, an equal per-household dividend (Household scenario), under which each household receives a uniform monthly transfer of €21.1 (as in, e.g., Berry (2019)). Second, an equal per-capita dividend (Capita scenario), under which each individual receives €9.2 per month; this headcount-based approach is common in the academic literature (Budolfson et al., 2021; Cronin et al., 2019;

[19] From Table A.1, we see that heating represents 73% of older households' total carbon payment, whereas it accounts for only 62% for households whose reference person is less than 65.

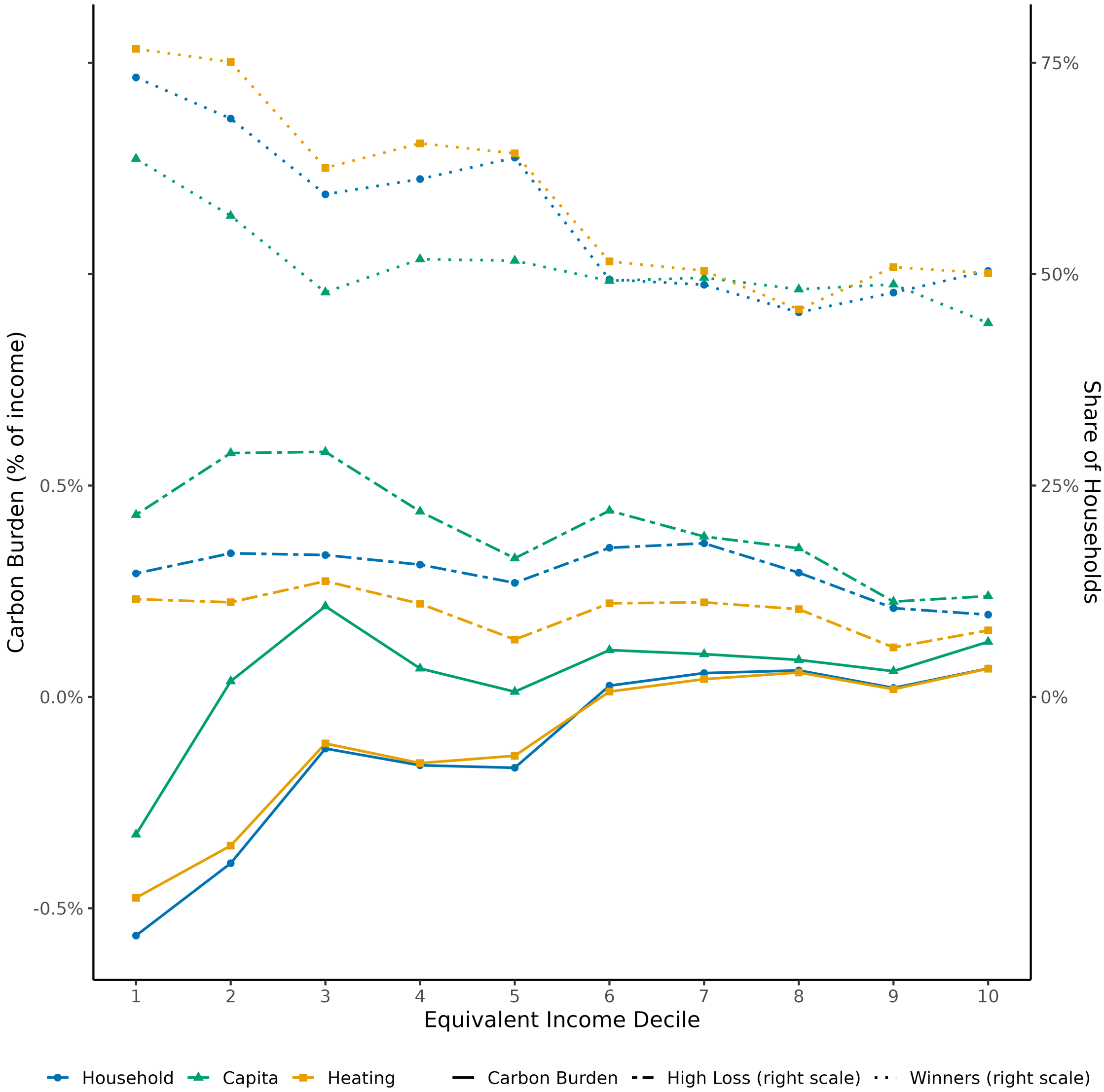
Rausch et al., 2011) and is applied elsewhere (e.g., Switzerland redistributes carbon revenues via uniform rebates on mandatory health insurance premiums, Austria redistributed direct per-capita transfers in the form of "climate bonus" Linden et al. (2025)). Third, a fuel-type-differentiated design (Heating scenario) that combines an even per-household component with targeted supplements: half of the revenue is returned evenly per household (€10.5 per month), and the remaining half funds fuel-type-specific supplements calibrated to budget neutrality, with oil-heated households receiving an additional €19.3 per month and gas-heated households an additional €9.65 per month.

1.4.1 Vertical distributive impact

To compare distributional impacts across income levels, Figure 1.2 plots, by decile, three series for each scenario: the average net carbon burden (solid; % of disposable income), the share of winners (dotted; households with a negative net burden), and the share of high-loss households (dashed; net burden $> 0.5\%$ of income). Three results emerge. First, the solid lines show that all scenarios are progressive: net burdens are most negative in the lowest decile (-0.56 p.p. (Household), -0.33 p.p. (Capita), and -0.48 p.p. (Heating) in the first decile) and rise with income. Across the distribution, the Household and Heating designs yield lower (more negative, or less positive) average net burdens than Capita. Second, the dotted lines show that the share of winners is higher in lower deciles—about 75% in the first decile for the Household and Heating scenarios—and declines steadily with income, reaching roughly 50% by the sixth decile across all scenarios. Third, the dashed lines show that large losses are rarer under the Heating design than under other schemes. The Capita scheme consistently leaves a thicker high-loss tail than Household, especially in the lower deciles. This corroborates concerns that per-capita recycling can concentrate large losses among poorer households (Rausch et al., 2011); by contrast, Household recycling lowers high-loss rates at the bottom and yields a flatter high-loss profile across the income distribution.

These differences stem from how transfers interact with household size and exposure. Per-capita payments scale with headcount, whereas much of the carbon payment—especially for heating—is borne at the household level and benefits from economies of scale. The Capita scenario therefore tends to overcompensate larger households and undercompensate smaller ones, regardless of income rank. By adding a fuel-type component, the Heating design better matches heterogeneity in heating exposure, thereby reducing the incidence of large losses without altering the overall progressive shape.

Figure 1.2: Net Burden, Winners and High Loss per Redistribution Scenario, by decile



1.4.2 Horizontal distributive impact

We now turn to the horizontal distributive dimension of carbon pricing, i.e., differences in impact among households with similar income levels. We proceed in two steps. First, we document horizontal heterogeneity in gross exposure by examining, within each equivalised-income decile, the 25th and 75th percentiles of monthly carbon payments. Second, we compare the intra-decile standard deviation of the net carbon burden across redistribution scenarios to assess how design choices shape within-decile dispersion.

Table 1.4a shows marked horizontal heterogeneity: households with comparable equivalised incomes face very different carbon payments. In the first decile, the 25th percentile is €6.5 while the 75th percentile is €21.9, an interquartile range (IQR) of roughly €15. Considering higher deciles, the dispersion increases further and remains high at the top. These wide spreads reflect substantial differences in energy consumption determinants (heating systems, dwelling characteristics, transport needs, occupancy) within each income group. This implies that carbon pricing creates substantial dispersion within income classes, beyond the vertical dimension usually emphasised. After redistribution, we quantify within-decile heterogeneity using the intra-decile standard deviation of the net carbon burden (Table 1.4b). Dispersion tends to be highest under the Capita scheme, though broadly comparable to No Redistribution and Household, and consistently lower under the Heating design. Uniform transfers do little to reduce within-decile heterogeneity (Capita even widens it) whereas a modest fuel-type differentiation compresses dispersion across all deciles.

Table 1.4: Distribution of Outcomes across Income Deciles

(a) Distribution of Carbon Payments

decile	P25	P75
1	6.50	21.9
2	4.79	24.6
3	9.67	27.4
4	8.95	27.2
5	9.63	27.2
6	12.4	32.8
7	12.8	32.0
8	12.4	33.6
9	11.3	32.4
10	12.0	34.2

(b) Intra-decile Net Carbon Burden Standard Deviation

decile	No Dividend	Household	Capita	Heating
1	1.07	1.15	1.30	0.92
2	0.97	1.01	1.03	0.76
3	0.85	0.85	0.92	0.69
4	0.65	0.68	0.71	0.54
5	0.51	0.58	0.55	0.46
6	0.56	0.55	0.62	0.44
7	0.51	0.51	0.55	0.45
8	0.45	0.45	0.49	0.38
9	0.37	0.38	0.40	0.32
10	0.40	0.39	0.42	0.36

These findings stand in stark contrast to Cronin et al. (2019), who report that recycling through existing transfer programs can roughly double the within-decile standard deviation, exacerbating horizontal inequity. Echoing this concern, Pizer and Sexton (2019) argue that even policy makers committed to horizontal equity may face limitations in their ability to achieve it, since proxies for energy use or geographic targeting (climate or urban/rural) often fall short. Contrary to the existing literature, we identify a revenue-recycling design that mitigates horizontal distributional effects. Our approach is guided by a detailed diagnostic of the main drivers of household carbon payments, which makes the targeting uniquely suited to the underlying exposure. Douenne (2020) explores targeting by heating system and by density; he finds that density-based targeting amplifies dispersion, while heating-type targeting has only a marginal effect limited to the lowest income decile. His study about France reveals that gas and heating oil exert a comparable influence on household carbon payments per consumption unit, leading his heating-type-targeted scenario to omit any distinction between the two systems. Our demonstration that a heating-type-targeted policy can reduce horizontal effects, specifically by differentiating between gas and heating oil, therefore constitutes a novel contribution to the literature.

1.4.3 Vulnerable households

As shown in Section 1.3, seniors (65+), singles, energy-poor households, and oil-heated households are the most vulnerable groups. We assess incidence for each group under the different recycling scenarios, first for each vulnerability dimension separately and then by combining age (below/above 65) and household type (couple/single) within each heating technology (gas vs. oil).

For single-dimension groups (Table 1.5), seniors and singles exhibit negative average net burdens only under the Household and Heating designs; under Capita they display positive net burdens and a higher high-loss share. Among energy-poor households, Heating yields the lowest average net burden and high-loss share, followed by Household, with Capita least favorable. Oil-heated households remain the most exposed in all cases, but Heating substantially lowers their average net burden and sharply reduces the share facing large losses relative to the two uniform schemes.

The compensation gap corroborates these patterns: across all vulnerable groups, Heating yields the smallest gap, Household is intermediate, and Capita the largest. For oil users, the gap under Heating is roughly half that under the uniform schemes; for seniors and singles, Household improves upon Capita, and Heating improves further.

Turning to combinations of vulnerability factors, Table A.3 (in appendix) confirms that heating system is the dominant driver of incidence. Without revenue recycling, all oil-heated subgroups—singles or couples, under or over 65—display average carbon burdens at or above 1.2% (vs. 0.85% in the full sample) and high-loss shares above 92% (vs. 66.8% overall). By contrast, gas-heated subgroups cluster much closer to population averages.

Lastly, we compare recycling designs within gas-heated (Table 1.6a) and oil-heated (Table 1.6b) subgroups, focusing on household type (number of adults and age). We observe only modest differences for gas-heated couples across scenarios; among singles, however, Capita is least favorable. For oil users, the pattern is stark: Heating dominates for all subgroups, while singles and seniors exhibit the highest high-loss shares under uniform

Table 1.5: Impact on Vulnerable Households

Group	Household	Capita	Heating
Avg. Carbon Burden (%)			
Total sample	-0.12	0.05	-0.10
Age 65+	-0.11	0.27	-0.14
Heating Oil	0.44	0.57	0.07
Single	-0.38	0.27	-0.33
Energy poor	0.21	0.84	0.05
High Loss (%)			
Total sample	14.8	20	10.1
Age 65+	18.1	30.5	10.6
Heating Oil	39.0	43.9	16.7
Single	12.7	31.4	8.79
Energy poor	36.6	59.8	27.8
Compensation Gap (€/hh)			
Total sample	6.03	6.48	4.88
Age 65+	5.86	8.78	4.08
Heating Oil	13.7	14.0	7.61
Single	3.28	7.63	2.48
Energy poor	8.62	13.2	6.27

schemes. In the most exposed category (oil, 65+, single), the high-loss rate is more than four times higher under Capita than under Heating and more than twice as high under Household as under Heating.[20]

Table 1.6: High Loss Share by Subgroup

(a) Focus on Gas Heating

Group	Household	Capita	Heating
Gas (all)	8.23	14.5	9.27
Couple <65	9.20	5.96	10.1
Couple 65+	7.74	8.41	8.27
Single <65	7.62	25.6	8.66
Single 65+	5.56	31.9	7.97

(b) Focus on Oil Heating

Group	Household	Capita	Heating
Oil (all)	39.0	43.9	16.7
Couple <65	39.3	24.9	17.6
Couple 65+	40.0	47.8	17.5
Single <65	33.3	60.2	13
Single 65+	48.4	84.6	19.5

1.4.4 Targeting performance

We finally assess the aggregate performance of the recycling scenarios using a compact set of indicators designed to capture both targeting and fairness. Specifically, we report: (i) the

[20]These conclusions also hold when using the compensation gap; see Section A.3 in appendix.

share of winners (households with a negative net carbon burden), (ii) the compensation gap, which captures the average uncompensated loss remaining after recycling, (iii) the share of households experiencing a high loss (net burden > 0.5% of disposable income), (iv) the energy poverty rate, and (v) the standard deviation of the net carbon burden (in percentage points). Formally, for any subgroup S, the compensation gap is defined as

$$CG(S) \;=\; -\frac{1}{\#S}\sum_{h\in S}\min\bigl(Y_h' - Y_h,\,0\bigr),$$

where Y_h is household h's initial disposable income and $Y_h' = Y_h - C_h + T_h$ is disposable income under the policy, with C_h the carbon payment and T_h the transfer received. Conceptually, this metric is inspired by the poverty-gap measure: it aggregates, within S, the shortfall of each losing household relative to a reference level (here, pre-policy income), and averages these shortfalls across the group. It is therefore the average amount, per household, required to bring every household in S back to its pre-policy income—i.e., to eliminate all losses. The measure increases with both the number of losing households and the magnitude of their losses, and it is zero if all households in S are already fully compensated (or net winners).

Table 1.7 compares the baseline carbon pricing without redistribution to the three dividend designs. Four main findings emerge. First, all recycling scenarios generate a majority of winners, with the Heating design performing best. Consistently, the compensation gap falls most under the Heating scenario (€4.88), compared with €6.03 (Household) and €6.48 (Capita), down from €21.1 without recycling. This pattern is intuitive: aligning part of the transfer with heating fuel type channels more resources to oil users facing structurally higher gross payments, thereby reducing the size of total losses.

Second, the upper tail of the incidence distribution shrinks markedly under all scenarios, with the strongest attenuation under the Heating design. The share of high-loss households falls from 62.7% (No Redistribution) to 14.8% (Household), 20.0% (Capita), and 10.1% (Heating). The Capita scenario performs worse than the Household scenario on this metric, consistent with per-capita transfers tending to favour larger households with children,

Table 1.7: Overall Impact

	No Dividend	Household	Capita	Heating
Winners (%)	0	56.8	51.2	59.3
Compensation Gap (€/hh)	21.1	6.03	6.48	4.88
High Loss (%)	62.7	14.8	20.0	10.1
Energy Poverty (%)	14.5	11.2	11.9	10.8
Standard Deviation of Burden (p.p.)	0.72	0.73	0.77	0.59

whereas per-household transfers provide relatively better protection to smaller households who are more frequently among the highly impacted (in relative). By contrast, fuel-type-specific supplements directly address heterogeneity in heating-related exposure, further compressing the loss tail.

Third, relative to the no-policy energy poverty rate of 11.1%, imposing the carbon price without recycling raises it to 14.5% (+3.4 p.p.). Recycling mitigates this increase: the Household scenario brings the rate close to its pre-reform level (11.2%; +0.07 p.p.), the Capita scenario remains higher (11.9%; +0.85 p.p.), and the Heating scenario lowers it below the no-policy benchmark (10.8%; −0.30 p.p.). This ranking reflects the overlap between energy-poor households and those with high heating needs and/or oil heating; differentiating transfers by fuel type strengthens protection for these vulnerable groups.

Fourth, turning to dispersion, the population-wide standard deviation of the net carbon burden declines only under the Heating scenario (from 0.72 to 0.59 p.p.), remains roughly unchanged under the Household scenario (0.73 p.p.), and rises slightly under the Capita scenario (0.77 p.p.). This again suggests that differentiating transfers by heating system better aligns compensation with underlying exposure, compressing the overall distribution of net burdens.

Finally, the relative ranking of the Household and Capita scenarios is sensitive to the unit of analysis. As shown in Section A.3, when outcomes are computed at the individual level, Capita yields a higher share of winners, a lower share of high-loss cases, and a smaller energy poverty headcount than Household; when outcomes are computed at the household level, the ranking reverses. By contrast, the dominance of the Heating scenario is robust to the choice of unit. Unlike these share-based indicators, the compensation gap is invariant to the unit of analysis—and on this metric the Household scenario outperforms the Capita scenario.

1.5 Discussion

1.5.1 Accounting for household behavioural response

Households can adjust energy use when gas and heating-oil prices rise. In the short run, they may lower indoor temperatures, reduce hot-water use, or cut car travel. Over longer horizons, households can adjust through capital investments, including energy-saving retrofits (e.g., insulation upgrades) and fuel switching towards lower-carbon options such as heat pumps. The empirical literature generally finds that energy demand is inelastic, with larger responses over longer horizons when price changes are persistent and salient (Andersson, 2019; Labandeira et al., 2017).

Incorporating behaviour into our analysis is not straightforward. A fully behavioural framework should (i) account for the welfare cost of foregone energy services when households reduce consumption (as in, e.g., Douenne (2020)) and (ii) include the capital costs of long-run investments (e.g. vehicle upgrades, heat pumps, insulation). Two empirical strategies are common (see Linden et al. (2026) for a review). The first infers behavioural reactions from observed data; although policy-induced responses may be stronger and qualitatively different (investment vs. short-run rationing) than market-driven adjustments, recent evidence suggests small and fairly homogeneous elasticities (see Coppens d'Eeckenbrugge and De Bevere (2025) and Labandeira et al. (2017)). If elasticities vary little across the income distribution, our main vertical-incidence conclusions are unlikely to change. The second strategy simulates investment under assumptions about decision rules (e.g., rational adoption). Using the Woonsurvey database with rich building characteristics, De Bevere et al. (2026) find that profitable investments are found across the whole income distribution and that undertaking home retrofits can decrease horizontal equity (profitability is higher for more exposed households), if liquidity constraints and the landlord–tenant dilemma are ignored. However, horizontal dispersion may widen—especially in the lower tail—if adjustment opportunities depend on ownership or access to credit. Our data lack several building variables needed to model these choices credibly; by contrast with Woonsurvey, the HBS offers nationally representative, verified expenditure data and detailed transport information, but only limited details on building features.

At the price level considered here (€45/tCO_2), we do not expect behaviour to overturn our qualitative findings. First, the incentive to undertake major changes is limited: many capital-intensive switches (heat pumps, EVs) typically require larger and more persistent relative price differentials to be financially attractive (see Chapter 3). Second, the combination of a low carbon price with low price elasticities implies modest adjustments, as illustrated by the following sensitivity analysis. In Table 1.8, we assume full pass-through and uniform elasticities of 0.40 for transport fuels and 0.25 for residential energy (midpoints of short- and long-run elasticities in the meta-analysis by Labandeira et al. (2017)). Doing so, the average carbon payment declines from €21.05 to €19.90 (- €1.15 per month), and the average energy bill falls by €8 per month relative to the no-adjustment case. Without behavioural change, the average monthly energy bill rises from €129 to €150; with behavioural change, it is €142. By reacting to carbon pricing, households save on energy expenditures, but receive a slightly smaller transfer (because total carbon payments are lower). Overall, these represent modest changes relative to baseline expenditures. Taken together, our static results can be interpreted as a conservative, "worst-case" benchmark. If households adjust, their net outlays improve relative to the no-adjustment case. Import-

Table 1.8: Behaviour, Energy Bill and Transfer

Scenario	Energy bill (carbon payment incl.)	Transfer
No Carbon pricing	129	0
Carbon dividend (no behaviour)	150	21.05
Carbon dividend & behaviour	142	19.9

antly, the policy ranking we report is unlikely to be overturned by plausible behavioural responses at €45/tCO_2.

1.5.2 Policy design: incentives and targeting

Providing more generous transfers to households equipped with heating systems with higher CO_2 intensity might discourage investments in energy-efficient infrastructure. This could reduce the environmental effectiveness of the policy and potentially lead to higher long-term energy costs, especially in light of the expected trajectory of increasing carbon prices. However, it should be noted that these support measures are generally not designed to be permanent. For example, the Social Climate Fund is expected to be operational between 2026 and 2032. Hence, households are encouraged to invest during the transitional phase to reduce their future energy consumption, as support programs will be gradually phased out. In addition, it is possible to mitigate these unintended disincentive effects. For example, support could be delivered in the form of investment subsidies, enabling homeowners to enhance the energy efficiency of their dwellings, rather than through unconditional cash transfers. Lastly, concrete policy designs could target low-income households who are likely locked into fossil-fuel consumption because they are financially constrained from investing in cleaner durables. Instead of providing financial help to cope with higher fossil energy prices, carbon revenues could be used to provide means-tested subsidies, easier access to credit, lower interest rates, and/or reduced electricity prices. Consequently, targeted redistribution based on heating type would not incentivise pollution, but rather foster home retrofits and the adoption of low-emission technologies among liquidity- and credit-constrained individuals.

1.6 Conclusion

This paper presented an ex-ante microsimulation analysis assessing the distributional effects of implementing a €45/tCO_2 carbon price on heating and transport fuel consumption among Belgian households. Our findings reinforce well-established results: carbon pricing is inherently regressive by disproportionately burdening lower-income households. However, revenue recycling can counteract this effectively. Importantly, our analysis highlights the significant heterogeneity in carbon payments among households with similar incomes, underscoring the prominence of horizontal distributional impacts on top of vertical equity concerns.

We demonstrate that the type of heating system is the most influential driver of the carbon burden, with households relying on heating oil facing substantially higher payments, placing lower-income oil users in a particularly vulnerable position. Singles and individuals aged 65+ are also identified as highly vulnerable. Our results indicate that a per-household redistribution scenario is more effective than a per-capita approach in reducing the carbon burden, particularly among vulnerable groups. In addition, providing larger transfers to oil-heated households, potentially through subsidies incentivising energy-efficient investments, proves even more effective in supporting the most impacted households and mitigating horizontal disparities.

Furthermore, this study pioneers an assessment of the capacity of different revenue-recycling policies to compensate losers and limit the increase in energy poverty. We introduce the concept of the “compensation gap”, which offers the advantage of being independent of the unit of analysis (household or individual). Additionally, we are the first to demonstrate that targeting transfers based on heating system type can better compensate vulnerable households and, crucially, reduce horizontal distributional effects. The prior literature has largely found that revenue redistribution tends to exacerbate horizontal impacts, with a prevailing consensus that mitigating such effects is intractable due to the multiplicity of factors correlated with the carbon burden.

Our core findings, the better targeting performance of heating-type-based transfers and the superiority of per-household compared to per-capita recycling, are robust across various distributional indicators. These results underscore the need for climate policies to account for the heterogeneity of households and the protection of the most vulnerable. This is a matter of distributional justice as much as of public acceptability and political feasibility.

Our results speak directly to the Belgian context, which features relatively small climatic gradients, a sizable legacy stock of oil-heated, older houses, and institutional features (e.g., social tariffs) that influence energy use. In settings with larger climate heterogeneity, different fuel mixes (e.g., district heating or higher shares of electric heating), or distinct housing stocks and urban forms, the relative magnitude of horizontal dispersion and the scope for heating-type targeting may differ. For example, Douenne (2020) finds in France that the carbon payment per unit of energy depends on the heating system, but that impacts on gas and oil are more similar, which reduces the gain from fuel-specific targeting in that context. Our results suggest that the oil–gas differential reflects carbon intensity and unobserved correlates of heating technology (dwelling size, insulation, and occupant profiles). This highlights an important implication for external validation: replication in other countries should jointly account for fuel type and other housing features (construction year, EPC ratings, dwelling type). Though the precise magnitudes will vary across countries, we expect the mechanism to be general: data-driven targeting along heating-system exposure can substantially improve protection for the most impacted households and reduce horizontal inequities.

The next two chapters integrate information on behavioural responses to energy prices (Chapter 2) and on residential buildings (Chapter 3), thereby helping assess the robustness of our results when households can adapt and invest. Even if behavioural responses are likely to be modest at €45/tCO_2, larger and more persistent price signals could elicit stronger and more heterogeneous adjustments depending on urban–rural context, tenure status, or credit constraints. More generally, linking detailed building and vehicle attributes with energy expenditure data would make it possible to model adaptation and investment choices more credibly (e.g., electric vehicles, heat pumps, insulation upgrades) and to examine recycling options that earmark revenues for investment support.

Chapter 2

Household Demand Responses to Carbon Pricing by Energy Poverty Status: Evidence from Belgium

Joint work with Daniel Coppens d'Eeckenbrugge

Abstract

In this chapter, we develop a behavioural microsimulation framework to analyse how carbon pricing affects energy vulnerable households in Belgium. We focus on two groups: energy poor (EP) households, who devote a large share of their income to energy, and hidden energy poor (hEP) households, who spend little on energy as they severely restrict their consumption. Based on eleven repeated cross-sections of the Belgian Household Budget Survey (2003–2016), we first document structural differences between EP and hEP households with logistic regressions. We then estimate a demographically specified Quadratic Almost Ideal Demand System (Banks et al., 1997) and develop a two-stage residual inclusion procedure to address the endogeneity of energy poverty statuses. The resulting price and income elasticities across vulnerability profiles are used to simulate responses and welfare impacts of a carbon price on heating and transport fuels. It appears behavioral adjustments are heterogeneous: lower-income and energy vulnerable households show higher fuel price elasticities than wealthier groups, with hEP households responding most strongly to price increases. The policy analysis reveals that EP households face substantial carbon costs but smaller relative welfare loss, whereas hEP households suffer higher marginal welfare burden despite their low expenditure-based exposure. These results reveal horizontal equity concerns that are invisible in income-based metrics alone and highlight the need to integrate detailed energy vulnerability profiles and welfare metrics into carbon pricing design.

2.1 Introduction

To meet its carbon-neutrality objectives, the European Union will introduce a new Emissions Trading Scheme (ETS 2) in 2028 covering the buildings and road-transport sectors. Together, these sectors accounted for 37% of EU CO_2 emissions in 2021 (European Environment Agency, 2024). By requiring fuel suppliers to purchase emission allowances, ETS 2 is expected to raise fuel prices. Part of the resulting revenue will fund the Social Climate Fund, designed to support households vulnerable to higher energy costs. Energy poverty, understood as the inability to access the energy services necessary for a decent standard of living and good health, is therefore a central concern of this policy agenda. In Belgium, 21.8% of households were energy poor in 2022 (Fondation Roi Baudouin, 2024). Identifying the households affected, understanding the determinants of energy poverty, and anticipating their behavioural responses to carbon pricing are therefore crucial for evaluating the distributional and welfare effects of ETS 2.

A substantial literature embeds household demand systems into microsimulation models to assess behavioural responses to carbon pricing reforms. These studies typically conclude that carbon taxes implemented without redistribution schemes are regressive, as low-income households allocate a larger share of their budgets to carbon-intensive energy goods (Costantini et al., 2025; Feindt et al., 2021; Nikodinoska & Schröder, 2016; Pashardes et al., 2014; Tovar Reaños & Wölfing, 2018). Recent work also highlights horizontal disparities: De Bevere and Grandjean (2023) shows that substantial variation in net burdens persists within income groups, even when carbon taxes are combined with targeted cash transfers (Douenne, 2020); Linden et al. (2024) document that the degree of regressivity depends on the country context and varies with households' expenditure patterns. However, systematic evidence on horizontal distributional effects remains limited, especially regarding how carbon pricing affects households with similar incomes but different energy needs and constraints.[21] Notably, behavioural microsimulation models seldom incorporate energy poverty indicators, even though income alone is an incomplete proxy for identifying households struggling to meet essential energy needs (Okushima, 2017). A few exceptions exist: Berry (2019) underscores the importance of accounting for energy poor households but relies on a simplified linear expenditure system and focuses mainly on revenue recycling; Charlier and Kahouli (2019) document heterogeneous price responses and distinguish between income and energy poverty, yet use only a single expenditure-based vulnerability indicator; and Tovar Reaños and Lynch (2022) include an energy poverty measure for Ireland but do not allow behavioural responses to vary across household types. In fact, none

[21]Such within-group disparities are likely to matter for perceived fairness, which crucially affects the political acceptability of carbon pricing (Douenne & Fabre, 2020).

of these studies goes beyond classical expenditure-based indicators of energy poverty that flag households spending a large share of their income on energy, thereby capturing only one dimension of energy vulnerability.

In this paper, we conduct a repeated cross-sectional study and develop a behavioural microsimulation model that explicitly incorporates multiple energy poverty statuses into a distributional analysis of carbon pricing, thereby going beyond traditional income-based classifications. We adopt and extend the indicator designed by Meyer et al. (2018) identify the "hidden energy poor" (households that severely restrict energy consumption to keep expenditures low), enabling us to model these households as a distinct energy vulnerable group. This expands the identified energy-vulnerable population by roughly one third and substantially broadens the scope of the subsequent behavioural and policy analysis. It also allows us to offer a detailed descriptive portrait of the energy vulnerable population in Belgium, showing how (hidden) energy poor households differ not only from the general population but also from households with similar income levels. We formalise these insights through the estimation of two logistic regressions that identify the most salient socio-demographic determinants of both statuses. This first set of results reveals substantial internal heterogeneity across region and dwelling type, with heating technology emerging as the most differentiating factor between energy poor and hidden energy poor households.

We then use the results from this first econometric stage for two purposes. First, the variables identified as the main socio-demographic drivers of (hidden) energy poverty are embedded in a demographic specification of the Quadratic Almost Ideal Demand System (QUAIDS) of Banks et al. (1997). Second, we include (hidden) energy poverty indicators in our specification and correct for their implied endogeneity by implementing a two-stage residual inclusion approach. To our knowledge, this is the first application to address endogenous energy poverty statuses within a demand system framework. These two elements allow behavioural responses to vary with household characteristics and energy vulnerability status when simulating demand adjustments in response to energy price increases. We first present results for the overall population and then disaggregate them by income groups and energy vulnerable groups. The aggregate results support the calibration of our demand system, with the inelastic demand for domestic energy goods confirming their status as necessities. The disaggregated results point to income as the dominant factor driving behavioural responses to carbon pricing. Yet, despite the relatively average behavioural responses of conventionally defined energy poor households, we find markedly higher price elasticities among hidden energy poor households. This difference underscores the importance of treating them as a separate group in the analysis.

Finally, we conduct a policy analysis of carbon pricing on household heating and transport fuels that replicates the scope of the forthcoming ETS 2 legislation. We evaluate its impact on households using two complementary metrics: equivalent variation and tax burden. This allows us to compare welfare losses with monetary burden associated with the price increase. We find that energy poor households, despite bearing a substantial carbon burden, undergo a relatively lower welfare cost. By contrast, hidden energy poor households (who consume little energy and thus appear less exposed in terms of tax payments) suffer disproportionately large relative welfare losses. This misalignment between financial exposure and welfare burden highlights the need to complement expenditure-based measures with a welfare perspective when designing carbon-pricing measures.

For the entirety of this paper, we use 11 cross-sections of the Belgian Household Budget Survey (HBS), covering the years 2003 to 2010 annually and 2010 to 2016 biennially, with each cross-section surveying between 4,000 and 6,000 households.[22] In total, our sample includes over 40,000 households, each reporting detailed expenditure records. This includes spending on food and transport fuels (gasoline and diesel) during the survey period. Heating (natural gas and heating oil) and electricity expenditures are derived from the most recent annual energy bill. Accordingly, when imputing prices using Statistics Belgium (Statbel)—Belgium's national statistical agency, responsible for producing the HBS data—monthly Consumer Price Indices (Statbel, 2026b), we apply a six-month lag for domestic energy products. In addition, the HBS contains extensive socio-demographic information, including income, age, and employment status of each household member, family composition, region of residence, housing type, and ownership of durable goods (e.g., cars and appliances).

Our contribution is threefold. First, we apply a novel methodological framework by augmenting a demographic QUAIDS demand system with a two-stage residual inclusion procedure, controlling for the endogeneity of energy vulnerability statuses. This is, to our knowledge, the first application of such an approach, allowing a more accurate estimation of price responses among these energy vulnerable groups. Second, by including hidden energy poverty, we provide new empirical evidence on how household demand elasticities and carbon price responses change across various energy vulnerability profiles. We thereby uncover distributional patterns that would be overlooked by analyses focusing solely on income or aggregate populations. Finally, we carry out a novel policy simulation of carbon pricing. Using two different indicators, we assess the carbon price's impact on household welfare across the income and energy vulnerability dimensions, and draw implications for

[22] Although EU-SILC is often cited as best suited for energy poverty measurement, access to detailed household expenditure data is essential for robust demand system estimation. Moreover, expenditure data has the advantage of allowing for the highest level of disaggregation in energy spending (Thomson et al., 2017), which can be particularly useful for measuring hidden energy poverty (see Tovar Reaños et al. (2025)) for an illustration.

the design of equitable carbon pricing and compensation schemes.

In the remainder of the paper, Section 2 introduces the main concepts and measurement challenges related to different forms of energy vulnerability, motivates our choice and adaptation of indicators, and presents descriptive and econometric evidence on energy vulnerable households. Section 3 describes our behavioural microsimulation and demand system estimation, including the demographic QUAIDS specification, the treatment of endogenous energy poverty statuses, and the resulting price elasticities. Section 4 reports the results of our carbon pricing simulation, highlighting the relevance of a welfare analysis disaggregated by income decile and energy vulnerability group, and drawing out the main implications for policy. Section 5 concludes.

2.2 The Energy Poverty Phenomenon

2.2.1 Literature Review

While the significance and multidimensional nature of energy poverty are widely acknowledged, there is still no consensus on its precise definition or underlying causes, and consequently no agreement on the most appropriate way to measure it. A pioneering contribution is the 10% fuel poverty ratio (FPR) introduced by Boardman (1991), which classifies a household as energy poor if its domestic energy costs amount to at least 10% of its income. He derived this threshold from British national statistics by approximating twice the median of modelled required energy expenditure. Expenditure-based indicators of this kind are the most widely used approaches to identifying energy poverty and typically focus on households whose domestic energy expenditure is disproportionately high relative to their income (hereafter referred to as *EP households*). In the same vein, Hills (2011) proposed the After Fuel Cost Approach (AFCA), which identifies households as energy poor if they are income poor after accounting for housing and energy costs. Building on this work, Hills (2012) introduced what became the widely used Low Income High Costs (LIHC) indicator. LIHC served as the national indicator for the United Kingdom until 2021 and is based on a double-threshold system: an energy poor household must be low income (below 60% of the median income after housing costs) and have disproportionately high energy needs (above the median of modelled energy bills). The FPR, AFCA, and LIHC measures have been criticised for their lack of transparency, particularly regarding the distinction between energy poverty and income poverty, and for their sensitivity to threshold choices, which can lead to inconsistent household classifications and potential false positives (Legendre & Ricci, 2015; Moore, 2012). A more recent and widely used indicator is the twice-the-median (2M) measure, which classifies households as energy poor if their energy expenditure relative to disposable income exceeds twice the national median (Rademaekers et al., 2016). In an effort to refine this indicator, which omits housing-related expenditure and tends to flag some high-income households as energy poor, Meyer et al. (2018) adapt the 2M measure in their construction of an energy poverty barometer for Belgium. Their version incorporates housing costs and excludes affluent households using a threshold based on equivalised household income.

However, relying exclusively on EP measures risks overlooking a significant share of energy vulnerable households who remain undetected when attention is limited to excessive energy spending. A more recent body of research highlights the existence of households who severely restrict their energy use due to financial constraints—referred to as hidden energy poor households (hereafter *hEP* households). This phenomenon is substantial: W. Anderson et al. (2012) report that in Great Britain, up to 63% of surveyed income poor households adopt coping strategies, such as regularly or entirely forgoing heating, even when their dwellings receive energy efficiency improvements.[23] There is even less agreement on the definition and underlying drivers of hEP, as these situations of self-imposed restriction are inherently difficult to detect, even through targeted support schemes or administrative data (Barrella et al., 2022). Rademaekers et al. (2016) argue that purely relative energy expenditure does not reliably indicate whether energy needs are met, and therefore advocate hEP measures based on absolute monetary thresholds rather than expenditure shares. Building on this rationale, several studies such as Bagnoli and Bertoméu-Sánchez (2022), Tovar Reaños et al. (2025), or Maier and Dreoni (2026) define hEP households as those whose energy expenditure falls below half the national median (M/2). Betto et al. (2020) expand the measure by accounting for regional climate variability, reflecting the specific requirements of the Italian context. Meyer et al. (2018) further refine the M/2 approach by incorporating dwelling insulation, excluding affluent households and comparing each household's energy expenditure to that of households with similar household size and dwelling size.

Beyond these expenditure-based indicators, the literature has proposed four other main approaches to measuring energy vulnerability: (i) subjective indicators based on household self-identification, (ii) minimum-income-standard-based indicators that assess the affordability of essential energy needs relative to a minimum standard of living, (iii) multidimensional composite indicators, and (iv) indicators based on the modeling of households' required energy consumption. Subjective indicators are excluded from our analysis due

[23] Yet, underconsumption of energy resulting in inadequate thermal comfort can have serious adverse effects on health (Cartagena-Farias et al., 2025), underscoring the need for policy intervention (Ormandy & Ezratty, 2012).

to data constraints[24] and their sensitivity to socio-cultural context and survey design (see Waddams Price et al., 2012, Maier and Dreoni, 2026, for a comparison of objective and subjective measures). We exclude the minimum-income-standard approach because it requires strong assumptions to construct budget standards and region-specific thresholds for absolute energy needs, making it more appropriate for regional or sub-regional analyses than for our setting and available price data (Romero et al., 2018). A growing number of multidimensional indices has been proposed, particularly for cross-country comparisons (e.g., Kahouli & Okushima, 2021; Tovar Reaños et al., 2025), but these measures remain sensitive to the choice of indicators, cut-offs, weights, and aggregation rules. Given our objective to analyse heterogeneous behavioural responses and distributional impacts with an application to a single country, we prefer to rely on several complementary unidimensional indicators rather than a single composite index. In the spirit of Rademaekers et al. (2016), and similarly to the approach adopted in the Belgian and French contexts (Meyer et al., 2018; ONPE & ADEME, 2025), we use a small set of targeted indicators to distinguish between different forms of energy vulnerability. Finally, we do not employ model-based indicators (including approaches based on predicted household energy expenditure from regression models or machine-learning methods) as these typically require strong assumptions, advanced engineering models, or extensive data on housing conditions (Ye et al., 2022).

In light of these considerations, we retain expenditure-based indicators as our preferred measures of energy vulnerability. They are well established in the literature, transparent in their construction, and compatible with the detailed spending data required for our analysis of heterogeneous behavioural responses.

2.2.2 Adopted Measures of (Hidden) Energy Poverty

For our analysis, we build on the two indicators developed by Meyer et al. (2018) to quantify (hidden) energy poverty.[25] These indicators have several attractive features. First, they are firmly grounded in the existing literature, as they adapt measures already widely used in research and policy analysis. Second, they are designed to capture the multidimensional character of energy deprivation in the Belgian context, while remaining applicable to other countries, particularly within the European Union where comparable data sources are available. Third, they can be monitored over time, as their annual recalibration ensures that threshold values remain responsive to evolving socio-economic conditions.

Operationally, we adapt the indicators proposed by Meyer et al. (2018) to our data

[24] Self-reported variables such as the *Ability to keep home adequately warm* are not included in our dataset.

[25] We use *(hidden) energy poverty* or *(h)EP* to refer to both types of energy vulnerability.

and introduce a refined version of their measure to better identify hidden energy poverty. A key methodological distinction lies in our use of Household Budget Survey (HBS) data rather than Statistics on Income and Living Conditions (SILC) data, as the former provides the detailed expenditure information required for demand system estimation. Despite this change, the indicators remain robust and internally consistent in identifying both forms of energy vulnerability. Moreover, the two measures capture largely distinct household groups: the overlap between EP and hEP households never exceeds 0.1% of the population. We also conduct extensive robustness checks, providing additional descriptive evidence and comparing our baseline indicators with alternative measures proposed in the literature; the corresponding results are reported in Appendix B.1.

Indicator for Energy Poverty

The objective of this indicator is to identify households whose spending on domestic energy is disproportionately high relative to their income, and to quantify the magnitude of this overspending. A household is classified as energy poor when its domestic energy expenditure (DEE, namely heating fuels and electricity) exceeds twice the population median ratio of DEE to household disposable income net of housing costs.[26,27] Formally, the threshold is defined as:

$$\text{EP threshold} = 2 \times \text{median}\left(\frac{\text{DEE}}{\text{household disposable income (- housing costs)}}\right)$$

To exclude affluent households whose energy consumption is more likely to reflect preferences than constraint, we drop households in the top half of the equivalised income distribution.[28] Consistent with standard poverty measurement approaches, the depth (or severity) of energy poverty is measured by the monetary gap between a household's observed domestic energy expenditure and the EP threshold.

Indicator for Hidden Energy Poverty

Hidden energy poor households are individuals who underspend on energy relative to what is required to achieve a basic standard of thermal comfort. The objective of this indicator is to identify such households and quantify the extent to which their expenditures fall short

[26] Following Meyer et al. (2018), housing costs are capped at twice the median level to isolate energy-related deprivation from hardship associated with excessive housing expenses.

[27] Housing costs include rent for tenants and half of imputed rent for homeowners with a mortgage.

[28] Appendix B.1 reports sensitivity tests for this exclusion rule. These show that the restriction mainly affects households in the sixth income decile, while households above the sixth decile are only very rarely classified as energy poor even in the absence of the exclusion.

of expected energy needs. The hEP threshold benchmarks each household's DEE against that of similar households. Specifically, the numerator is defined as the average of four medians: (i) the median DEE of households with the same size, (ii) the median DEE of households living in dwellings with the same number of rooms, (iii) the median DEE of households with the same dwelling type, and (iv) the median DEE of households using the same type of heating system. By incorporating dwelling type and heating system, our approach extends Meyer et al. (2018), who consider only household and dwelling sizes. These additional criteria account for key structural and technological factors (insulation profile and heating technology) that substantially influence energy needs. As in the original indicator, households living in well-insulated dwellings are excluded to avoid misclassifying those with explainable low energy needs.[29] To maintain comparability with the energy poverty indicator, we apply the same exclusion rule and again drop households from the top half of the equivalised income distribution.[30]

The resulting threshold, which builds on the original M/2 logic, serves as a proxy for basic energy needs[31] and is constructed as follows:

$$\text{hEP threshold} = \frac{\begin{array}{c} 0.25 \cdot \text{median DEE of all HH with similar HH size} + \\ 0.25 \cdot \text{median DEE of all HH with similar dwelling size} + \\ 0.25 \cdot \text{median DEE of all HH with similar dwelling type} + \\ 0.25 \cdot \text{median DEE of all HH with similar heating system type} \end{array}}{2}$$

In line with standard measures of poverty intensity, the depth of hidden energy poverty is defined as the monetary gap between a household's actual energy expenditure and the reference expenditure implied by the hEP threshold. This metric reflects the extent to which a household's energy spending falls short of a basic level of thermal comfort.

[29] Unlike Meyer et al. (2018), who use direct insulation data available in SILC, we follow Okushima (2017) and Betto et al. (2020) and use the construction year of the dwelling as a proxy for insulation quality. Dwellings built after 1990 are considered well-insulated, consistent with the introduction of major thermal regulations in Belgium.

[30] Appendix B.1 reports robustness and sensitivity analyses of our modifications to the original indicator. We start from the simple M/2 indicator, then sequentially introduce the changes proposed by Meyer et al. (2018), and finally implement step by step our own adaptations.

[31] Despite these methodological refinements, the identification of hEP households remains imperfect, because the relevant notion of need is inherently unobserved. The indicator may therefore still capture households with atypical preferences, old but renovated dwellings, or genuinely low energy requirements, for example because they are frequently absent from home. Households falling below the hEP threshold should thus be interpreted as being *at risk of hidden energy poverty* rather than as hidden energy poor with certainty.

2.2.3 Descriptive Statistics

We now analyse the extent and characteristics of (hidden) energy poverty in Belgium. As shown in Table 2.1, energy poor (EP) households are more prevalent in the sample than hidden energy poor (hEP) ones. However, including hEP households expands the population considered vulnerable to energy costs by approximately one third, underlining the importance of considering both groups.[32] We also observe a strong concentration of energy vulnerability at the bottom of the income distribution. More than half of hEP households belong to the first two deciles, compared with roughly two thirds of EP households.

Table 2.1: Cumulative Distribution of (hidden) Energy Poor Households across Income Deciles

Income Decile	EP Share (%)	hEP Share (%)
1	41.0	29.3
2	67.1	52.6
3	83.0	70.7
4	93.3	86.5
5	100.0	100.0
Whole Sample Rate	**13.6**	**4.64**

Notes: EP = Energy Poverty, hEP = hidden Energy Poverty. Shares represent the distribution across the bottom five income deciles. Upper deciles are not displayed as, by definition, they do not contain any (h)EP household. The final row reports the headcount rate for the total population. We do not report the overlap, as it never exceeds 0.1% within any decile.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Both EP and hEP households exhibit deeper socio-economic vulnerability than the rest of the population.[33] As Table B.10 in the Appendix shows, only 29% of EP households and 36.4% of hEP households include at least one wage earner, compared to 62% in the general population. Educational attainment is also lower: more than one third of EP and hEP households have no or only primary education, and tertiary education is rare. Housing conditions further reflect the disparities between (h)EP households and the rest of the population: they are far more likely to be renters,[34] tend to live in smaller dwellings with

[32] Tovar Reaños et al. (2025) also acknowledge the significant contribution of hidden energy poverty to their composite index, accounting for around 20% of their composite energy poverty indicator across EU countries.

[33] Appendix B.1 documents the corresponding patterns using alternative (h)EP metrics.

[34] One possible concern is that (h)EP households treat rent and energy expenditure as substitutes (e.g. paying higher rents for better-insulated dwellings). However, as shown in Table B.9, the correlation between rent and energy expenditure is weakly negative, providing no strong evidence of such substitution.

fewer rooms, and a majority reside in old buildings. Regional patterns differ across the two groups: EP households are overrepresented in Wallonia, whereas hEP households are disproportionately concentrated in Brussels. Housing type and heating sources also vary: more hEP households live in flats or rely on solid fuels for heating. The latter may reflect restrictions in the use of central heating in favour of room-specific, on-demand heating systems.

Finally, demographic composition also differs. Both EP and hEP households are more likely to consist of single adults, either active or retired, and are more often single-parent families. We also find fewer children in these households. While these descriptive statistics offer valuable insight into the socio-economic and housing profiles of energy poor households, a proper identification of the determinants of (hidden) energy poverty requires formal econometric study.

2.2.4 Econometric Analysis of the Determinants of (Hidden) Energy Poverty

To analyse the socio-demographic drivers of (hidden) energy poverty, we estimate two logit models, one for each energy vulnerability status. This approach allows us to quantify how each covariate is associated with the odds of being EP or hEP. Both models are estimated on a restricted sample including only households in the bottom half of the income distribution. This restriction increases comparability by focusing on a more homogeneous group and concentrates the analysis on the population at risk, consistent with the income thresholds used for the indicators. Income is excluded as an explanatory variable since it directly enters the definition of EP and would otherwise induce a mechanical association. Similarly, construction-year variables are excluded from the hEP specification, as they are already used to implement the insulation-based exclusion in the indicator.

Formally, let $(h)EP_i^*$ denote a latent variable capturing household i's unobserved propensity to be (hidden) energy poor. The same specification is used for both energy poverty and hidden energy poverty (hence, $(h)EP_i^*$):

$$(h)EP_i^* = \boldsymbol{x}_i'\beta + \varepsilon_i, \tag{2.2.1}$$

where $\boldsymbol{x}_i$ is a vector of socio-demographic covariates, β a vector of coefficients, and ε_i an error term assumed to follow a logistic distribution. The observed outcome equals one when the latent propensity exceeds zero (a normalised cutoff), $(h)EP_i = 1\{(h)EP_i^* > 0\}$, and equals zero otherwise.[35]

[35]The probability of being (hidden) energy poor is given by $\Pr[(h)EP_i = 1 \mid \boldsymbol{x_i}] = \Lambda(\boldsymbol{x}_i'\beta)$, where $\Lambda(\cdot)$ is the logistic cumulative distribution function. The fitted probability is hence $\widehat{(h)EP_i} = \Lambda(\boldsymbol{x_i}'\hat{\beta})$.

Model robustness is assessed using standard diagnostics. Pseudo-R^2 values and Area Under the Curve (AUC) statistics indicate satisfactory explanatory and discriminatory power for the EP model, whereas the hEP model performs less well. As visible in Appendix B.1, given the relative rarity of hidden energy poverty, we also estimated a complementary log-log (cloglog) specification following Legendre and Ricci (2015), but the results were qualitatively similar.[36,37] This likely reflects the intrinsic difficulty of capturing the determinants of hidden energy poverty using HBS data, as this form of deprivation combines behavioural and structural underconsumption patterns that are more heterogeneous and less easily explained than the more "classic" energy poverty.

Table 2.2 reveals both shared and distinct determinants of each of the energy vulnerability statuses.[38] While several covariates are statistically significant in both models, estimated associations with hEP are more often not statistically distinguishable from zero and the model exhibits weaker overall discriminatory power, consistent with its lower fit and which may partly reflect fewer effective events and weaker systematic variation in hEP relative to EP. The regressions highlight three key dimensions that differentiate the two forms of deprivation: region, housing type, and heating system. EP is significantly more prevalent in Wallonia, among households living in detached houses, or among those relying on oil-based heating. By contrast, hEP is more common in Brussels and is associated with flats or solid-fuel heating systems. Some counterintuitive results emerge relative to the descriptive patterns documented in Section 2.2.3, such as the negative associations between the number of children or retired household members and the likelihood of being (hidden) energy poor; hence we prefer not to draw definitive conclusions about these variables' impact on energy vulnerability.

Finally, all variables with statistically significant associations in either model are retained as demographic controls in the subsequent behavioural model. This allows us to control for key determinants of specific energy consumption patterns and more precisely identify price reactions to carbon pricing.

[36]The cloglog link, which is right-skewed, is particularly suited to modeling rare events, yet it provided only marginal improvements in fit.

[37]We also computed variance inflation factors, which showed no evidence of multicollinearity.

[38]Appendix B.1 reports and discusses similar econometric results using alternative (h)EP metrics. Appendix B.3 reports the coefficients of each model when going from the reduced form to the complete one; underlining the importance of dwelling-related variables.

Table 2.2: Logit Estimates and Average Marginal Effects for Energy Poverty (EP) and hidden Energy Poverty (hEP)

Variable	**EP**		**hEP**	
	Coef.	AME (p.p.)	Coef.	AME (p.p.)
Wage Earner	–0.91***	–14.6	–0.05	–0.4
No Education (ref. cat.)				
Primary Education	–0.15**	–2.4	–0.11	–0.9
Secondary Education	–0.18***	–2.9	–0.20***	–1.6
Tertiary Education	–0.30***	–4.9	–0.09	–0.8
Renter (ref. cat.)				
Owner with Loan	–1.31***	–22.8	–0.16*	–1.2
Owner without Loan	–1.59***	–26.4	–0.05	–0.4
# Cars	–0.21***	–3.3	–0.23***	–1.8
HH Type: Couple Active (ref. cat.)				
Couple Retired	–0.54***	–7.8	–0.07	–0.5
Many Adults	–0.60***	–8.5	–0.52***	–2.9
Single Active	0.64***	+11.4	0.46***	+3.8
Single Retired	0.34***	+5.7	0.32***	+2.5
# Children	–0.35***	–5.6	–0.15***	–1.2
Region: Brussels (ref. cat.)				
Flanders	0.00	0.0	–0.71***	–6.9
Wallonia	0.40***	+6.6	–0.89***	–8.1
Detached House (ref. cat.)				
Flat	–0.62***	–9.6	0.48***	+3.7
Terraced House	–0.44***	–7.1	0.28***	+2.0
Construction: After 2000 (ref.)				
Before 1970	0.32***	+4.9	—	—
1970–1990	0.36***	+5.6	—	—
# Rooms	0.16***	+2.6	–0.08***	–0.6
Heating System Type: Electricity (ref. cat.)				
Gas	0.22***	+3.2	–0.50***	–3.8
Oil	0.84***	+13.6	0.00	0.0
Other	–0.38	–4.8	0.00	0.0
Solid	–0.04	–0.5	1.18***	+15.2
Time Controls				
Years After 2000	0.00	0.0	–0.04***	–0.3
Year 2008–09	0.03	+0.4	–0.10	–0.7
Years After 2011	–0.06	–1.0	–0.37***	–2.6
Mean of dependent variable	13.6%		4.6%	
McFadden's R^2	17.1%		9.2%	

Note: Coef = raw logit coefficient. AME = average marginal effect on the response scale, expressed in percentage points (p.p.); for indicator variables, AMEs correspond to average discrete changes relative to the reference category. *Significance levels:* *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

2.3 Demand System Estimation

In this section, we estimate a behavioural demand system to obtain price and income elasticities of household energy consumption. The model is augmented with indicators for (hidden) energy poverty and explicitly accounts for the potential endogeneity of these variables. This allows us to report elasticities at the general population level, but also on specific sub-groups such as (h)EP households.

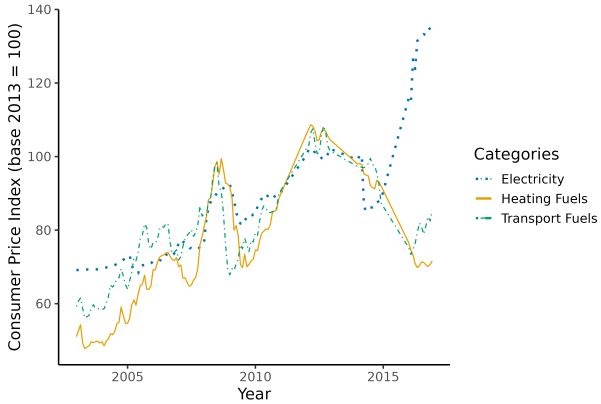
2.3.1 Price and Expenditure Patterns

Identifying price elasticities reliably requires sufficient price variation over time. Figure 2.1a illustrates the evolution of consumer prices for energy-related goods, indexed to 2013 price levels. These prices exhibit substantial volatility over the 2003–2016 period. This pronounced variation strengthens the identification of price elasticities for these categories. Figure 2.1b complements this evidence by displaying trends in household expenditure shares. The smoothed series show noticeable shifts over time, highlighting the relevance of examining how energy demand responds—or fails to respond—to price changes.

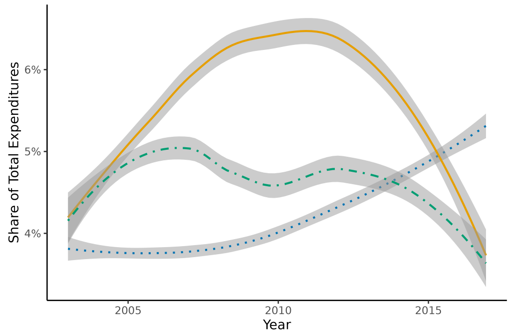
Figure 2.2a shows that expenditure shares devoted to energy-related goods decline as income increases. This pattern is primarily driven by a decrease in the share allocated to domestic energy (electricity and heating), while expenditure shares for transport fuels display a weaker trend across deciles. Figure 2.2b compares expenditure patterns across energy poverty categories and within the bottom half of the income distribution (both including and excluding (hidden) energy poor households). The figure reflects the core logic behind our classification: EP households are identified as overspending on domestic energy, whereas hEP households are characterised by low energy expenditure.

Figure 2.1: Descriptive Figures for Energy Goods (2003-2016)

(a) Price Variation

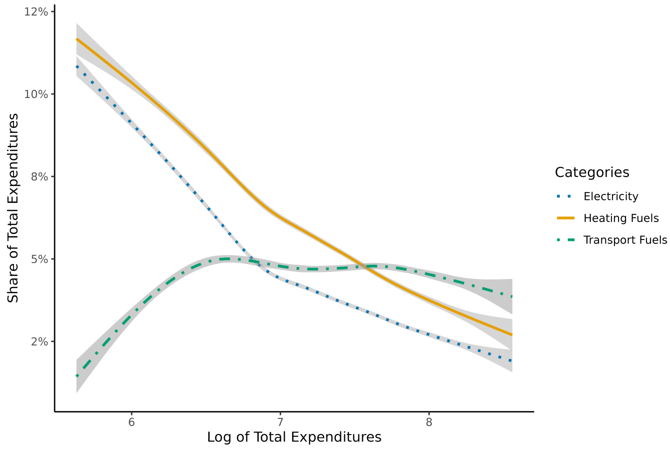


(b) Evolution of Expenditure Shares



Notes: Smoothed trends across the population. The area in grey is the 95% confidence interval.

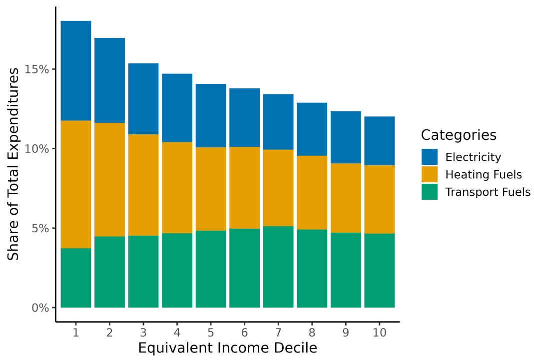
(c) Engel Curves



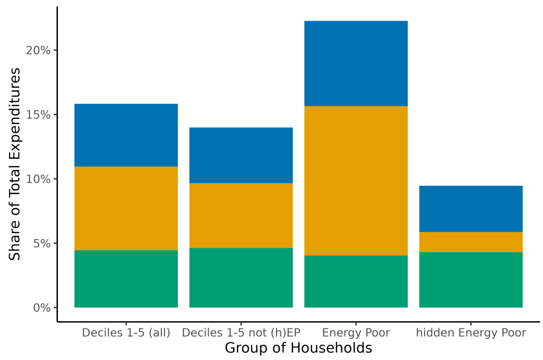
Sources: Statbel (2026b) and HBS data for Belgium (2003–2016).

Figure 2.2: Household Expenditure Shares by Income and Vulnerability Group

(a) Expenditure Shares by Income Decile



(b) Expenditure Shares by Household Groups



Source: Authors' calculations based on HBS data for Belgium (2003–2016).

2.3.2 Specification of the Demand System

The Quadratic Almost Ideal Demand System

Following common practice in the literature (Brännlund & Nordström, 2004; Douenne, 2020; Labandeira et al., 2006; Semet, 2024), we employ the Quadratic Almost Ideal Demand System (QUAIDS), as defined by Banks et al. (1997). QUAIDS extends the Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980) by allowing for non-linear relationships between expenditure shares and budget, commonly referred to as Engel curves. In Figure 2.1c, they are displayed for energy goods in a non-parametric form, reflecting the need for a quadratic specification. This model is particularly suited for estimating elasticities while satisfying fundamental properties derived from neoclassical demand theory.[39] In addition, its flexibility in integrating demographic variables makes it fitted to our analysis, as it allows key determinants of energy consumption to enter the model. It is defined as follows:

$$w_i^h = \alpha_i^h + \sum_{j=1}^{I} \gamma_{ij} \ln p_j + \beta_i \ln \frac{m}{a(\boldsymbol{p})} + \frac{\lambda_i}{b(\boldsymbol{p})} \ln \left(\frac{m}{a(\boldsymbol{p})} \right)^2 + u_i \tag{2.3.1}$$

where w_i^h is the share of total expenditure allocated to good i by household h, α_i^h is the intercept, p_j is the price index of goods bundle j, and m is total expenditures. γ_{ij}, β_i and λ_i are parameters of interest, and u_i is the error term. $a(\boldsymbol{p})$ and $b(\boldsymbol{p})$ are two different price aggregators.[40] We define each term in more detail here-below.

The dependent variable w_i^h represents the share of total expenditures spent on goods i by household h. To construct these shares, we distinguish five consumption bundles i: food, transport fuels (gasoline and diesel), electricity, heating fuels (natural gas, liquid and solid fuels), and a residual category "other"[41] regrouping non-durable goods excluding investments in durables.[42] We include food and electricity consumption categories as they

[39] Homogeneity is imposed through the use of relative prices, while symmetry is enforced via the optimum minimum distance estimator (Blundell, 1988; Browning & Meghir, 1991). The additivity (or adding-up) condition is inherently satisfied by the structure of the demand system: expenditure shares always sum to one, ensuring that total expenditures align with the sum of category expenditures after estimation; during the estimation process, one category is excluded, with its coefficients later recovered by enforcing additivity.

[40] In the indirect utility function underlying QUAIDS, $\ln v(\boldsymbol{p}, m) = \left[\left\{ \frac{\ln\left(\frac{m}{a(\boldsymbol{p})}\right)}{b(\boldsymbol{p})} \right\}^{-1} + \lambda(\boldsymbol{p}) \right]^{-1}$, the term $a(\boldsymbol{p})$ represents the cost of subsistence (the minimum expenditure required to reach the arbitrarily smallest utility level), while $b(\boldsymbol{p})$ scales utility by the cost of bliss, or the expenditure needed to achieve an arbitrarily high utility (Banks et al., 1997). $\lambda(\boldsymbol{p}) = \sum_i \lambda_i \ln p_i$ governs the strength of the quadratic extension: it shifts the mapping from (price-deflated) expenditure to utility in a way that allows Engel curves to exhibit second-degree curvature.

[41] "Other" notably includes clothes, health expenses, transport expenses (other than fuel), communication expenses, leisure, culture, hotels, restaurants, and personal care expenses.

[42] We do not use data on durable-goods expenditures, as these reflect long-term investment decisions

present specific substitution patterns with fossil fuels.[43]

The term α_i^h is a household-specific intercept capturing demographic heterogeneity. Following Lecocq and Robin (2015), we express it as $\alpha_i^h = (\boldsymbol{\alpha\prime}_i)\boldsymbol{x}_h$, where $\boldsymbol{\alpha}_i$ is a vector of coefficients, and $\boldsymbol{x}_h$ represents socio-demographic controls. This translating approach (Pollak & Wales, 1981) shifts the intercept according to household attributes, thus accounting for heterogeneity in preferences and needs. We include variables found relevant for (hidden) energy poverty: labour market status, education level, ownership and mortgage status, dwelling type and size, household composition (size, elderly presence), and region.[44]

The summation term $\sum_j \gamma_{ij} \ln p_j$ introduces the price effects, with γ_{ij} capturing cross-price relationships between goods i and j (γ_{ii} for own price effects). Prices p_j correspond to consumer price indices of each of the five good bundles described above.

The next term, $\beta_i \ln \frac{m}{a(\boldsymbol{p})}$, represents the response of expenditure shares to changes in real total expenditures (defined as the sum of the five consumption bundles i), and allows for income effects. Since total expenditures are subject to endogeneity in the estimation of demand systems, household income is used as instrument using the residual-inclusion approach as developed by Lecocq and Robin (2006, 2015). The translog price index $a(\boldsymbol{p})$ acts as deflator of nominal total expenditure m and is defined as follows:

$$\ln a(\boldsymbol{p}) = \alpha_0 + \sum_i \alpha_i^h \ln p_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j \tag{2.3.2}$$

The quadratic component $\frac{\lambda_i}{b(\boldsymbol{p})} \ln \left(\frac{m}{a(\boldsymbol{p})}\right)^2$ extends the AIDS model to the QUAIDS specification (Banks et al., 1997), introducing curvature in Engel curves. Here, the price aggregator is defined as $b(\boldsymbol{p}) = \prod p_i^{\beta_i}$.

The estimators are obtained by fitting the share equations (2.3.1) jointly as a nonlinear system.[45] After estimation, the parameters' values are used to compute budget and price

rather than day-to-day consumption. Nevertheless, we document the stability of durable expenditures over time in Figure B.3 in the Appendix. Since we do not model durable investments explicitly, their long-run substitution effects may appear in elasticity estimates. We provide descriptive evidence on heating system switches in Figure B.4, which shows a moderate substitution from heating oil to natural gas.

[43] The "heat or eat" dilemma is an evidence of substitution pattern between heating and food (Bhattacharya et al., 2003; Zabel & Hendlin, 2025). Substitution between electricity and heating may arise when people switch from fossil-powered central heating to on-demand electricity appliances. Moreover, adding food and electricity improves convergence and stability in the estimation. Indeed, both categories have large, reliably observed budget shares for most households, so including them adds signal and improves numerical convergence. They also introduce extra relative-price variation that reduces price collinearity and strengthens identification, while shrinking the residual "all other goods" aggregate that can otherwise absorb misspecification and leave cross-price effects weakly pinned down.

[44] Two time dummies (2008-2009 and 2012 onwards) control for methodological changes in the survey. We also exclude construction year as it directly defines hidden energy poverty, as status later used to report group-specific elasticities.

[45] The system is estimated in Stata using the *demandsys* routine (StataCorp LLC, 2024), which fits the

elasticities by log-derivation of w_i^h with respect to total expenditure and prices. Doing so, we first obtain μ_i and μ_{ij}:

$$\mu_i = \frac{\partial w_i^h}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})} \ln \frac{m}{a(\boldsymbol{p})} \tag{2.3.3}$$

$$\mu_{ij} = \frac{\partial w_i^h}{\partial \ln p_j} = \gamma_{ij} - \mu_i \left(\alpha_j + \sum_k \gamma_{kj} \ln p_k \right) - \frac{\lambda_i \beta_j}{b(\boldsymbol{p})} \left(\ln \frac{m}{a(\boldsymbol{p})} \right)^2 \tag{2.3.4}$$

These values are then translated into the budget elasticities η_i and the uncompensated (own- or cross-) price elasticities θ_{ij}:

$$\eta_i = 1 + \frac{\mu_i}{w_i^h} \tag{2.3.5}$$

$$\Theta_{ij} = -\delta_{ij} + \frac{\mu_{ij}}{w_i^h} \tag{2.3.6}$$

where δ_{ij} is Kronecker delta with $\delta_{ij} = 1 \ \forall \ i = j$ (own-price elasticity), and $\delta_{ij} = 0 \ \forall \ i \neq j$ (cross-price elasticity).

We obtain group-specific reactions to prices (Baker et al., 1989; Blundell et al., 1993) by computing elasticities for the different energy vulnerability groups, as well as for income deciles. Elasticities are evaluated at the average values of prices, demographic variables and total expenditures for each group using equations 2.3.5 and 2.3.6. As α_i^h directly enters these formulas through $a(\boldsymbol{p})$, our estimation strategy allows the energy vulnerability statuses to shift households' estimated behaviours.

Estimation Strategy for (hidden) Energy Poverty

Energy-vulnerability indicators are endogenous to the demand system. This endogeneity is mechanical in our context: (h)EP indicators are constructed from domestic energy expenditures, which are dependent variables of the demand system (electricity and heating fuels). As a result, unobserved preference shocks affecting energy shares also affect the probability of being classified as (h)EP, generating correlation between $(h)EP_i$ statuses and the QUAIDS errors u_i. To account for this, we build on the treatment of total expenditures' endogeneity as in Lecocq and Robin (2006) and implement a Two-Stage Residual Inclusion (2SRI) approach. Drawing on the results from the logit regressions in

share equations jointly and iterates to convergence using feasible generalised least-squares (IFGLS). This method accommodates the fact that parameters appear not only as coefficients but also within the price indices (Deaton & Muellbauer, 1980). One equation is omitted to impose the adding-up restriction, and its coefficients are recovered from the adding-up condition; Barten (1969) shows that the choice of the omitted equation does not affect the results.

Section 2.2, we use the fitted probabilities of energy-vulnerability statuses $\widehat{(h)EP}_i$ as a generated instrument (based on observed characteristics) for the actual indicators.[46] The first-stage regression is:

$$(h)EP_i = \alpha + \gamma\, \widehat{(h)EP}_i + controls + \varepsilon_i \tag{2.3.7}$$

where $(h)EP_i$ is the observed individual status and $\widehat{(h)EP}_i$ is obtained from 2.2.1. Consistent with the demand system estimation, the same socio-demographic control variables are kept here. In a second step, we add the endogenous variables for (hidden) energy poverty $(h)EP_i$ to α_i^h (the intercept in equation 2.3.1), along with the estimated residuals of the first step $\widehat{\varepsilon_i}$, as additional control variables of the demand system. We prefer this residual-control-function approach for correcting the endogeneity rather than the direct use of predicted values; indeed, Terza et al. (2008) shows that the two-stage predictor substitution (2SPS) can lead to inconsistent results and that 2SRI should be preferred.[47]

Treatment of Zero Expenditure

In our sample, a significant proportion of households report zero expenditure on transport fuels, ranging from 23% to 30% depending on the year. This arises primarily from two factors.

First, infrequency of purchase might lead to mismeasurement. While the one-month survey period of the Household Budget Survey (HBS) is generally sufficient to capture most consumption patterns, some low-volume consumers may not purchase transport fuels within the survey window. They are therefore considered as non-consumers whereas they might actually consume little fuel. However, this issue is likely to concern mainly low-volume consumers, so the resulting mismeasurement should be limited in magnitude.

Second, car ownership predetermines the need for transport fuels. The absence of private vehicle ownership is significant, with, depending on the year, 17% to 20% of households not owning a car.[48] Without correcting for this, the related zero expenditures might be misclassified as optimal corner solutions rather than the result of ex-ante decision-making or constraints.[49] To address this issue, we assume the ownership decision is taken

[46] Thus, we construct our instrument as a linear prediction of exogenous parameters, using the determinants of (h)EP already identified in Section 2.2.

[47] In nonlinear second-stage models, replacing the endogenous regressor by its fitted value generally does not purge the correlation with the structural error term and can therefore be inconsistent, whereas residual inclusion controls directly for the endogenous component via a control–function term (Terza et al., 2008). Additional information about this procedure is presented in Appendix B.2.

[48] Company cars are non-negligible in Belgium, but because they usually come with a fuel card paid by the employer (in 90% of the cases, May et al. (2019)), they are left out of our analysis focusing on private car ownership and use.

[49] Note that when private vehicle owners do not report any transport fuel expenditures, this is still

ex-ante and we employ a Heckman-type two-step procedure following Labandeira et al. (2022). We start by estimating a Probit regression of the ownership status (binary) over an enriched set of demographic variables for the entire sample. The resulting Inverse Mills Ratio (its inclusion corrects for the selection bias as shown by Heckman (1979)) is then included as a correction term in the equations of w_i. We extend the correction to heating fuels, as some households do not heat with gas or oil (8% to 18%, depending on the year). We end up pooling both ownership statuses into one (owners of both a vehicle and a fossil heating system), and apply the Heckman correction at once. Consequently, the final model is estimated on households owning both a vehicle and a fossil-fuel heating system (which restricts our sample by 25%, to 33,269 observations).

2.3.3 Elasticity Results

This subsection presents the (Marshallian) uncompensated own-price elasticities and budget elasticities (relative to total expenditures). Budget elasticities directly contribute to the uncompensated price elasticities by inclusion of the income effect that adds-up to substitution patterns in Marshallian elasticities (for Hicksian/compensated price elasticities, see appendix B.3).

Table 2.3: Elasticities and Model Fit – Full Population

Consumption	**Price Elasticity**	**Budget Elasticity**	R^2
Food	-0.46^{***} *[–0.70 ; –0.22]*	0.91^{***} *[0.88 ; 0.94]*	0.29
Transport	-0.22^{***} *[–0.31 ; –0.12]*	0.80^{***} *[0.73 ; 0.86]*	0.14
Electricity	-0.66^{***} *[–0.79 ; –0.54]*	0.40^{***} *[0.35 ; 0.45]*	0.40
Heating	-0.16^{***} *[–0.23 ; –0.10]*	0.68^{***} *[0.62 ; 0.73]*	0.36
Other	-0.77^{***} *[–0.85 ; –0.69]*	1.11^{***} *[1.09 ; 1.12]*	0.48

Note: Uncompensated (Marshallian) price and budget elasticities with 95% confidence intervals.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on HBS data for Belgium (33,269 observations spanned across survey waves from 2003 to 2016).

In Table 2.3, we observe that all the consumption groups are price inelastic, with elasticities below 1 in absolute value. This is particularly the case for transport and heating fuels, whose uncompensated elasticities are respectively –0.22 and –0.16. These low values suggest limited price responsiveness in these domains, which is consistent with their

considered as a utility-maximising behaviour in our model (*e.g.*, absence of consumption in the face of high prices).

necessity status. By contrast, electricity shows a much higher elasticity (–0.66) compared to heating consumption which is more rigid in the short run. The food elasticity (–0.46) lies in a mid-range, while "other goods" display the highest elasticity (–0.77), as expected for a more heterogeneous category that includes price-elastic expenses.

These patterns align with other empirical findings using the same method. For example, Douenne (2020) finds uncompensated elasticities of –0.45 for transport and –0.2 for housing energies in France, both close to our own results. Similarly, Semet (2024) reports values of –0.3 for food and –0.2 for home energy. Our electricity elasticity is close to those in Labandeira et al. (2022) for Mexico (–0.67 to –0.71) or Nikodinoska and Schröder (2016) for Germany (–0.81). Our transport fuel price elasticity lies in between the separate elasticities for gasoline and diesel obtained by Calvet and Marical (2011), estimated at -0.35 and -0.11 respectively. Importantly, the general ranking across categories we observe is in line with the rest of the literature: our elasticities are close to the short-term estimates found by Labandeira et al. (2017) in their meta-analysis, except electricity for which the demand system methodology seems to consistently lead to higher price elasticities (in absolute term) than other methods. Finally, the low elasticity for heating fuels we observe (–0.16) suggests very limited substitutability or adaptation capacity for heating consumption in the Belgian context.

In Table 2.3, we also report the budget elasticities across consumption categories. Most of them are strictly positive and close to 1, indicating that the goods are normal and that expenditure shares remain relatively stable with budget; except domestic energies (electricity and heating) that clearly emerges as necessities with smaller budget elasticities. The elasticity for other goods is the highest at 1.11, making it the most income-sensitive category, consistent with the fact that it includes non-essential and luxury items.

These results are in line with findings from the empirical literature. Semet (2024) reports budget elasticity of 0.8 for food, which aligns with our estimate, although it seems above other studies (0.41 for Nikodinoska and Schröder (2016), 0.6 for Labandeira et al. (2022)). For domestic energy, our results echo the low values observed by Douenne (2020) (around 0.5 for housing energy), Labandeira et al. (2022) (0.27 for electricity), as well as Nikodinoska and Schröder (2016) (0.5 for electricity). The last study also reports higher budget elasticities for transport fuels (0.8), as our result, though Douenne (2020) find relatively smaller estimates (around 0.5). Overall, our budget elasticities display a classical Engel pattern, with higher-income households allocating proportionally less to necessities and more to luxury-type expenditures. This supports the validity of our model and aligns with international evidence.

Table 2.4: Uncompensated Price Elasticities by Group and Consumption Category

Group	n	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All Population	33,269	−0.46***	−0.22***	−0.66***	−0.16***	−0.77***
Deciles 1–3	7,728	-0.55***	-0.35***	-0.64***	-0.26***	-0.77***
Deciles 4–5	6,822	-0.49***	-0.25***	-0.67***	-0.19***	-0.77***
Deciles 6–10	18,719	-0.41***	-0.15***	-0.67***	-0.10***	-0.78***
Deciles 1–5 (all)	14,550	-0.52***	-0.30***	-0.65***	-0.23***	-0.77***
Hidden Energy Poor	1,061	-0.61***	-0.35***	-1.16***	-0.44***	-0.80***
Energy Poor	3,342	-0.60***	-0.39***	-0.55***	-0.21***	-0.77***
Deciles 1–5, non-EP	10,150	-0.49***	-0.27***	-0.66***	-0.22***	-0.77***

Note: Marshallian price elasticities evaluated at (sub)sample means.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

In Table 2.4, we break down uncompensated price elasticities by group. In the upper part of the table, we concentrate on the income dimension with the three first deciles (where most (h)EP are found), the deciles 4 and 5 (completing the bottom half of the income distribution, i.e., the population at risk of energy vulnerability), and the upper half of the distribution (deciles 6 to 10). We observe a gradient with lower income households exhibiting stronger reactions to price variation, except for electricity and "other" for which elasticities remain close across income groups. Looking at the lower half of the table, we observe hidden energy poor being twice as sensitive to domestic energy price variations than other categories. For Food and Transport fuels, both EP and hEP show higher price elasticities than the rest of the population. Although income appears as the main dimension at play to explain the differences between EP and the rest of the population (their elasticities are close to those of similar-income households), hEP are particularly more sensitive to domestic energy prices despite being slightly richer on average than EP. This finding is key in explaining their under-consumer status, suggesting strong restriction in the face of higher prices, and preference for cutting back on heating and electricity consumptions rather than on other necessities such as food or transport fuels.

We finally report budget elasticities by group in Table 2.5. Though poorer households show slightly higher budget elasticities than richer ones (except for electricity), the gradient observed in price elasticities is not as clearly reproduced here. Differences in budget elasticities for (h)EP compared to same-income population (Dec. 1–5 non EP) are not striking, except for heating. Interestingly, EP show lower budget elasticities on domestic energy than hEP, especially for heating. Yet, the trends obtained in the uncompensated price elasticities are not solely the result of differences in budget elasticities. Indeed, looking at Table B.15 in the Appendix, we see that all groups show significant substitution patterns as well.

Table 2.5: Budget Elasticities by Group and Consumption Category

Group	n	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All Population	33,269	0.91***	0.80***	0.40***	0.68***	1.11***
Deciles 1–3	7,728	0.95***	0.84***	0.37***	0.70***	1.12***
Deciles 4–5	6,822	0.94***	0.81***	0.40***	0.70***	1.10***
Deciles 6–10	18,719	0.88***	0.78***	0.40***	0.65***	1.11***
Deciles 1–5	14,550	0.95***	0.83***	0.39***	0.70***	1.11***
Hidden Energy Poor	1,061	0.93***	0.76***	0.55***	1.44***	1.05***
Energy Poor	3,342	1.06***	0.87***	0.34***	0.52***	1.14***
Dec. 1–5, non (h)EP	10,150	0.92***	0.82***	0.39***	0.76***	1.10***

Note: Total expenditure elasticities evaluated at (sub)sample means.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Overall, despite both reacting like monetary poor households do, EP and hEP exhibit different energy consumption patterns. While EP seem to be constrained by high-level domestic energy expenditure and showing less adaptation to prices and budget variations, hEP severely under-consume and react strongly to prices and budget changes. Distinguishing these groups from the rest of the population is therefore central and relevant for the impact analysis of carbon pricing.

2.4 Analysis of Carbon Pricing Impact

2.4.1 Monetary Welfare Approach

In this policy analysis, we simulate the effect of a carbon price applied to household consumption of transport and heating fuels (€180/tCO_2 expressed at 2016 HBS price levels). This corresponds to a 68% increase in heating fuel prices and a 37% increase in transport fuel prices.[50] To measure the impact of such price changes on households, we report two measures: the monetary Tax Burden (TB) and the welfare Equivalent Variation (EV). Both are computed using estimates from our demand system and provide money-metric measures that capture individual substitution patterns at new (after-tax) prices. The TB

[50] Using relative price changes allows us to simulate carbon pricing consistently over time, with the carbon price scaled to past price levels.

is defined as $TB = \Delta p \times Q_1$, where Q_1 denotes post-reform quantities,[51] and $\Delta p = (p_1 - p_0)$ the corresponding price increase due to carbon pricing. The Equivalent Variation (EV) is defined following King (1983):

$$EV = m - E(\mathbf{p_0}, u_1) \tag{2.4.1}$$

with the underlying QUAIDS expenditure function:

$$E(\mathbf{p_0}, u_1) = a(\mathbf{p_0}) \cdot \exp\left(\frac{u_1 \cdot b(\mathbf{p_0})}{1 - \lambda(\mathbf{p_0}) \cdot u_1}\right) \tag{2.4.2}$$

and the indirect utility function:

$$\log u_1(\mathbf{p_1}, m) = \frac{1}{b(\mathbf{p_1})}\left[\log\left(\frac{m}{a(\mathbf{p_1})}\right) + \lambda(\mathbf{p_1})\left(\log\left(\frac{m}{a(\mathbf{p_1})}\right)\right)^2\right] \tag{2.4.3}$$

Here, $\mathbf{p_0}$ and $\mathbf{p_1}$ denote the pre- and post-tax price vectors, u_1 is the household's post-tax utility, and m are total expenditures (budget). $a(\boldsymbol{p_1})$ and $b(\boldsymbol{p_1})$ are obtained from the price aggregators defined in subsection 2.3.2, and $\lambda(\mathbf{p}) = \sum_i \lambda_i \ln p_i$; all are estimated with the parameters from the previous section. For each household, we first recover u_1 from equation 2.4.3, plug it into equation 2.4.2 to obtain $E(\mathbf{p_0}, u_1)$, and then compute EV using equation 2.4.1. With our sign convention, the EV is reported as a positive welfare loss under a price increase.[52]

Intuitively, TB is the extra amount paid for carbon pricing based on after-tax fuel quantities, abstracting from utility losses and substitution costs (additional amounts paid on other commodities after substituting). The EV is the change in wealth that would be *equivalent* to the price change in terms of welfare impact. It can be interpreted as the willingness to pay in order to avoid the price increase due to carbon pricing. The EV includes the welfare cost of adaptation to new prices. Accordingly, the TB offers a lower bound for the EV, and the difference between EV and TB is the deadweight loss (DWL) of taxation (King, 1983). DWL therefore captures the welfare cost of carbon pricing beyond the tax revenue collected, that is, the cost of moving households away from their preferred consumption bundle. Expressing DWL relative to TB yields the Average Excess Burden (AEB), which measures the additional welfare loss associated with raising one euro of carbon tax revenue. Taken together, EV, TB, DWL, and AEB allow us to distinguish between direct financial exposure and welfare impact across household groups.

[51] Q_1 are model-predicted quantities obtained using the behaviours estimated in the previous section

[52] Analogically, we could have reported the compensating variation $CV = E(\mathbf{p_1}, u_0) - m$, which takes as arguments post-tax prices and pre-tax utility; we also computed the CV and results are close. Following King (1983), EV is preferred here for the computation of the deadweight loss as it evaluates the welfare change at a common (pre-reform) reference price vector.

Our analysis abstracts from the external benefits of carbon pricing. A complete welfare assessment would also account for the value of emission reductions, for instance through a social cost of carbon applied to abated CO_2 emissions. Our focus, however, is on the short-run microeconomic impacts of higher energy prices across household types. Unless these climate benefits were assumed to vary across households, including them would not alter the distributional patterns at the core of our analysis (see Baranzini et al. (2000) on the complexity of evaluating the environmental effects of carbon taxes). Likewise, although revenue recycling is central to the overall incidence and political acceptability of carbon pricing, it is analytically distinct from the question studied here, in addition to being treated elsewhere (e.g., see Berry (2019) on whether revenue-recycling policies can address energy poverty).

2.4.2 Results of the Policy Analysis

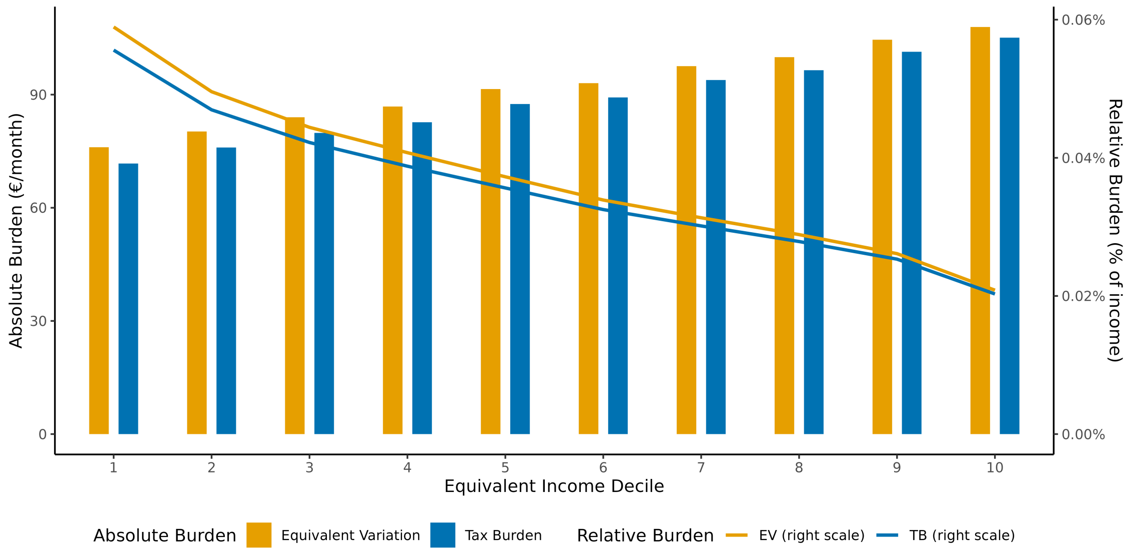
First, we compare outcomes across the income distribution in Figure 2.3. Both the TB and the EV increase in absolute terms across income deciles, reflecting higher average fuel expenditures among richer households, while displaying the usual regressive pattern when expressed relative to income. If we were to redistribute all revenues to each household in a lump-sum fashion, poor households would be net winners on average as they contribute less (in absolute) than the transfer they would get. The EV, accounting for the welfare costs of substitution away from fuels, is always higher than TB, even though this effect is moderate in our setting[53] and does not lead to substantial variation in the income dimension.[54]

Second, we disaggregate the analysis by energy vulnerability statuses. In addition to the TB and the EV, we report in Table 2.6 the deadweight loss ($DWL = EV - TB$) from carbon pricing and the average excess burden ($AEB = 100 \cdot DWL/TB$). These are classic measurements for efficiency loss in the literature and relate to the concept of marginal cost of funds (except our AEB measure is not derived at the marginal level). They show important discrepancies between energy poor (EP) and hidden energy poor (hEP) households. For EP households, who devote a large share of their budget to energy, the TB shows high exposure, their EV follows the same path, and they exhibit the largest DWL. Nevertheless, when the latter is expressed relative to the TB, leading to the AEB, the impact appears less disproportionate: the welfare cost of raising 1€ of tax revenue from them through carbon pricing would be only 4.5 cents. This finding is key as it suggests relatively low marginal utility from energy use and leaves room for compensating

[53]With population-level uncompensated price elasticities of −0.22 and −0.16 for transport and heating fuels, the price increases of 37% and 68% translate into average consumption drops of −8.1% and −10.88%, respectively.

[54]We observe slightly larger differences between the EV and the TB for lower-income deciles as they exhibit stronger behavioural reactions, reducing their TB further than more affluent households.

Figure 2.3: Tax Burden and Equivalent Variation by Income Decile



EP households for reduced energy consumption at a moderate societal cost. By contrast, hEP households spend little on energy and therefore appear less exposed under TB and EV, with a lower DWL. Their AEB, however, is much higher. Because of their atypically low spending on domestic energy, collecting revenues on such restricted consumption incur at a higher marginal welfare cost for them. With an AEB twice the average one, imposing carbon pricing on hEP seem rather inefficient from a social planner perspective.

Table 2.6: Comparison of Equivalent Variation and Tax Burden Across Groups

	€/month			**cents/1€**
Group	**Tax Burden**	**Equivalent Variation**	**Deadweight Loss**	**Average Excess Burden**
Total Sample	89.5	93.2	3.74	5.07
Deciles 1–3	76.4	80.6	4.23	5.82
Deciles 4–5	85.1	89.2	4.07	6.67
Deciles 6–10	97.1	101	3.40	4.11
Deciles 1–5	80.4	84.5	4.15	6.21
Hidden Energy Poor	35.9	39.7	3.88	10.6
Energy Poor	99.3	103	4.20	4.48
Dec. 1–5, non–(h)EP	78.5	82.7	4.17	6.34
None (h)EP	90.2	93.9	3.68	4.93

Notes: Positive Equivalent Variation and Tax Burden values represent financial losses under the simulated carbon tax on heating and transport fuels. Monetary values are in constant 2016 euros per household per month.

The deadweight loss (DWL) measures the efficiency loss from the tax beyond the revenue it raises; $DWL = EV - TB$.

The average excess burden (AEB) is the DWL per euro of tax revenue; $AEB = 100 \cdot DWL/TB$.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Overall, these results underscore the value of jointly considering TB, EV, and the derived DWL and AEB measures. TB captures the immediate monetary burden of carbon pricing, whereas EV measures the income required to restore households to their pre-reform level of welfare. DWL and AEB, in turn, quantify the associated efficiency cost in absolute and relative terms. For EP households, a lower AEB suggests that targeted transfers can offset welfare losses at a relatively limited social cost. At the same time, their strong dependence on fuel use points to a degree of lock-in to carbon-intensive consumption patterns, potentially because financial constraints limit investment in cleaner durables or home retrofits. Subsidies and other accompanying measures, such as easier access to credit or lower borrowing costs, therefore appear particularly relevant for this group. For hEP households, the picture is different. Their already restricted energy use leaves little room for further adjustment without cutting into basic needs. As a result, further price increases may generate welfare losses that are much larger than suggested by their low tax burden. This discrepancy illustrates the value of a welfare-based assessment, which can reveal vulnerabilities that standard exposure-based measures understate when households already restrict their energy use. More broadly, it underscores the importance of complementing conventional energy poverty indicators with hidden energy poverty metrics. Because these households may require specific policy attention despite their low apparent exposure, further research is needed to better understand their profiles and the struggles they face in meeting basic domestic energy needs.

2.5 Conclusion

This paper has examined the distributional effects of carbon pricing from a behavioural perspective, with particular attention to heterogeneity across income levels and energy vulnerability status. Using 11 cross-sections of the Belgian Household Budget Survey, we estimated a demographically specified Quadratic Almost Ideal Demand System and embedded it in a behavioural microsimulation that draws on the forthcoming EU ETS 2 for heating and transport fuels. By integrating a two-stage residual inclusion correction for endogenous energy vulnerability statuses, we allowed price responses to differ systematically between energy poor (EP) and hidden energy poor (hEP) households, thus linking the energy poverty literature to the microsimulation of carbon taxation in a novel way.

Traditional energy poverty metrics often fail to capture households that restrict their energy consumption below adequate levels due to financial constraints. Our analysis shows that hEP households, although undetectable using standard over-expenditure indicators, represent a substantial share of the vulnerable population. Logistic regressions suggest that (hidden) energy poverty is embedded within broader socio-economic disadvantages, while showing that region, housing type, and heating systems are key in differentiating the two groups.

Our results confirm that domestic energy (heating fuels and electricity) and transport fuels are price-inelastic necessities. Nevertheless, we uncover substantial behavioural heterogeneity. Lower-income and EP households typically exhibit higher fuel price elasticities than wealthier or non-vulnerable groups, although much of this difference is explained by income itself. By contrast, hEP households stand out. Despite having on average slightly higher incomes than EP households, they display the strongest price sensitivity for most fuels. These patterns align with the multidimensional nature of energy vulnerability.

Incorporating these behavioural differences into a welfare analysis reveals a misalignment between financial losses and welfare burdens. EP households indeed bear a high nominal carbon cost, but their welfare loss can be effectively compensated through redistribution of the carbon pricing proceeds. hEP households, by contrast, pay relatively little in carbon taxes (because their energy use is low), yet they suffer large relative welfare burdens when prices rise. This divergence underscores the importance of complementing traditional monetary metrics with welfare-based incidence measures.

These findings have important implications for the design of carbon pricing and related compensation mechanisms. Policies that rely solely on income or observed energy expenditure to target support risk severely undercompensating the less visible hEP households. An equitable allocation of the Social Climate Fund and similar instruments should therefore take explicit account of energy vulnerability profiles and calibrate transfers more closely to welfare losses rather than tax payments alone. In parallel, structural measures, such as building renovation, heating system upgrades, and support for clean, efficient appliances, are essential to reduce long-run dependence on carbon-intensive energy and to lower vulnerability at its source.

By bridging detailed demand-system estimation with energy poverty metrics, this paper contributes to the literature on the distributive effects of green taxation and offers a new perspective on horizontal equity in carbon pricing. Future work could refine the identification of energy vulnerability, incorporate richer information on housing quality and thermal needs, and extend the analysis to broader policy packages that combine carbon pricing with targeted transfers (De Bevere & Grandjean, 2023) and endogenous investment in energy efficiency (De Bevere et al., 2026). Such extensions would help design climate policies that are not only environmentally effective but also socially equitable and politically sustainable.

Chapter 3

Incorporating the Prebound Effect in Retrofit Policy Analysis: Distributional Results for Belgium

Joint work with Gilles Grandjean and François Meuwissen

Abstract

In this chapter, we compare the distributional incidence of three decarbonisation instruments in the Belgian residential sector: EPC-based minimum standards, carbon pricing with an equal per-household dividend, and renovation subsidies financed by a uniform lump-sum tax. Using Woonsurvey 2018 and a dwelling-level microsimulation model that evaluates renovation profitability on observed energy use, we quantify household monetary impacts, renovation take-up, and equity (across and within income groups) for budget neutral policies calibrated to common CO_2 targets. Three results stand out. First, EPC standards concentrate burdens on low-income and low-use households and generate high dispersion because they compel renovations where realised savings are small. Second, universal subsidies are costly on average and distribute benefits unevenly, with sizable transfers to infra-marginal projects. Third, carbon pricing with revenue recycling yields the lowest and most evenly distributed household burdens, largely because it triggers heat-pump adoption in dwellings with the highest energy consumption. We further show that combining a modest carbon price with targeted heat-pump support can meet the same emissions target at lower cost and with a smaller variance of household impacts than under the carbon dividend. Results are robust to rebound, landlord–tenant limits, and reasonable variations in discounting, time-horizons, energy prices, and costs.

3.1 Introduction

Residential buildings are pivotal to Europe's decarbonisation. Globally, buildings account for about 26% of greenhouse gas (GHG) emissions (International Energy Agency, 2023). Achieving the EU's Fit for 55 target and climate neutrality by 2050 requires a sustained renovation wave (European Commission, 2021). Policy design in the residential sector primarily relies on two instrument families: (i) price-based instruments (e.g., carbon pricing on fossil heating fuels) and (ii) subsidies (e.g., grants, tax credits, soft loans) that lower upfront costs for heat pumps, insulation, or photovoltaic panels. Both are already deployed at EU level: Member states strengthened the use of subsidies as a key policy instrument to incentivise energy-efficient residential renovations, while the EU is establishing a separate Emissions Trading System for buildings and road transport (ETS2), slated to start in 2028 (European Union, 2023a, 2023c, 2024). However, existing policy instruments may prove insufficient to achieve the EU's decarbonisation objectives, raising the prospect of more stringent regulatory interventions in the residential sector. In particular, minimum energy performance standards—implemented through EPC[55] obligations under the Energy Performance of Buildings Directive—have increasingly been discussed as a complementary policy lever. For instance, the Citizens' Convention for Climate (2020) proposed the French government to impose on homeowners and landlords to achieve a minimal level of energy performance by 2040. More recently, the Brussels-Capital Region has introduced ambitious energy performance requirements for residential buildings, mandating the renovation of inefficient dwellings by 2033, with further tightening expected in subsequent years (Bruxelles Environnement, 2025). Considering the rental market, other jurisdictions such as the United Kingdom and France made it illegal to rent out housing with an energy performance certificate below a specific threshold (Gouvernement français, 2023; UK Department for Energy Security and Net Zero, 2025).

In this paper, we analyse the household-level distributional impacts of three budget-neutral policies for residential decarbonisation: (i) EPC-style performance standards, (ii) carbon pricing with equal per-household lump-sum recycling (a carbon dividend), and (iii) subsidies to renovation investments financed by lump-sum taxation. Our focus is on households' monetary incidence: who bears costs, who benefits, and how net financial impacts are distributed across and within groups. We use these comparisons to test whether climate policy entails efficiency-equity trade-offs.

Distributional justice matters on normative grounds (to avoid exacerbating inequalities

[55] An Energy Performance Certificate is a standardised rating that summarises a dwelling's energy efficiency, typically expressed as annual energy use (for heating, domestic hot water and auxiliary energy) per square meter ($kWh/m^2/year$) and often translated into a label (e.g., A = efficient to F = inefficient).

and protect vulnerable groups), and pragmatically as it influences policy feasibility and public acceptability. Distributional impacts of carbon pricing are widely studied. Across this literature, carbon pricing is typically found to be regressive; lump-sum recycling can render it progressive; and sizable within-decile dispersion underscores the importance of horizontal alongside vertical equity (Cronin et al., 2019; De Bevere & Grandjean, 2023; Fischer & Pizer, 2019; Landis et al., 2019; Rausch et al., 2011).

Subsidies and tax credits are typically found to be regressive, as they disproportionately benefit higher-income households with sufficient liquidity to undertake energy-efficiency investments (Bourgeois et al., 2021; Lekavičius et al., 2020). While much of this literature emphasises the role of market failures such as credit constraints or split incentives, Fernández et al. (2024) show that regressivity may persist even in their absence, since subsidies can be capitalised into housing values and thus accrue primarily to homeowners, who are on average wealthier. Beyond these vertical equity concerns, subsidies may also generate substantial horizontal inequities by conditioning transfers on heterogeneous investment opportunities across households (Bourgeois et al., 2021). For example, two households with similar incomes may face very different net positions if one lives in a poorly insulated house with many eligible retrofit options while the other lives in an apartment or an already efficient dwelling with little scope to benefit, yet both contribute to financing the scheme.

Relative to carbon pricing and subsidy-based instruments, the distributional implications of regulatory standards have received less attention. In the automotive sector, a broad consensus holds that efficiency and emissions standards tend to be regressive, as compliance costs represent a larger share of income for low-income households, while higher-income households capture a larger share of the benefits given their higher consumption of energy services (Davis & Knittel, 2019; Fullerton & Muehlegger, 2019; Levinson, 2019). On top of this, in the residential building sector, distributional concerns may be even more salient because low-income households are disproportionately concentrated in poorly insulated dwellings (Ryckewaert et al., 2019). Yet, to our knowledge, no study has quantified the distributional incidence of EPC-based standards in the residential building sector.

A wide range of modelling approaches can be used to assess the distributional impacts of climate policies (Linden et al., 2026; Montenegro et al., 2021). Input-output models, for instance, quantify both the direct and supply-chain (indirect) effects of carbon pricing on household expenditures (Steckel et al., 2021). Computable general equilibrium models can further capture economy-wide adjustments and evaluate the income effects of a broader set of policies (Vandyck et al., 2022). By contrast, although they abstract from general-equilibrium feedbacks and indirect effects, microsimulation models with endogenous investment decisions are particularly well suited to measuring distributional impacts not only across groups but also within them. To account for policy impacts over time, some studies rely on dynamic microsimulation frameworks (Giraudet et al., 2021; Müller et al., 2024). However, their dynamic structure requires strong assumptions regarding stock turnover, which can constrain distributional granularity. In addition, these models often represent the housing stock through archetypal dwellings and incorporate average market frictions calibrated from external evidence. A smaller set of studies instead adopts static microsimulation approaches to provide better incidence assessments (Soubelet et al., 2024; Torné & Trutnevyte, 2024, 2026). Recently, Torné and Trutnevyte (2026) use such a model to study the distributional effects of alternative policy mixes, but focus on deep (rather than partial) retrofits, do not impose budget neutrality or common abatement targets, do not consider EPC standards, and impute heating demand from building archetypes and household size.

A key empirical regularity in residential dwellings is prebound: actual pre retrofit energy use is often below theoretical consumption (Sunikka-Blank & Galvin, 2012). This reduces expected profitability and realised savings from renovations (Galvin, 2024), and can shift abatement away from envelope retrofits and toward fuel switching options with larger private returns. Ignoring prebound biases instrument comparisons and incidence: EPC-style thresholds calibrated to theoretical needs can force low-return renovations on low-use households, while pricing anchored in actual consumption may tilt abatement toward fuel switching (e.g., heat pumps). Because these frictions vary across households, the incidence of policies is highly sensitive to whether models are based on observed bills or theoretical consumption. Beyond correcting prebound, billing data embed otherwise unobserved behaviours (occupancy patterns, comfort/temperature preferences, attention to energy costs, environmental consciousness) that are central for exposure and thus distributional analysis. To our knowledge, no study compares the distributional incidence of residential building-sector policies while anchoring energy use in observed household energy bills.

In this paper, we develop a microsimulation model with endogenous investment for Belgium that computes renovation profitability using actual (rather than theoretical) energy consumption, explicitly capturing the prebound effect. Across the three budget-neutral policies, the carbon dividend consistently yields the smallest increase in households' energy spending over the next 25 years. To achieve a 20% reduction in residential emissions, the average cost borne by households is 3.7 times higher under performance standards and, under subsidies, it is 5.7 times the one under carbon dividend. The carbon dividend also performs best for low-income households, generates the lowest within-quintile dispersion in impacts, and leaves a majority of households financially better off compared with the two alternative designs. Singles and households with a low ratio of actual to theoretical energy consumption are strongly penalised under standards, whereas carbon pricing distributes costs more evenly. Subsidies hurt owners of apartments and energy-efficient dwellings as they do not benefit from them, yet, they must finance others' investments. Rebound effects have only a minor influence on realised emissions, particularly at higher ambition levels where decarbonisation is driven mainly by heat pump installation rather than envelope insulation. While quantitative magnitudes vary with modelling assumptions (discount rate, investment horizon, investment costs), the qualitative ordering of policies is robust. Finally, accounting for the prebound effect is critical: when profitability is computed from theoretical rather than actual consumption, the same carbon price yields three times as much emissions reduction, a result that relies on a systematic overestimation of retrofit profitability.

Relative to the literature, our paper makes three advances. First, we exploit linked household microdata that combine actual energy bills, detailed dwelling energy characteristics, and household socio-demographics to simulate the distributional incidence of building sector climate policies when households endogenously choose renovations. Computing profitability using observed energy bills allows us to internalise prebound and to recover revealed behaviours that are central to exposure and incidence but typically unobserved in surveys. Second, we deliver a microdata anchored comparison of EPC standards, carbon pricing and subsidies, allowing partial retrofit; we make policy levers directly comparable by imposing government budget neutrality and tracing continuous policy response curves over various CO_2 reduction objectives. Third, by combining microsimulation with endogenous investment, we credibly capture nonlinearities (profitability thresholds, complementarities between insulation and heat pumps) and isolate the investment channel from pure demand response (sobriety) effects. We preserve the individual level granularity to quantify vertical equity, horizontal equity, and incidence across fine household subgroups. This positioning clarifies why our results differ from studies that rely on representative households, archetype-based theoretical consumption, or purely price elastic demand responses.

The structure of this paper is as follows. Section 3.2 presents the data. Section 3.3 details the model and scenario design. Section 3.4 presents the main results, and Section 3.5 discusses robustness.

3.2 Data

3.2.1 Woonsurvey

The Woonsurvey 2018[56] (Flanders) provides rich microdata on housing conditions with an emphasis on energy performance. It covers about 3,000 dwellings and reports: (i) Envelope quality for windows, roof, walls, and floors (three categories: poor, intermediate, good); (ii) Dwelling attributes (type, floor area, tenure, construction year, heating system); (iii) Household socio-demographics (size, income, age/education/employment of the reference person) ; and (iv) annual energy expenditures by carrier (natural gas, heating oil, electricity, wood/other solid fuels). Because end-use detail is not observed, we allocate total carrier use across services using heating technology information. If the dwelling uses a gas or oil boiler, we assume a single boiler supplies space heating and domestic hot water and split the carrier consumption in proportion to theoretical needs. Otherwise, domestic hot water is assumed to be produced by a dedicated electric boiler.[57]

3.2.2 Augmented Woonsurvey

We augment the Woonsurvey in two complementary ways: (i) we derive theoretical energy consumption from building characteristics, equipment, and year of construction, and (ii) we recover physical energy quantities from observed bills. The theoretical measure is used to model engineering-predicted savings from renovations, while observed consumption anchors projected bills and private profitability under renovation and policy scenarios. Accordingly, we account for the prebound effect.

Theoretical energy consumption

The theoretical energy consumption of buildings in Europe is determined within the framework of the Energy Performance of Buildings Directive (European Union, 2024). This directive has been transposed by each member state, and, in Belgium, by each region. Our analysis relies on the Flemish methodology for EPC score calculation (Vlaamse Overheid, 2022), detailed in our technical online appendix.[58] In short, theoretical consumption is computed as:

$$E_{\text{th}} = E_{\text{heat}} + E_{\text{dhw}} + E_{\text{aux}} - E_{\text{PV}} \tag{3.2.1}$$

[56] Data have been made available by Agentschap Wonen in Vlaanderen and collected by Steunpunt Wonen.

[57] Details on cleaning rules are provided in Section 1 of the Technical Report available online at https://cape-saintlouis.be/working_papers/.

[58] see footnote above

where the terms reflect space heating, domestic hot water, auxiliaries (appliances), and photovoltaic panels electricity generation. By construction, E_{th} depends only on dwelling physics and equipment (household behaviour/occupancy is standardised in the EPC) and is dominated by space heating (about 70% on average).

Real energy consumption

Woonsurvey reports annual energy expenditures by carrier but not physical quantities. We recover quantities by dividing expenditures by carrier-specific prices (2017–2018 averages).[59]

3.2.3 Actual vs. theoretical energy consumption for heating

We compare billed household heating consumption with theoretical requirements. The ratio of actual to theoretical consumption is a standard measure of the prebound effect. Table 3.1 shows that, on average, billed use is about half of theoretical needs (mean 52%; median 46%). This implies that analyses based on theoretical consumption tend to overstate bill savings from renovations and, consequently, the private profitability of such investments. The table also reveals marked heterogeneity. The 90th-percentile ratio is roughly 5 times the 10th-percentile ratio; 25% of dwellings lie below 0.29, while another 25% exceed 0.69. These differences likely reflect variation in occupancy patterns, desired indoor temperatures, environmental attitudes, and attention to energy costs. Ignoring actual consumption therefore not only overestimates average benefits from renovation, but also masks key distributional effects linked to household-specific composition, needs and behaviours.

Table 3.1: Distribution of actual-to-theoretical heating consumption ratios

	P10	P25	P50	P75	P90	Average
Ratio	20%	29%	46%	69%	97%	52%

Source: Own calculations based on Woonsurvey 2018.

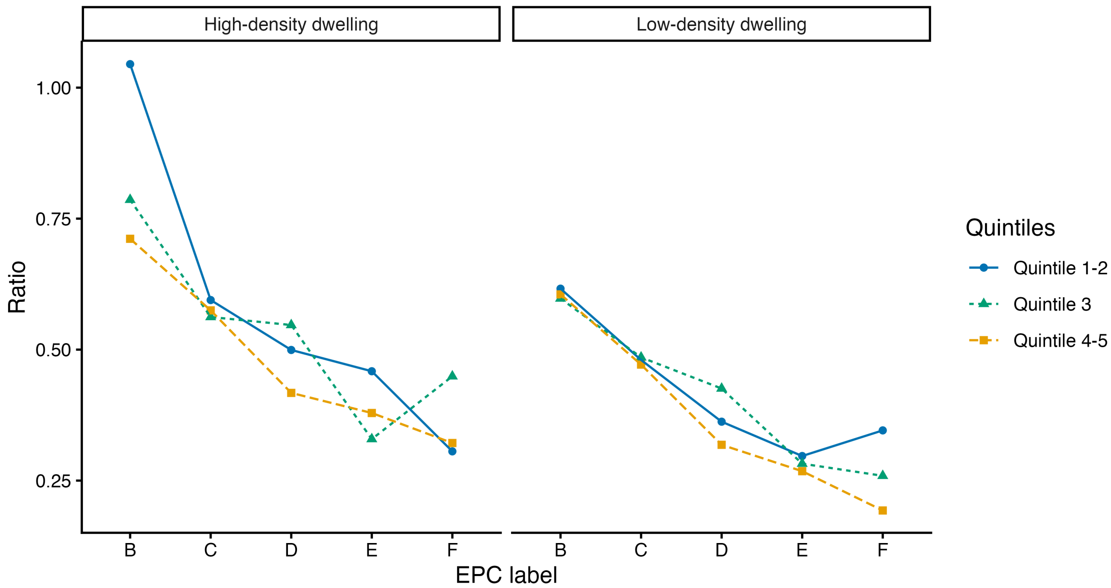
Figure 3.1 documents how the ratio varies with dwelling characteristics. For comparability, we restrict to houses (about 80% of the Flemish stock; see Appendix C.1). The left panel covers dwellings with living area per occupant below 75 m^2 (the median), the right panel those above the median. Each horizontal axis reports the EPC rating from

[59] Sources: CREG residential baskets 01/2017–06/2018 (gas/electricity), FPS Economy (heating oil), Valbiom (logs/pellets). See Section 1 of the Technical Report for values.

best (left) to worse (right), and households are split into the bottom two income quintiles (red) versus the top two quintiles (blue).

Three patterns stand out. First, conditional on energy performance and dwelling density, there is little systematic income gradient in the ratio, suggesting a low income elasticity of heating demand. Second, the ratio increases with energy performance: as dwellings become more efficient, the effective price of thermal comfort (i.e., a degree-hour of heating) falls, and households consume more heating services, narrowing the gap between actual use and theoretical needs. Third, higher occupancy density is associated with greater realised heating needs, which likewise pushes the ratio upward.

Figure 3.1: Ratio of Actual-to-theoretical Heating Consumptions



Notes: The figure reports actual-to-theoretical heating consumption ratios for houses, by EPC rating, household income group, and dwelling density.
Source: Own calculations based on Woonsurvey 2018.

3.3 Methodology

This section presents the RenoBel model and the design of the counterfactual and policy scenarios.

3.3.1 The RenoBel model

RenoBel is a household-level microsimulation model that assesses the profitability of residential energy-renovation investments using microdata from Woonsurvey 2018. It combines detailed building characteristics with observed household energy consumption (bills).

Renovation options For each dwelling, the model enumerates technically feasible renovation options and evaluates their economic attractiveness. The option set includes upgrades to the four envelope components—roof, walls, floor, and windows—and the potential installation of a heat pump. For insulation, each component can either remain unchanged or be upgraded to "good" performance (see Section 1 of the Technical Report). Combining four binary envelope decisions with heat pump adoption yields 32 configurations per dwelling. We restrict heat pump installation to dwellings with EPC scores below 350kWh/m^2/year (see Technical Report, Section 4).

Renovation costs Insulation costs are derived from Ryckewaert et al. (2019), with component-specific costs that depend on surface areas, insulation levels, location, and construction period. Heat pump installation costs depend on the required capacity, determined by dwelling heat load and standardised domestic hot water needs based on living area. Cost benchmarks come from industry sources and are updated over time using the ABEX construction price index.[60] Full cost formulas, sources, and parameters are documented in the Technical Report (Section 3).

Energy savings We value future energy savings at current real prices[61] discounted at fixed annual rate of 3%, consistent with standard appraisal practice (European Commission, 2014). A defining feature of RenoBel is that profitability is evaluated using households' *actual* energy consumption. Theoretical consumption reflects engineering characteristics under normative usage and typically overestimates observed use. RenoBel computes real energy savings by applying the ratio of observed-to-theoretical consumptions (both available ex-ante) to theoretical energy savings (projected by the EPC calculations), in line with the approach of Belaïd et al. (2021). This preserves the relative efficiency gains implied by renovations while anchoring savings in revealed behaviour. By construction, this assumes no rebound effect; we assess robustness to that assumption in Section 3.5.1. We do not consider within-period demand response to price changes in the face of carbon pricing;[62] adjustments operate through investment choices rather than sobriety-type

[60] The latest values can be found here: https://abex.be/en/abex-index/

[61] We use 2023-2025 average residential prices by carrier and hold them constant in real terms throughout the horizon: natural gas and electricity from CREG residential baskets (https://www.creg.be/sites/default/files/assets/Publications/Studies/F20250514EN.pdf), heating oil from StatBel (2022), and firewood/pellets from Valbiom market reports (https://www.valbiom.be/actualites/suivi-mensuel-des-prix-des-combustibles-bois)

[62] In his meta-analysis, Labandeira et al. (2017) found low price elasticities for domestic energy ranging from -0.185 to -0.684 in the long run. The very low price elasticities obtained for heating fuels in Coppens d'Eeckenbrugge and De Bevere (2025) confirm that the distributional picture of carbon pricing is not likely

adjustments. Finally, throughout the analysis, electricity consumption in the residential sector is treated as carbon-free at the household level because emissions from power generation are assumed to be covered upstream under EU ETS 1.

Life-cycle cost framework For each dwelling and renovation option i, we compute a 25-year life-cycle cost (LCC):

$$\mathrm{LCC}_i = I_i + \sum_{t=1}^{25} \frac{E_i}{(1+r)^t} \tag{3.3.1}$$

where I_i is the upfront investment and E_i the yearly energy expenditure under renovation option i, discounted at a real rate $r = 3\%$. Energy prices are held constant in real terms unless altered by carbon pricing. We assume no salvage value beyond the 25-year horizon.[63]

Investment decision Households are assumed to be fully rational in their investment decisions and choose the renovation option that minimises LCC. We exclude liquidity constraints: any privately profitable project can be financed.[64] For rental units, the baseline adopts a tenant-favourable limit in which renters undertake profitable renovations and retain the associated bill savings.[65] The main modelling assumptions are summarised in Table 3.2.

to hinge on short-term behavioural responses to increased energy prices

[63]Robustness analyses at different discount rates, energy prices and time horizons are conducted in section 3.5.2

[64]We relax that assumption in section 3.5.5

[65]Section 3.5.3 reports bounds under a landlord-surplus-capture limit.

Table 3.2: Main modelling assumptions

Assumption	Description
Time-horizon	25-year evaluation window for life-cycle costs (LCC); no salvage value beyond the horizon.
Discount rate	Real annual discount rate of 3% (homogeneous across households).
Post-renovation behaviour	Indoor temperature held constant (no direct rebound).
Demand response	No within-period demand response to prices; adjustment operates via investment, not sobriety.
Energy savings	Real energy saving are obtained by scaling theoretical heating needs using actual energy use information (from billed consumption)
Energy prices	Constant real base-year prices in the counterfactual; policy scenarios alter effective prices where relevant.
Investment choice	Households select the option with the lowest LCC.
Liquidity constraints	None: all privately profitable investments can be financed.
Landlord–tenant	Tenant-favourable limit: renters undertake profitable renovations and retain bill savings.
Heat pumps	Feasible only for dwellings with EPC $<$ 350 kWh /m^2/ year.
Electricity carbon-content	Electricity consumption is treated as carbon-free.

3.3.2 Scenario design

No-policy counterfactual

Although many energy renovations are privately profitable, they are not systematically undertaken in practice. As a common baseline, we first construct a no-policy counterfactual in which all privately profitable options are implemented. This isolates policy-induced investments from autonomous renovation behaviour. In doing so, we abstract from liquidity constraints, bounded rationality, and landlord-tenant split incentives, and assume that households adopt a homogeneous discount rate and undertake all profitable investments (we discuss implications in Section 3.5). A key mechanism behind unrealised "profitable" investments is the prebound effect: theoretical consumption exceeds observed use, so engineering assessments overstate savings and profitability. Once we evaluate profitability on observed consumption, some theoretically cost-effective projects are no longer profitable. In our data, 40% of dwellings would renovate if profitability were assessed on theoretical savings; this falls to 8% when based on observed consumption. Only the latter renovation cases are assumed to be undertaken in our no-policy counterfactual. This result shows the added value of incorporating the prebound effect into our framework.

Policy scenarios

We compare the no-policy counterfactual to three budget-neutral policy families: Norm, Carbon dividend and Subsidy (see Table 3.3). Within each family, we vary the key parameter (norm threshold, carbon price, subsidy rate) to span emissions reductions from 0% to 40% with respect to the no-policy counterfactual. This design supports like-for-like comparisons at common environmental and public-budget outcomes.

Table 3.3: Summary of the policy scenarios

Scenario	**Description**
1. Norm	All dwellings must reach an energy score below a threshold (in kWh/m^2/year).
2. Carbon dividend	A carbon price (in €/tCO_2) is imposed on heating fuels (natural gas and heating oil). Revenues are redistributed equally to all households.
3. Subsidy	A universal subsidy rate (in %) covers a fraction of renovation investment costs, financed by a one-time equal lump-sum tax on each household.

3.4 Results

This section presents results under the baseline assumptions. We proceed in two steps. First, we map response curves for each policy family by calibrating parameters to deliver any sectoral CO_2 reduction between 0% and 40% (see Section 3.4.1). This comprehensive exploration provides a robust comparison: rather than tying conclusions to a single, potentially arbitrary target, it reveals non-linearities and shows how outcomes evolve as ambition rises; it makes clear which findings are stable across the full range and which appear only in specific regions (e.g., at low or high emission reduction targets). By contrast, studies that compare two policies at one common target can miss these differences. Second, we fix the target at 20% and provide a granular distributional analysis at a common environmental outcome. Throughout, the monetary impact on households, ΔLCC, is the percentage change in life-cycle cost net of transfers and taxes under the policy (LCC^{Pol}) relative to the no-policy counterfactual (LCC^{Count}). It is the additional financial burden on households due to the implementation of a given policy.

$$\Delta LCC = \frac{\text{LCC}^{Pol} - \text{LCC}^{Count}}{\text{LCC}^{Count}} \tag{3.4.1}$$

We compute the post-policy life-cycle cost over a 25-year horizon as

$$\text{LCC}^{Pol} = (1-s)I^{Pol} + \sum_{t=1}^{25} \frac{E^{Pol} - Tr}{(1+r)^t} + T \tag{3.4.2}$$

where I^{Pol} is the upfront renovation investment, E^{Pol} the annual energy expenditure, r the real discount rate, s the subsidy rate (with $s = 0$ in the norm and carbon-dividend scenarios), Tr the annual equal-per-household lump-sum transfer in the carbon-dividend scenario (Tr = 0 otherwise), and T the equal lump-sum tax used to finance subsidies in the subsidy scenario ($T = 0$ otherwise). Relative to the counterfactual, E^{Pol} reflects three channels: (i) lower heating needs if insulation is undertaken, (ii) higher unit prices for fossil fuels when a carbon price applies, both for heating and domestic hot water consumptions, and (iii) fuel switching if a heat pump is installed (with the corresponding change in energy carrier and price).

3.4.1 Response curves

To obtain smooth response curves along the 0–40% range of CO_2 reductions, we simulate a grid of 20 scenarios within each policy family. Norm thresholds range from 440 to 250kWh/m^2/year in steps of 10kWh/m^2/year; carbon prices range from 0 to 210 €/tCO_2 in steps of 10 €/tCO_2; subsidy rates range from 47.5% to 97.5% in steps of 2.5%. This parameterisation aligns environmental outcomes and imposes government-budget neutrality for all instruments, ensuring direct comparability.

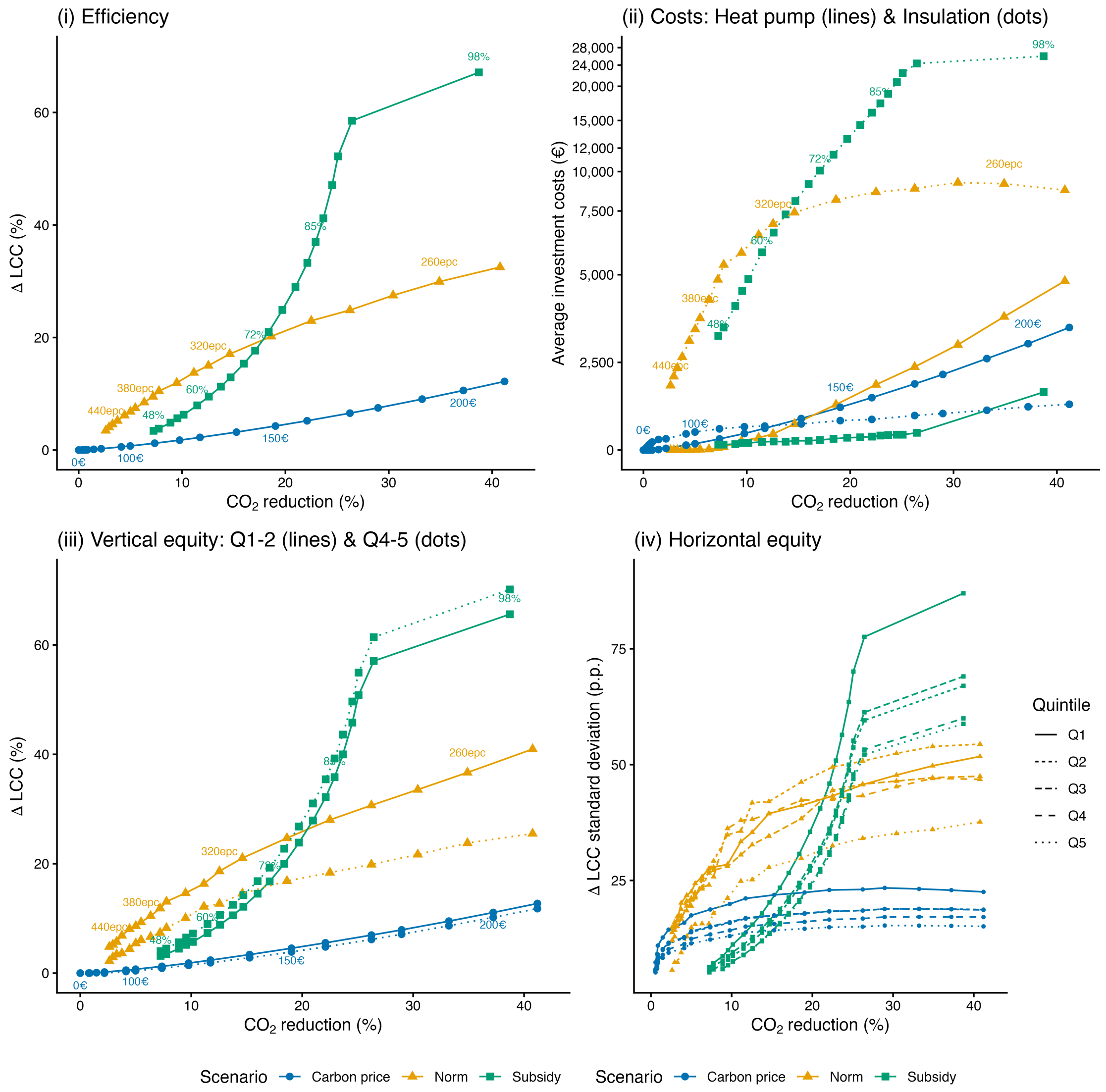
Figure 3.2 compares the three policy families. The horizontal axis reports the achieved sector-wide reduction relative to the no-policy counterfactual; the vertical axis differs by panel. Panel (i) shows average ΔLCC (in %), our efficiency indicator. Panel (ii) reports the renovation mix by technology, presenting the average investment costs for heat-pump installations and for insulation measures (incl. zeros for non-renovating households). Panel (iii) reports average ΔLCC for the bottom two income quintiles (Q1-Q2), isolating the impact on low-income households, our measure of vertical equity. Panel (iv) presents the standard deviation of ΔLCC within each income quintile, our measure of horizontal equity: lower values indicate a lesser dispersion in monetary impacts between households of similar income.

Three main results follow. First, efficiency and renovation composition are two sides of the same coin (panels (i) and (ii)). The carbon dividend typically delivers the lowest ΔLCC at a given environmental outcome because, once the price signal crosses a profitability threshold, heat-pump adoption scales quickly and most abatement comes from fuel switching. Given our carbon-free-electricity assumption, each heat pump yields a total abatement of heating and domestic hot water emissions, implying a low cost per ton relative to envelope retrofits. At medium to high ambition, panel (ii) also shows that average investment outlays for both heat pumps and insulation are lower under the carbon dividend than under the norm: pricing allocates electrification to dwellings with the highest private returns, whereas a uniform standard forces installations in units constrained by the norm where they are not necessarily cost-effective. Under norms, low stringency mainly induces insulation (with heat pumps still unprofitable), making costs per ton high when many targeted dwellings have low actual energy use. As the EPC-threshold tightens, electrification-oriented bundles (sometimes paired with targeted envelope upgrades) enter the LCC-minimising set for a growing share of dwellings, stabilising the efficiency gap compared to pricing. Subsidies outperform norms at low ambition because households self-select the insulation projects with the largest private bill savings. At higher ambition, however, electrification scarcely occurs under subsidies—heat pumps appear only at very high subsidy rates (above 90%)—so meeting the target increasingly relies on expensive envelope retrofits that deliver modest bill savings, raising the cost per abated tCO_2.

Second, panel (iii) shows that the ranking across instruments on a vertical equity basis broadly follows the efficiency ordering, but with some differences across the income distribution. For carbon pricing, ΔLCC remains very similar for Q1-Q2 and Q4-Q5 over the full range of CO_2 targets, suggesting limited vertical differentiation. By contrast, norms impose substantially larger losses on Q1-Q2 than on Q4-Q5, and this gap widens as ambition increases. The contrast is mild for subsidies. These results suggest that, while carbon pricing affects poorer and richer households relatively similarly, subsidies and especially norms generate stronger vertical disparities through uneven renovation burdens, gains, and financing incidence.

Third, panel (iv) shows that horizontal inequities vary across instruments. At high ambition levels, carbon pricing with a dividend is the least unequal instrument, with relatively low within-quintile dispersion and only limited divergence across quintiles. From a 10% reduction in emissions, the norm generates a higher dispersion within the quintiles, consistent with heterogeneity in baseline energy use and unequal burden sharing implied by renovation requirements. Subsidies display the steepest increase in within-quintile variance: dispersion is the lowest at low ambition, but rises sharply as uptake expands. High subsidy rates also benefit households investing at low rates and thus receiving large inframarginal gains, while others contribute to financing without renovating. This increase is especially pronounced in lower quintiles, indicating that universal subsidies create the largest horizontal disparities among low-income households.

Figure 3.2: Response curves



Source: Own calculations based on Woonsurvey 2018.

3.4.2 Distributional analysis

We next fix the target at a 20% sectoral reduction[66] and analyse the distributional outcomes in greater detail. The calibrated policy parameters that achieve this objective are: 153 €/tCO_2 in the carbon-dividend scenario, an EPC threshold of 297 kWh/m^2/year under the norm, and a subsidy rate of 77.5%.

Impact by subgroup

Table 3.4 compares the average household impact, ΔLCC (in % of no-policy counterfactual Life Cycle Cost), for policies calibrated to the 20% target. At the aggregate level, the carbon dividend imposes the lowest burden (+4.6%), norms are higher (+17%), and subsidy-financed packages are highest (+26%). This ranking reflects not only how many heat-pump installations occur but in which dwellings they occur. Under norms, heat pumps are more numerous but often placed in dwellings where private returns are low; under pricing, fewer heat pumps are installed overall, but they are allocated to the highest-return dwellings, lowering average costs. With a 77.5% subsidy, no heat pump is privately profitable, so the 20% target is met entirely through insulation, which raises the cost per ton relative to electrification.

Low-income households more often occupy poorly insulated dwellings; therefore, they bear larger burdens under standards mandating renovations in those units (see Section C.1). Even if they are more likely to qualify for subsidies, their benefits are limited because they typically live in smaller homes, leaving the average burden under the subsidy scenario broadly balanced across income deciles. A similar pattern holds under the carbon dividend, consistent with absolute space-heating outlays across income groups (and the equal per-household transfer that offsets carbon payments).

Results also differ by dwelling type and efficiency. Apartments, with lower baseline heating needs, often gain under the carbon dividend (the transfer exceeds carbon payments), face small average costs under norms, and bear large burdens under subsidies when few profitable investments are undertaken but the uniform tax still applies. Houses bear higher costs due to larger heating loads and greater renovation scope, irrespective of the instrument chosen. Based on initial EPC level, norms perform as intended: costs concentrate on D-F while A-C dwellings are virtually unaffected, the carbon dividend dis-

[66] This target is in line with Belgium's ambition of reaching -47% of emissions reduction in the residential building sector by 2030 (compared to 2005 levels) set in the Effort Sharing Regulation (ESR, European Union (2023b)). In Belgium, emissions from buildings had already been reduced by 24% in 2017, mainly through the residential sector (FPS Health, 2020). In Flanders, the emissions under the ESR should reach -40% by 2030, with scenario-based improvements in the housing stock's energy performance ranging from 18% to 33% between 2020 and 2030. Altogether, these figures confirm that the -20% target is policy-relevant in the medium-run.

tributes costs/benefits more evenly across both groups, and the subsidy pushes more cost onto efficient dwellings that invest little but still finance the scheme.

Table 3.4: Impact by categories for $\Delta^{-}CO_2 = 20\%$ (Δ LCC)

	Carbon dividend	Norm	Subsidy
Total	+4.6%	+17%	+26%
Income quintile			
1st and 2nd quintile	+4.9%	+23%	+25%
3rd quintile	+4.8%	+15%	+24%
4th and 5th quintile	+4.2%	+12%	+28%
Type of dwelling			
Apartment	-11.9%	+2.5%	+43%
House	+7.5%	+20%	+23%
Initial EPC			
A, B and C	+4.6%	+0.4%	+35%
D, E and F	+4.7%	+40%	+17%
Actual to theoretical energy consumption			
<0.5	+2.8%	+29%	+26%
≥ 0.5	+6.7%	+3.8%	+26%
Tenure			
Owner-occupier	+6.5%	+15%	+24%
Renter	-3.8%	+24%	+33%
Household composition			
Couple + Children	+7.5%	+9.6%	+24%
Couple	+4.3%	+14%	+24%
Single + Children	+5.1%	+24%	+28%
Single	+1%	+28%	+30%

Source: Own calculations based on Woonsurvey 2018.

Finally, the prebound margin explains much of the cross-household dispersion under norms: low-use households are strongly penalised when mandated renovations yield small realised bill savings, while households whose actual use is closer to theoretical needs face much smaller costs. Pricing and subsidies align better with private incentives, which tempers dispersion in ΔLCC relative to norms. Renters gain on average under the carbon dividend, consistent with lower baseline use and smaller dwellings; by contrast, they are hit harder by norms (compliance falls more often on the units they occupy) and under subsidies. Household composition matters primarily through heating needs and floor area: singles face particularly high costs under norms, which is concerning given they must absorb these charges on a single income, whereas larger households tend to bear somewhat higher costs under pricing, in line with higher heating and domestic hot water demands.

Popularity

Table 3.5 reports the share of households that are better off under carbon pricing relative to the norm and the subsidy scenarios, by income quintile. The table shows that 56.5% of households are financially better off under the carbon pricing than under the norm, and that this share is mildly decreasing across income quintiles. It also reveals that 84% of them prefer the carbon dividend to the subsidy, and that this rate is even larger among high-income individuals.

Table 3.5: Share of households better off under carbon dividend, by income quintile

Carbon price $\succ$	Norm	Subsidy
Total	56.5%	84.0%
Q1	65.0%	79.2%
Q2	62.4%	83.7%
Q3	52.9%	80.3%
Q4	53.5%	90.1%
Q5	50.4%	87.6%

Source: Own calculations based on Woonsurvey 2018.

3.5 Discussion

In this section, we assess the robustness of the baseline findings along four dimensions. First, we incorporate a direct rebound effect and compare achieved CO_2 reductions with and without rebound. Second, we study the sensitivity of our results to key model parameters, such as the discount rate and the investment horizon. Third, we re-estimate outcomes when renovation profitability is anchored in theoretical (rather than observed) consumption, thereby quantifying how prebound affects the set of privately profitable projects and distributional incidence. Fourth, we analyse two frictions that can materially alter who invests and who benefits: the landlord-tenant dilemma (by bounding outcomes between a tenant-favourable limit and a landlord-surplus-capture limit) and liquidity constraints, which we proxy by restricting renovations to higher-income households. Together, these checks ensure that our results are stable across different modelling choices and alternative assumptions. Lastly, we compare our main results to a heat-pump targeted scenario implementing a moderate carbon price funding subsidies towards heat-pump installation.

3.5.1 Rebound effect

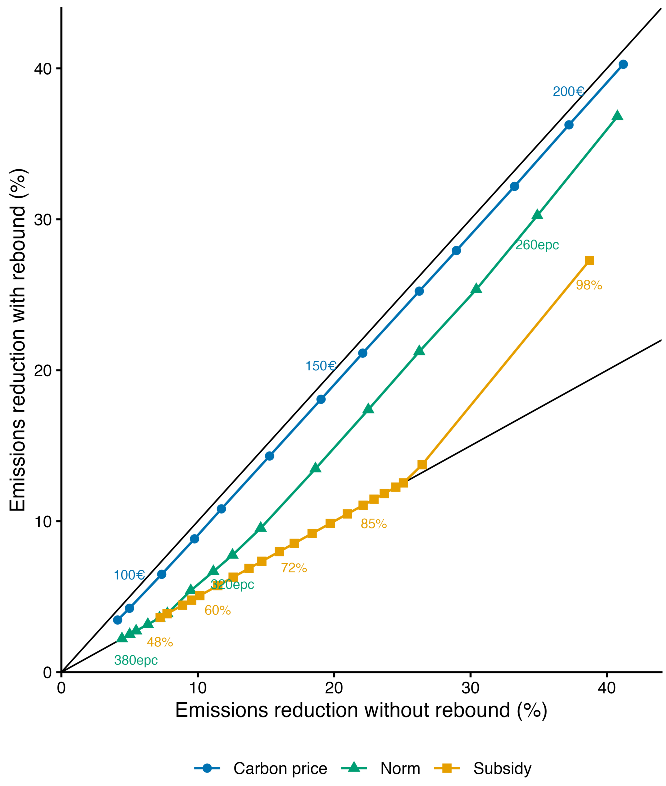
When building efficiency improves, households may choose higher indoor temperatures or longer heating durations because thermal comfort becomes cheaper. This behavioural response—the rebound effect—reduces realised energy savings relative to engineering predictions. The empirical literature typically finds a direct rebound for residential heating in the range of roughly 10-30% in OECD settings, with context-specific variation; reviews conclude that rebounds are meaningful but rarely large enough to erase most savings (Sorrell et al., 2009). In our data, the ratio of actual to theoretical heating consumption rises with energy performance, which is consistent with rebound: as efficiency lowers the effective "price" of thermal comfort (i.e., a degree-hour), households consume more heat services, narrowing the gap between actual consumption and theoretical needs. Our baseline scenarios abstract from rebound to keep the monetary incidence transparent. We assess below how this assumption matters:

Vertical equity We find little systematic income gradient in the actual-to-theoretical ratio once we condition on energy performance and dwelling density (Figure 3.1). This suggests that incorporating a rebound effect is unlikely to meaningfully alter our conclusions about vertical equity across income groups.

Household welfare Our money metric (ΔLCC) is an adequate proxy for welfare when indoor comfort is held constant: in the absence of rebound, the policy affects only energy-related expenditures and renovation outlays, so the monetary incidence aligns with welfare changes. By contrast, if renovations induce a positive rebound, households that consume more heat services enjoy additional utility (comfort gains) relative to a fixed-behaviour counterfactual. From a purely monetary perspective, ignoring rebound overstates bill savings and thus understates net costs; from a comprehensive welfare perspective, however, ignoring rebound is conservative, because it omits the comfort surplus (relative to the cost increase) households derive from higher service consumption.

Environmental effectiveness Even with a large rebound (we test 50%), the impact on achieved CO_2 reductions is limited and highly technology-dependent. In Figure 3.3, we plot reductions with a 50% rebound (vertical axis) against the original no-rebound reductions (horizontal axis). For low ambition, points lie on the line with slope 1/2 (indicating that a 50% rebound halves the achieved reduction) up to about -2% under the carbon dividend, -8% under the norm, and -25% under the subsidy. Beyond these thresholds, the relationship switches to the 45-degree line (slope 1): additional abatement is no longer attenuated by rebound. The break in slopes mirrors the transition in the abatement mix: once electrification (heat-pump-led fuel switching) dominates, rebound no longer reduces achieved abatement because electricity is assumed to be carbon-free at the consumption level. Accordingly, incorporating a sizable rebound does not overturn our main results on environmental effectiveness; it only dampens low-ambition outcomes before electrification becomes the LCC-minimising option.

Figure 3.3: Impact of a 50% rebound effect on emissions reduction



Source: Own calculations based on Woonsurvey 2018.

3.5.2 Sensitivity analysis

This section reports four complementary diagnostics for the carbon-dividend scenario at the 20% emissions-reduction target. In Table 3.6, we vary, one at a time, the heat-pump eligibility constraint, the real discount rate, the investment horizon, and investment costs. For each perturbation, the table reports (i) how counterfactual CO_2 emissions (no-policy) change relative to the augmented Woonsurvey baseline, and (ii) the carbon price required to achieve a 20% sectoral reduction under the new parameter values. We focus on the carbon-pricing scenario because these parameters rarely affect investment choices under the norm and have similar qualitative effects under the subsidy scenario.

Table 3.6: Sensitivity analysis – Carbon pricing

	Δ^- CO_2 Counterfactual	**Carbon Price**	**Δ LCC**	**Heat Pump Cost Share**
Baseline scenario	-2.9%	153 €/tCO_2	4.6%	60.2%
Heat pump threshold				
300 EPC score	-2.9%	162 €/tCO_2	4.6%	57.6%
400 EPC score	-2.9%	147 €/tCO_2	4.3%	62.1%
Real discount rate				
5%	-1.9%	188 €/tCO_2	5.6%	68.8%
1%	-4.5%	118 €/tCO_2	3.3%	47.3%
Investment horizon				
30 years	-3.6%	135 €/tCO_2	3.9%	55.3%
20 years	-2.0%	178 €/tCO_2	5.3%	67.7%
Investment costs				
−20%	-4.5%	122 €/tCO_2	3.7%	50.1%
+20%	-1.9%	182 €/tCO_2	5.4%	68.0%
No initial quality discount	-1.6%	150 €/tCO_2	4.6%	66.0%
Energy price shock				
−20%	-1.8%	153 €/tCO_2	5.9%	72.0%
+20%	-4.1%	150 €/tCO_2	3.6%	51.8%

Source: Own calculations based on Woonsurvey 2018.

For each parameter, we consider a lower and a higher value than in the baseline, remaining within empirically plausible ranges. The resulting effects are largely symmetric around the baseline. Tightening or relaxing the heat-pump feasibility threshold has no effect on counterfactual emissions and only a marginal effect on the required carbon price, consistent with the fact that heat pumps in the baseline scenario are predominantly installed in dwellings with theoretical needs below 300 kWh/m^2/year. By contrast, the discount rate, the investment horizon, and investment costs matter: a lower discount rate or a longer horizon increases the value of energy savings, raising counterfactual abatement and reducing the carbon price needed to meet the 20% target; lower investment costs similarly expand the set of prior-policy privately profitable projects and reduce the required carbon price. Counterfactual emissions reduction is also sensitive to uniform energy price shocks: higher energy prices increase the value of energy savings, which strengthens renovation incentives and raises prior-policy abatement, whereas lower prices weaken these incentives and reduce abatement. However, because the carbon price is calibrated relative to each scenario-specific baseline, these price shocks translate into only limited changes in the carbon price required to meet the target. Across all sensitivity checks the variation in the carbon price remains moderate (within the ±25% margins), the composition of investments marginally changes (±10 p.p. in heat pumps), and, because carbon payments are recycled lump-sum, the impact on household LCC is contained. These results indicate that our main conclusions are not driven by any single parameter choice and are robust to reasonable alternatives.

3.5.3 Theoretical versus actual energy consumption

Table 3.7 shows that evaluating renovations with real (billed) energy use delivers markedly different conclusions than using theoretical consumption. First, the counterfactual renovation rate drops from 40% (theoretical) to 8% (real), and the implied autonomous CO_2 reduction falls from 22% to 2.9%. This indicates that many projects that look cost-effective on paper cease to be so once actual usage is considered—an assessment that better aligns with observed low adoption rates and limits the apparent pool of "profitable but unrealised" renovations. Second, under a carbon dividend of 153€/tCO_2, the distributional picture changes: with theoretical consumption, average burdens (Δ LCC) are slightly closer across income groups. In other words, relying on theoretical consumption masks some of the income-related differences that emerge once actual usage is taken into account. Third, the composition of investment shifts toward electrification when using real consumption: the heat-pump share in total renovation cost rises from 37% (theoretical) to 60% (real). When actual heating consumption is roughly half of theoretical needs, insulation (which reduces demand by a percentage) yields much smaller monetary savings and thus becomes relatively less attractive. By contrast, heat-pump electrification can remain worthwhile, because prebound does not diminish domestic hot-water loads[67] and fuel switching lowers unit costs for both space heating and hot water.

Table 3.7: Comparison of outcomes based on real versus theoretical energy consumption

	Real	**Theoretical**
Counterfactual		
Δ-CO_2 emissions (%)	-2.9	-22
Renovation rate (%)	8.1	39.7
Carbon dividend (Price = 153 €/tCO_2)		
Δ-CO_2 emissions (%)	-20	-59
Renovation rate (%)	14	49
Heat pump share in total renovation cost (%)	60	37
Δ LCC for Q1–Q2 households (%)	4.9	9.6
Δ LCC for Q4–Q5 households (%)	4.2	9.1

Source: Own calculations based on Woonsurvey 2018.

3.5.4 Landlord-tenant dilemma

In our main analysis, we adopt a tenant-favourable limit case: renters undertake privately profitable renovations and fully retain the associated bill savings. The opposite limit is one in which landlords can fully extract the surplus via rent increases equal to the value of realised energy savings. Because the landlord identity is not observed at the unit level, we cannot model capitalisation directly in the population; instead, we bound renter outcomes by comparing these two limits for the norm and the carbon-pricing scenarios.

Under carbon pricing, if landlords capture the entire surplus from energy-saving renovations, a tenant's position is effectively the same as facing a higher energy price without the option to renovate. Under a standard, if the landlord is obliged to retrofit and can increase the rent by the full value of realised savings, the tenant's net position is unchanged relative to no renovation (the lower bill is exactly offset by a higher rent). Preference shares under both limits (Table 3.8) show that the results are very similar across these two extreme cases.

[67]Domestic hot-water accounts for 25% of total energy demand using real consumption while it is only 15% when considering the theoretical approach

Table 3.8: Share of tenants better off under carbon pricing than norm

	(a) Tenant-favourable	(b) Landlord-capture
Carbon dividend $\succ$ Norm	74.9%	73.6%
Δ LCC (Carbon dividend)	-3.8%	-2.9%
Δ LCC (Norm)	23.8%	23.8%

Source: Own calculations based on Woonsurvey 2018.

3.5.5 Liquidity constraints

A large literature documents that liquidity constraints and high implicit discount rates[68] deter households (especially low-income) from undertaking privately profitable energy-efficiency investments. Constraints arise from limited access to credit, higher perceived borrowing costs, short planning horizons, or risk and hassle costs that effectively raise the investment hurdle rate (Allcott & Greenstone, 2012; Fowlie et al., 2018; Gillingham & Palmer, 2014). In this environment, tighter financing conditions are expected to depress renovation take-up and alter the distribution of policy impacts across income groups.

We proxy liquidity constraints with a stark bound: households in the first two income quintiles (Q1-Q2) are assumed unable to undertake any renovation in response to the policy, in line with the results from Lekavičius et al. (2020). Holding the carbon price at its baseline value would then cause achieved abatement to fall from 20% to 13.2%. To recover the 20% emissions target under this constraint, the required carbon price rises to 187 €/tCO_2.

Table 3.9 shows that this recalibration only slightly increases the overall cost of the policy, but it opens a clear gap between constrained and unconstrained households. The burden for liquidity-constrained (low-income) households rises because they cannot invest, and remain exposed to a higher carbon price; by contrast, unconstrained households invest, reduce their exposure, and benefit from a larger transfer since carbon revenues are higher at 187 €/tCO_2. As a result, average ΔLCC for Q1-Q2 increases sharply (+50%), while ΔLCC for higher-income groups falls relative to the baseline.

Even as an extreme bound, this highlights that financing frictions can affect both efficiency and equity. If credit constraints are significant, targeted low-cost financing and grants for low-income households can ease constraints, raise take-up of high-return renov-

[68] Related evidence from Belgian residential solar PV panels adoption points to substantial implicit discounting of future energy benefits, around 15% per year (De Groote & Verboven, 2019). This evidence suggests that households may also heavily undervalue delayed energy-related gains.

ations, and improve equity.

Table 3.9: Liquidity constraints

	Baseline	Liquidity constraints
Carbon price (€/tCO_2)	153	187
Δ LCC Q_1–Q_2 (%)	4.9	7.5
Δ LCC Q_3–Q_5 (%)	4.4	4.0
Achieved emissions reduction	-20 %	-13.2 %

Source: Own calculations based on Woonsurvey 2018.

More broadly, this liquidity-constraint exercise suggests that the performance of a carbon price depends not only on the price signal itself, but also on whether households can respond to it through forward-looking renovations. Related Belgian evidence from residential solar PV panels adoption indicates that households heavily discount future energy-related benefits, so equivalent upfront support may be more effective than delayed incentives (De Groote & Verboven, 2019). This provides an additional rationale for considering policy mixes in which a carbon price is paired with targeted support, alleviating investment barriers and enhancing early adoption of retrofit or heat pumps.

3.5.6 Policy mix: carbon pricing and heat pump subsidy

We draw three lessons from the main simulations. First, heat pumps deliver large emissions reductions at relatively low cost. Second, their adoption is highly sensitive to the relative price of gas versus electricity. Third, very high subsidy rates are typically needed to trigger widespread electrification; applying the same subsidy rate to both heat pumps and insulation is therefore expensive and inefficient. Motivated by these facts, we search for combinations of carbon price and heat-pump-only subsidy that achieve a 20% sectoral reduction. Among the feasible combinations, we retain a scenario with a 30 €/tCO_2 price funding an 80% heat-pump subsidy. Carbon revenues cover the subsidy bill and the small residual left is redistributed equally across households to ensure budget neutrality.

Table 3.10 shows that this heat-pump scenario is very close to the carbon-price-and-rebate benchmark in terms of average cost and distributional impacts by income, while yielding a similar overall renovation rate. Its distinguishing feature is a much higher heat-pump share in total renovation spending (76% vs. 60%), indicating that the policy primarily shifts choices within the renovation set toward electrification rather than insulation. Horizontal equity also improves relative to the dividend case because the carbon price is five times lower, which reduces cross-household dispersion in monetary impacts driven by heterogeneous energy use. Finally, the smaller impact on energy prices under a 30 €/tCO_2 signal may help with social acceptability, while targeted support ensures that electrification occurs where it is privately and socially most cost-effective.

Table 3.10: Comparison of calibrated scenarios vs. heat-pump targeted policy

	Carbon dividend	Heat pump subsidy
Carbon price (€/tCO_2)	153	30
ΔLCC (%)	4.6	4.5
ΔLCC Q1–Q2 (%)	4.9	4.6
ΔLCC Q4–Q5 (%)	4.2	4.6
ΔLCC standard deviation (p.p.)	18	3
Renovation rate (%)	14	15
Heat pump share in total costs (%)	60	76

Note: Both scenarios deliver same environmental performance and are budget-neutral.
Source: Own calculations based on Woonsurvey 2018.

3.6 Conclusion

Residential buildings sit at the core of Europe's decarbonisation challenge, and EU countries' policy mixes increasingly combine price instruments, subsidies, and regulatory obligations. This paper asks the following question: when policies are designed to achieve the same emissions outcome under budget neutrality, how do their household-level monetary impacts compare—both across income groups (vertical equity) and between households of similar income (horizontal equity)? To answer it, we built on a microsimulation model for Belgium (RenoBel) that endogenises renovation choices and, crucially, anchors profitability in observed energy use from household bills. This design internalises the prebound effect and embeds revealed behaviour—occupancy, comfort preferences, attention to energy costs—that is central for exposure and distributional incidence but typically unobserved in engineering-based assessments.

Three findings stand out. First, under a common abatement target, policy instruments follow a clear ranking: carbon pricing with equal lump-sum recycling (a carbon dividend) consistently delivers the lowest average increase in life-cycle costs, while EPC-style performance standards and uniform subsidies impose substantially larger burdens. The mechanism is not merely the number of home retrofits undertaken, but the type of renovations and their allocation across dwellings. Once profitability thresholds are crossed, pricing triggers heat-pump electrification in dwellings with high private returns; by contrast, a uniform standard can force costly measures in constrained units with low realised savings, and a uniform subsidy can channel large transfers toward insulation works.

Second, the equity implications differ across instruments, and the efficiency-equity trade-off is not inevitable. With lump-sum recycling, carbon pricing produces broadly even burdens. Standards tend to hit low-income households hardest because they more often live in dwellings compelled to renovate. Lump-sum-financed subsidies shift costs onto households with few profitable projects (e.g., apartments, already efficient homes, low-actual-use individuals) while directing funds to those with many eligible, costly measures; they can therefore appear pro-poor in terms of recipients yet still generate high average burdens and sizable losses across all income groups.

Third, horizontal equity is a first-order concern with standards. For equal abatement, cost dispersion is substantially larger under norms than under the carbon dividend. Low-use households are disproportionately penalised because standards mandate renovations that deliver small realised bill savings for them. Policy evaluations that ignore observed energy use miss this channel and can therefore mis-rank instruments.

Our robustness analyses reinforce these conclusions. Incorporating rebound dampens low-ambition outcomes when abatement hinges on insulation, but the ranking of instruments is unchanged once electrification dominates. Reasonable changes to the discount rate, investment horizon, and cost parameters shift the calibrated carbon price only within moderate bounds. By contrast, valuing profitability on theoretical rather than billed consumption materially enlarges the set of "profitable" projects and alters incidence, underscoring the importance of using observed energy use. Regarding frictions behind the energy-efficiency gap, a landlord–tenant surplus-capture bound leaves our qualitative rankings essentially intact, whereas liquidity constraints may create vertical gaps. Finally, mixing instruments can be attractive: pairing a modest carbon price with targeted heat-pump support reaches the same CO_2 target at lower cost and with smaller cross-household dispersion, while requiring a much lower (more politically acceptable) carbon price.

This paper is limited to partial-equilibrium and monetary in scope. We abstract from general-equilibrium feedbacks, from housing-market capitalisation beyond our bounds, and from within-period demand response to prices; we also assume homogeneous discounting and no liquidity constraints. These choices preserve transparency in incidence and isolate the investment channel, but they also point to a research agenda. Future work should integrate richer behavioural heterogeneity and model the landlord-tenant dilemma more precisely. More broadly, our results suggest that the "energy-efficiency gap" is not only about investment barriers: it is also about the *mis-measurement* of private returns when models substitute theoretical for observed consumption (prebound effect). Bringing revealed behaviour into policy evaluation is therefore essential for credible distributional analysis and for designing building-sector climate policies that are both effective and publicly acceptable.

General Conclusion

This dissertation is composed of three self-contained studies (Chapters 1, 2, and 3) about the distributional impacts of climate policy in Belgium using microsimulation, with a particular attention to carbon pricing in the presence of heterogeneous households. Below is a summary of the focus and contribution of each chapter.

Chapter 1: Immediate Impacts and Revenue Recycling Design. This study assesses the day-after incidence of a carbon price on Belgian households' heating and transport fuel expenditures. It simulates a uniform carbon tax on these fuels and uses a microsimulation model (calibrated with the 2016 Household Budget Survey) to identify which households would bear the highest initial costs. We compare several revenue-recycling schemes: equal lump-sum rebates per household, equal rebates per person, and a tailored transfer giving extra compensation to households using fossil-based heating. This analysis reveals how different recycling choices can, or cannot, protect vulnerable groups. We find that an equal-per-household dividend tends to favour smaller and poorer households more than a per-capita dividend, which can undercompensate singles and the elderly. Adding a fossil-based heating supplement further reduces disparities, preventing spikes in energy poverty while preserving the reform's overall progressivity. The insights from this chapter demonstrate that policy design matters enormously when introducing carbon pricing: even if regressive before recycling, well-thought-out revenue-recycling schemes can neutralise or even reverse regressivity, thereby addressing fairness concerns that are pivotal for public acceptance. Moreover, redistribution can help address horizontal disparities and cushion vulnerable individuals from disproportionately large losses. These findings directly inform the political feasibility debate by showing a menu of options for revenue use and their expected social outcomes.

Chapter 2: Behavioural Adjustments and Short-Term Distribution. This study shifts to a short-term perspective, recognising that households will alter their consumption in response to carbon price signals. It adopts a behavioural microsimulation approach that integrates econometric demand modelling for household energy use. Using repeated cross-sectional data from 14 years of Household Budget Surveys, it estimates how different types of households (especially those prone to energy vulnerability) adjust their energy consumption when prices rise. A Quadratic Almost Ideal Demand System is used to obtain energy price elasticities differentiated by households' vulnerability status (e.g., whether they are "energy poor" or "hidden energy poor"). These behavioural responses feed into simulations of how carbon pricing would change consumption patterns and welfare across the population. The chapter's contribution lies in uncovering heterogeneity in behavioural responses: lower-income and energy-vulnerable groups are found to have higher fuel price elasticities on average, meaning they reduce consumption more sharply when fuel becomes expensive. While hidden energy poor experience small net financial losses, they may suffer greater relative welfare losses as they are already at minimum energy use. By contrast, households in (classic) energy poverty incur large nominal carbon burdens, but could be effectively compensated through redistribution. As a result, the analysis exposes horizontal inequities that are invisible if one looks only at income. Chapter 2's findings emphasise that who is hurt depends not just on direct incidence, but on behavioural and need-based factors as well. This has direct policy relevance: to maintain public support in the short run, carbon mitigation strategies must consider these nuanced vulnerability profiles. It suggests that complementary measures (such as targeted energy efficiency assistance) might be needed alongside the carbon price to avoid undue hardship on certain groups.

Chapter 3: Medium-Term Transitions and Policy Mix for Residential Decarbonisation. This study extends the analysis to a longer horizon, where households can respond to carbon pricing through investment decisions and technology adoption. Chapter 3 focuses on the residential housing sector, examining how a carbon price compares with other policy instruments like building renovation mandates and subsidies. Using detailed dwelling-level data (Woonsurvey 2018) and an engineering-economic microsimulation model, this chapter accounts for the so-called "prebound effect": the tendency for actual energy consumption to be lower than the theoretical prediction underlying the Energy Performance Certificate. By simulating household decisions to retrofit or install low-carbon heating under different scenarios, this chapter evaluates the distribution of costs and benefits for different low-emission strategies. Three policy scenarios: (i) energy performance standards that require inefficient homes to be upgraded, (ii) carbon pricing with equal per-household dividend, and (iii) renovation subsidies financed by a lump-sum tax, are calibrated to achieve the same aggregate CO_2 reduction in the residential sector. The results show marked contrasts in distributional outcomes. Regulatory standards concentrate costs on certain individuals (often lower-income households in poorly insulated dwellings) who are forced to invest in upgrades that can yield modest energy savings. Untargeted subsidy programmes, on the other hand, can end up regressive in incidence because large grants flow to wealthier households, while everyone finances the policy. In comparison, a carbon dividend achieves the emission target with lower average cost and more equitable burden-sharing. It encourages high-consumption profiles to adopt cleaner heating (like heat pumps), and with revenues returned lump-sum, more low-income households come out roughly whole or better. Furthermore, Chapter 3 finds that a hybrid policy such as a modest carbon price combined with subsidy for heat-pump adoption can outperform either approach, delivering the required emissions cuts at lower cost and with less inequality in outcomes. These medium-term insights highlight how carbon pricing can be part of an effective policy mix: by leveraging market incentives and revenue-recycling, it can drive green investment while avoiding the pitfalls (financing, political and social acceptability) of pure regulatory or subsidy schemes. For policymakers, the message is that carbon pricing, if coupled with strategic revenue use and complementary measures, can achieve deep emissions reduction goals in the residential sector without necessarily burdening vulnerable households.

In summary, the three chapters of this thesis each address a piece of the carbon pricing puzzle across different time scales. Chapter 1 establishes the baseline immediate incidence and demonstrates that the design of revenue recycling critically determines who gains or loses, setting the foundation for public acceptability. Chapter 2 adds the dimension of behavioural change, revealing that household responses can mitigate or exacerbate perceived burdens and that special attention is needed for energy-vulnerable households. Chapter 3 incorporates structural transitions, comparing carbon pricing to other instruments and showing how, when designed thoughtfully, carbon pricing can achieve equitable medium-term outcomes. Together, these studies provide a cohesive narrative: they illustrate that carbon pricing need not be at odds with equity. By anticipating how impacts unfold from the moment of implementation to years down the line, and by tailoring policy design at each stage, it is possible to align climate policies with the principles of political feasibility and fairness.

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A Appendix for Chapter 1

A.1 Descriptive statistics

Sociodemographic characteristics, carbon payment and income

Table A.1 reports average monthly carbon payments for heating and transport, total disposable income, and equivalised income by household composition and by the age of the reference person. Two facts stand out regarding household composition. First, the presence of children has only a modest effect on carbon payments: relative to childless households with the same number of adults, transport payments are only slightly higher when children are present, and heating payments are very similar. By contrast, the number of adults is the primary driver of payments: multi-adult households spend more on both heating and transport in absolute terms. Second, couples have higher disposable and equivalised incomes than one-adult households, which makes the latter more prevalent in the lower equivalised-income deciles. These patterns help explain the incidence across recycling scenarios: because children barely affect carbon payments but materially increase transfers under a per-capita rule, headcount-based recycling tends to concentrate gains on larger families. Turning to the age of the reference person, the composition of energy use shifts with age from transport to heating. Seniors typically drive less but spend more time at home, which raises space-heating needs. Combined with lower disposable incomes, this leads to higher carbon burdens for seniors.

Table A.1: Household size, carbon payment and income

Group	CP Heating	CP Transport	Income	Equivalent Income
Household Composition				
Couple with child	14.4 €	10 €	4370 €	2002 €
Couple without child	15.5 €	8.8 €	3536 €	2155 €
Single with child	11.6 €	5.5 €	2312 €	1452 €
Single without child	11.2 €	4.7 €	1792 €	1792 €
Age<65	13.1 €	8 €	3287 €	2010 €
Age>=65	15.3 €	5.7 €	2370 €	1772 €

Heating system by housing type in HBS

Table A.2 reports housing characteristics for dwellings equipped with gas and heating-oil systems in the Household Budget Survey. We observe that 76.6% of heating-oil systems are installed in dwellings built before 1981, 41.8% of them are classified as high-efficiency, and 90.0% are in houses. These three dimensions help explain why households heating with oil have, on average, higher energy needs than those heating with gas.

Table A.2: Housing characteristics by heating system

Heating system	Built before 1981	High-efficiency system	House
Oil	76.6%	41.8%	90.0%
Gas	67.9%	79.2%	73.6%

A.2 Vulnerability among subgroups

Table A.3 confirms that heating system is the dominant driver of incidence. All oil-heated subgroups—singles or couples, below or above 65—exhibit average carbon burdens at or above 1.2% of income, compared with 0.85% in the full sample, and high-loss shares above 92%, versus 66.8% overall. By contrast, gas-heated subgroups cluster much closer to population averages: singles have somewhat higher average burdens, but the levels remain far below those observed for oil users. Conditioning on household type and heating also indicates that age plays only a limited role: differences between the under-65 and 65+ subgroups within the same heating and household-type cell are small. This suggests that the greater vulnerability of the 65+ group in aggregate is largely compositional—older adults are more likely to be single (43% of them are singles in our data, while it is the case for 38% of the 65- group) and heat with oil. A similar pattern appears for energy poverty and its change: both the level and the increase are systematically larger for oil-heated households and for singles, whereas gas-heated couples remain closer to the population benchmarks.

Table A.3: Carbon Pricing Impact per Subgroup

Group	Avg. CB	High Loss	EPoverty	Δ EPoverty
Total sample	0.85 %	66.8 %	10.57 %	+ 2.9 p.p.
Subgroup				
Oil + Single + Age>=65	1.56 %	95.0 %	14.9 %	+ 2.1 p.p.
Oil + Single + Age<65	1.51 %	95.6 %	25.0 %	+ 9.5 p.p.
Oil + Couple + Age>=65	1.2 %	92.8 %	9.34 %	+ 4.6 p.p.
Oil + Couple + Age<65	1.21 %	93.1 %	11.5 %	+ 4.2 p.p.
Gas + Single + Age>=65	0.83 %	70.2 %	12.5 %	+ 3.2 p.p.
Gas + Single + Age<65	0.92 %	69.9 %	15.8 %	+ 3.6 p.p.
Gas + Couple + Age>=65	0.74 %	71.1 %	9.47 %	+ 2.5 p.p.
Gas + Couple + Age<65	0.76 %	66.6 %	6.82 %	+ 1.8 p.p.

A.3 Robustness checks

Income versus expenditure deciles

We assess the sensitivity of our findings to the choice of ranking variable by comparing results based on expenditure deciles with those based on income deciles. The literature has long noted that distributional conclusions for energy and carbon pricing are sensitive to this choice: when ranking by expenditures (and especially when expressing burdens as a share of expenditures), estimated regressivity often weakens and results can even appear proportional (see, e.g., Pizer and Sexton (2019)). Using expenditure deciles is therefore motivated by the view that expenditures better reflect long-run ability to pay—mitigating the influence of temporary income dips (students, short-term unemployment) and life-cycle effects—whereas income deciles align with how most social policies are targeted in practice. In our setting, the qualitative conclusions are robust across the two rankings (see Tables A.4 and A.5). Without redistribution, incidence remains clearly regressive across the distribution; with redistribution, all three dividend designs deliver a progressive profile on average, and the fuel-type–differentiated scenario continues to provide the strongest protection by sharply reducing the prevalence of large losses in every part of the distribution. The relative ranking between Household and Capita is also stable.

Table A.4: Impact by equivalent income decile

	No Dividend		Household		Capita		Heating	
Decile	Avg.CB	High loss	Avg.CB	High loss	Avg.CB	High loss	Avg.CB	High loss
1	1.27	73.5	-0.56	14.6	-0.33	21.5	-0.48	11.6
2	1.08	66.6	-0.39	17.0	0.04	28.8	-0.35	11.2
3	1.13	78.2	-0.12	16.8	0.21	29.0	-0.11	13.7
4	0.88	67.4	-0.16	15.7	0.07	21.9	-0.16	11.0
5	0.75	66.5	-0.17	13.5	0.01	16.4	-0.14	6.78
6	0.80	68.2	0.03	17.6	0.11	22.0	0.01	11.1
7	0.73	62.6	0.06	18.2	0.10	19.0	0.04	11.2
8	0.66	58.8	0.06	14.7	0.09	17.6	0.06	10.4
9	0.54	49.8	0.02	10.5	0.06	11.3	0.02	5.85
10	0.47	35.4	0.07	9.72	0.13	11.9	0.07	7.87

Table A.5: Impact by equivalent expenditure deciles

	No Dividend		Household		Capita		Heating	
Decile	Avg.CB	High loss	Avg.CB	High loss	Avg.CB	High loss	Avg.CB	High loss
1	1.04	66.1	-0.81	11.2	-0.94	12.0	-0.58	8.55
2	1.01	74.5	-0.39	12.6	-0.24	16.4	-0.33	9.18
3	0.96	70.1	-0.25	15.7	-0.07	17.6	-0.23	11.0
4	0.92	71.2	-0.17	16.7	0.02	21.4	-0.16	11.8
5	0.86	70.4	-0.12	15.1	0.05	20.8	-0.12	11.0
6	0.84	76.7	-0.03	13.7	0.10	19.6	-0.03	10.0
7	0.85	70.9	0.05	19.0	0.21	26.3	0.02	14.8
8	0.78	68.8	0.07	18.8	0.21	25.2	0.04	11.8
9	0.73	59.5	0.09	17.0	0.25	24.0	0.09	13.8
10	0.51	39.6	0.09	11.4	0.18	18.1	0.08	7.56

Unit of analysis

Table A.6 compares outcomes when the unit of analysis is the individual versus the household. The main conclusion is robust: the Heating scenario consistently performs best, with fewer high-loss cases, more winners, and a lower energy poverty rate under both units. By contrast, the ranking between Household and Capita depends on the unit. With individuals as the unit, Capita looks more favorable; with households as the unit, Household performs better. Intuitively, Capita scales transfers with headcount, which benefits larger families, whereas a flat per-household transfer advantages smaller households. When outcomes are counted per individual, larger families carry more weight in the statistics; when counted per household, each family carries the same weight on average.

Table A.6: Individual versus household level

	Household	Capita	Heating
Individual level			
Winners (%)	51.5	61.0	52.5
High Loss (%)	15.1	13.3	10.5
Energy poverty (%)	10.5	10.7	10.4
Household level			
Winners (%)	56.8	51.2	59.3
High Loss (%)	14.8	20.0	10.1
Energy Poverty (%)	11.2	11.9	10.8

Compensation gap for vulnerable groups

Table A.7: Compensation Gap by Subgroup

(a) Focus on Gas Heating

Group	Household	Capita	Heating
Gas (all)	4.24	4.77	4.57
Couple <65	5.94	3.63	6.37
Couple 65+	4.42	5.03	4.79
Single <65	2.24	6.09	2.43
Single 65+	1.43	6.31	1.62

(b) Focus on Oil Heating

Group	Household	Capita	Heating
Oil (all)	13.7	14	7.61
Couple <65	17.1	11.2	10.2
Couple 65+	13.4	14.9	7.28
Single <65	8.49	15.5	3.71
Single 65+	10.9	21.5	5.58

This section reassesses subgroup results using the compensation gap rather than the high-loss share used in the main text. We report the compensation gap for combinations of characteristics—age (below/above 65) and household type (couple/single)—within each heating technology (gas vs. oil), and compare its qualitative ranking with that obtained from high-loss incidence.

Three robust conclusions emerge. First, among gas-heated households, differences across scenarios are modest for couples. Second, headcount-based transfers (Capita) often yield the smallest compensation gap for younger couples. By contrast, Capita performs poorly for singles and for seniors. Third, among oil-heated households, the pattern is stark and fully consistent with the high-loss results in the main text: the Heating design dominates across all subgroups, yielding the lowest compensation gaps by a clear margin. Household is systematically intermediate, while Capita produces the largest gaps, especially for singles and seniors.

Compensation Gap with Threshold

We generalise the compensation gap to allow for a loss threshold $x \in [0, 1]$, interpreting x as the maximum acceptable loss (as a share of disposable income) for each household in a group S. The measure answers: what is the average amount, per household in S, needed to ensure that no household's net loss exceeds x of its income?

Formally, let Y_h denote household h's initial disposable income and $Y'_h = Y_h - C_h + T_h$ its disposable income under the policy, with C_h the carbon payment and T_h the transfer received. The compensation gap for group S at threshold x is

$$CG(S, x) \;=\; -\frac{1}{\#S} \sum_{h \in S} \min\bigl(Y'_h - (1-x)\, Y_h,\, 0\bigr).$$

Table A.8: Compensation Gap $x = 0.005$

Group	Household	Capita	Heating
Total sample	1.64	2.33	1.10
Age 65+	2.03	3.65	1.21
Heating: oil	4.22	5.75	1.88
Single	1.33	3.67	0.91
Energy poor	4.92	8.32	3.32

Setting $x = 0.005$ aligns with our definition of "high loss": $CG(S, 0.005)$ is the average amount per household needed in group S to ensure that no household's net loss exceeds 0.5% of income.

In the main text, we reported the compensation gap with a zero threshold (x=0), which measures the average amount per household needed to eliminate all losses. Table A.8 presents the same metric evaluated at x=0.005. As expected, absolute values are smaller at x=0.005 than at x=0 because the metric now targets only the upper tail of losses. Crucially, the qualitative ranking across scenarios and groups is unchanged: the Heating design systematically requires the least resources to eliminate high losses, the Household scenario is intermediate, and Capita requires the most funds. This ordering holds for all vulnerable groups we consider. Oil-heated households remain the most demanding group even at the 0.5% threshold, but the Heating design substantially reduces their required funds relative to the two uniform scenarios. Among seniors, singles, and energy-poor households, the Household scenario consistently improves on Capita, while Heating lowers required funds further.

B Appendix for Chapter 2

B.1 Robustness & Sensitivity Checks for our Adopted Measures of (Hidden) Energy Poverty

For the following analyses, we compare our adaptation of the energy poverty (EP) indicator proposed by Meyer et al. (2018) (hereafter "Meyer_EP") with the widely used Low Income High Costs indicator of Hills (2012) (hereafter "LIHC_EP"). We do not compare our EP indicator with the After Fuel Cost Approach (AFCA), as AFCA yields outcomes that are very similar to the standard at-risk-of-poverty (AROP) indicator for monetary poverty, whereas our objective is precisely to go beyond monetary poverty by capturing the specific features of energy vulnerability.

For hidden energy poverty (hEP), we assess the incremental effect of each refinement when moving from the simple M/2 indicator to our preferred measure. To this end, we construct and compare the following indicators:

1. **Md2_HEP**: the M/2 indicator, capturing hidden energy poverty based on the half-median energy expenditure threshold.

2. **Md2_Inc_HEP**: adds an income exclusion by restricting the eligible population to households below the median income.

3. **Md2_Inc_Socio_HEP**: further adds the comparison of households with peers of similar household size and dwelling size, consistent with the medians used in Meyer et al. (2018).

4. **Meyer_HEP**: adds a restriction to well-insulated dwellings, yielding the original hEP indicator of Meyer et al. (2018).

5. **Meyer_Dwelling_HEP**: additionally uses medians defined within groups of households living in similar dwelling types.

6. **Meyer_Dwelling_Heating_HEP**: further introduces medians within groups of households with a similar type of heating system; this is our main hEP measure.

For comparison, we also report the metrics obtained with the different energy vulnerability indicators alongside those obtained with a literature-standard vulnerability indicator, namely the EU's official AROP monetary poverty measure.

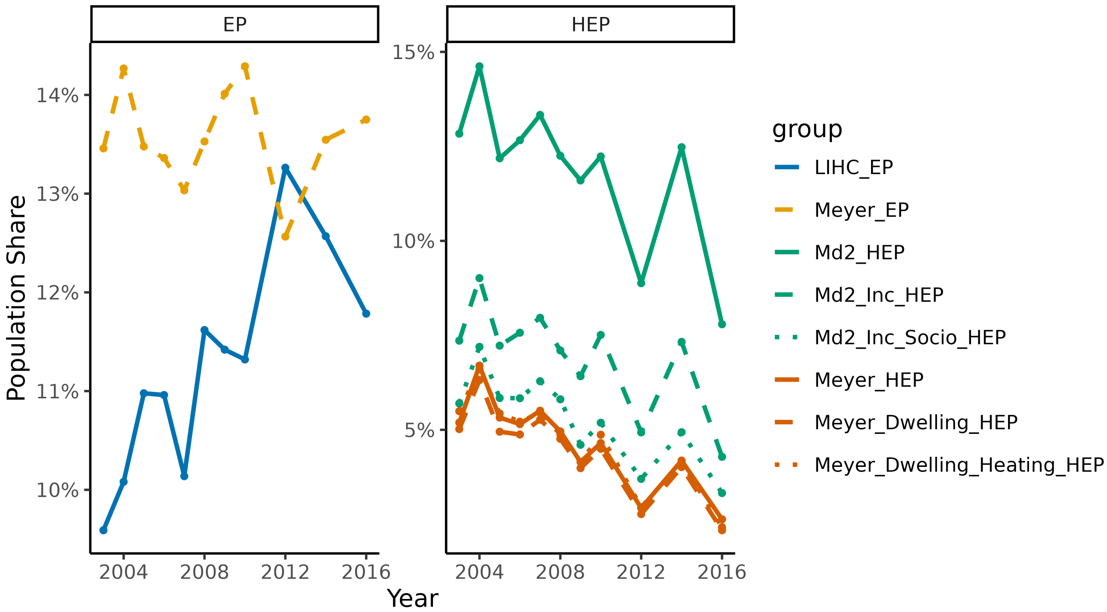
Descriptive statistics on energy vulnerability

Table B.1: Prevalence (rate) and average depth across indicators

Indicator	Rate (%)	Avg. depth (€)
AROP	12.4%	194.0 €
LIHC–EP (income gap)	11.3%	328.0 €
LIHC–EP (energy gap)	11.3%	85.6 €
Meyer–EP	13.6%	59.4 €
Md2–HEP	11.8%	18.9 €
Md2–Inc–HEP	6.9%	19.1 €
Md2–Inc–Socio–HEP	5.3%	16.5 €
Meyer–HEP	4.6%	16.6 €
Meyer–Dwelling–HEP	4.4%	16.8 €
Meyer–Dwelling–Heating–HEP	4.6%	17.1 €

Notes: LIHC requires meeting both income and energy conditions; its rate is shown once and paired with the two corresponding average gaps. Rates are converted to percentages from proportions and rounded to one decimal place.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

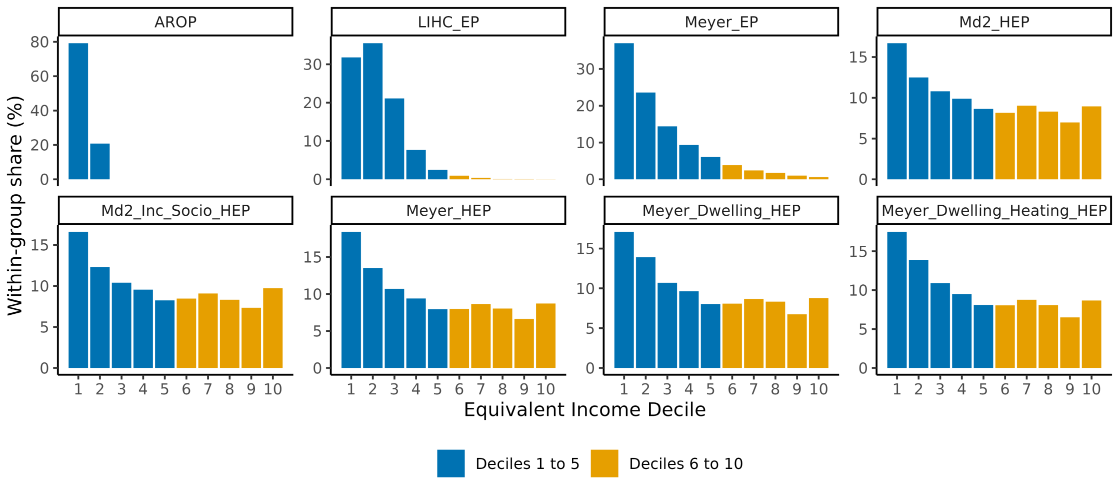
Figure B.1: Energy vulnerable populations over time by indicator.



Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Importance of the exclusion rule for high-income households

Figure B.2: Distribution of vulnerable groups across income deciles with VS without the income exclusion threshold



Notes: This figure illustrates how various vulnerable household groups are distributed across income deciles with VS without the income exclusion threshold after Decile 5. *Source:* Authors' calculations based on HBS data for Belgium (2003–2016).

Socio-economic descriptive statistics with the different indicators

Table B.2: Household Socio-demographic Characteristics Across Subgroups and Indicators

Characteristic	All	AROP	LIHC EP	Meyer EP	Md2 HEP	Md2–Inc HEP	Md2 Inc–Socio HEP	Meyer HEP	Meyer Dwelling HEP	Meyer Dwel–ling–Heating HEP
Income (Inc)	3001.	1358.	1876.	1406.	2241.	1498.	1674.	1646.	1618.	1572.
Equivalised Income (EQ_Inc)	1889.	850.	1101.	1074.	1754.	1187.	1180.	1164.	1174.	1172.
Wage Earner Ref	62.4%	30.6%	47.5%	29.3%	54%	36.7%	40.6%	39%	37.3%	36.4%
Education: No Education	7.2%	17.9%	13.9%	15.6%	9.1%	13.7%	13.6%	14%	15.2%	15%
Education: Primary	13.6%	22.4%	21.5%	21.8%	14%	19.4%	20.4%	20.9%	21.3%	20.9%
Education: Secondary	63.7%	53.7%	58.1%	55.9%	59.3%	57.2%	56.4%	55.3%	54.3%	54.8%
Education: Tertiary	15.5%	5.9%	6.5%	6.7%	17.6%	9.6%	9.6%	9.8%	9.2%	9.4%
Ownership: No	29%	69.3%	46.8%	62%	50.8%	64%	56.4%	56.8%	54.9%	57.2%
Ownership: With Loan	36.1%	10.6%	22.9%	11.5%	23.9%	12.1%	16%	14.3%	14.3%	13.5%
Ownership: Without Loan	34.9%	20.2%	30.3%	26.5%	25.3%	23.9%	27.7%	28.9%	30.8%	29.3%
Number of Cars	1.04	0.638	0.924	0.692	0.743	0.610	0.689	0.662	0.676	0.647
HH Type: Couple Active	34.1%	25.9%	27.5%	17%	22.2%	16.6%	22.4%	22.2%	20.1%	18.6%
HH Type: Couple Retired	15.5%	15.2%	18%	14.4%	9.9%	11.7%	14.3%	14.8%	15.5%	14.7%
HH Type: Many Adults	12.4%	13%	18.7%	5.6%	3.1%	3.2%	6.8%	6.9%	6.2%	5.3%
HH Type: Single Active	25.7%	33.5%	22.6%	37.1%	46.1%	43%	36.4%	35.8%	36.1%	38.4%
HH Type: Single Retired	12.2%	12.3%	13.2%	25.9%	18.7%	25.4%	20.1%	20.2%	22.1%	22.9%
Older Person Present	32.7%	31.6%	36%	42.2%	32.5%	38.2%	36.3%	36.9%	39.3%	39.2%
Number of Children	56.5%	72.6%	79.2%	35.5%	24.9%	29.5%	50.7%	49.4%	41.5%	37.8%
Region: Brussels	10.5%	18.5%	7.3%	12%	23.8%	24.4%	23.9%	26%	23.3%	24.2%
Region: Flanders	57.1%	41.1%	46%	43.4%	51.7%	48.4%	46.4%	43.1%	45.6%	44.5%
Region: Wallonia	32.4%	40.4%	46.6%	44.6%	24.5%	27.1%	29.7%	30.9%	31.1%	31.3%
House Type: Detached	50.7%	30.2%	53.7%	41.7%	22.9%	19.7%	26.9%	26.6%	31.3%	27.2%
House Type: Flat	28.3%	48.2%	22.3%	39.4%	64%	66.3%	55.9%	54.7%	50.1%	54%
House Type: Terraced	21.1%	21.6%	23.9%	18.9%	13.1%	14%	17.2%	18.7%	18.6%	18.8%
Construction Year: After 1990	16.8%	7.9%	7.6%	7.5%	17.9%	13.8%	12.2%	–	–	–
Construction Year: Before 1970	55.8%	59.8%	63.5%	61.3%	55.2%	57.2%	60.2%	68.5%	67.8%	68.3%
Construction Year: 1970–1990	27.4%	32.3%	28.9%	31.2%	26.9%	29%	27.6%	31.5%	32.2%	31.7%
Number of Rooms	5.94	5.33	6.08	5.50	4.98	4.80	5.29	5.29	5.27	5.14
Heating: Electric	6.7%	5.2%	4.1%	4.8%	9.5%	10.1%	9.7%	7.9%	7.7%	7.7%
Heating: Gas	55.2%	60.3%	44.4%	51.1%	59.3%	58%	50.9%	50.8%	49.4%	49.3%
Heating: Oil	33.1%	27.5%	45.4%	39.4%	23.7%	22.6%	27.4%	29.5%	30.1%	31.4%
Heating: Other	0.5%	0.4%	0.5%	0.3%	0.7%	0.6%	0.9%	0.6%	0.7%	0.4%
Heating: Solid	4.6%	6.6%	5.5%	4.4%	6.8%	8.7%	11.1%	11.2%	12.2%	11.2%
Season: Autumn	17.1%	17%	18.2%	17%	16.1%	15.5%	15.3%	15.2%	15.3%	15.1%
Season: Spring	16.8%	15.9%	15.9%	16.7%	17.5%	16.4%	15.3%	15.3%	15.5%	15.6%
Season: Summer	33.1%	35.1%	33.2%	34.9%	33.6%	35.4%	35.6%	36.2%	36.6%	36.4%
Season: Winter	33%	32%	32.8%	31.4%	32.7%	32.8%	33.7%	33.2%	32.6%	32.9%
At Risk of Poverty (AROP)	12.4%	100%	39.7%	47.9%	20.5%	35%	35.1%	37%	35.4%	36.1%
Single Parent Family	5.8%	14.2%	10.6%	10.4%	5.9%	8.6%	11%	10.9%	9.8%	9.7%

Note: Shares printed as percentages; numeric variables (income, rooms, cars) are means. "–" denotes not available.

Source: Authors' calculations based on Belgian HBS data (2003–2016).

Econometrics results with the different indicators

Table B.3: Logit Estimates for Energy Poverty Indicators

Variable	**EP**	
	LIHC	**Meyer**
Wage Earner (ref. person)	–0.91***	–0.91***
No Education (ref. cat.)		
Primary Education	–0.13**	–0.15**
Secondary Education	–0.56***	–0.18***
Tertiary Education	–1.26***	–0.30***
Renter (ref. cat.)		
Owner with Loan	–1.38***	–1.31***
Owner without Loan	–1.35***	–1.59***
# Cars	–0.24***	–0.21***
HH Type: Couple Active (ref. cat.)		
Couple Retired	0.03	–0.54***
Many Adults	1.05***	–0.60***
Single Active	0.01	0.64***
Single Retired	–0.30***	0.34***
# Children	0.41***	–0.35***
Region: Brussels (ref. cat.)		
Flanders	0.33***	–0.00
Wallonia	0.69***	0.40***
Detached House (ref. cat.)		
Flat	–0.76***	–0.62***
Terraced House	–0.12***	–0.44***
Construction: After 2000 (ref.)		
Before 1970	0.66***	0.32***
1970–1990	0.58***	0.36***
# Rooms	0.06***	0.16***
Heating System Type: Electricity (ref. cat.)		
Gas	0.17**	0.22***
Oil	0.80***	0.84***
Other	0.20	–0.38
Solid	0.19*	–0.04
Season: Winter (ref. cat.)		
Autumn	0.12***	0.04
Spring	–0.05	0.06
Summer	0.01	0.09**
Time Controls		
Years After 2000	0.02***	0.00
Year 2008–09	0.08*	0.03
Years After 2011	0.12	–0.06
Observations	44,207	21,200
McFadden's R^2	14.4%	17.1%
AIC	26,794	20,871

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on Belgian HBS data (2003–2016).

Table B.4: Logit Estimates for Hidden Energy Poverty Indicators

Variable	**hEP**					
	Md2	**Md2–Inc**	**Md2–Inc–Socio**	**Meyer**	**Meyer Dwelling**	**Meyer–Dwelling–Heating**
Wage Earner (ref. person)	0.00	0.00	–0.06	–0.07	–0.06	–0.05
No Education (ref. cat.)						
Primary Education	–0.12*	–0.10	–0.07	–0.05	–0.10	–0.11
Secondary Education	–0.14**	–0.09	–0.15**	–0.15**	–0.22***	–0.20***
Tertiary Education	0.01	0.03	–0.03	–0.03	–0.11	–0.09
Renter (ref. cat.)						
Owner with Loan	–0.01	–0.03	–0.04	–0.16**	–0.20**	–0.16*
Owner without Loan	–0.02	–0.02	0.02	0.03	–0.07	–0.05
# Cars	–0.13***	–0.16***	–0.17***	–0.25***	–0.21***	–0.23***
HH Type: Couple Active (ref. cat.)						
Couple Retired	–0.13*	–0.12	–0.16	–0.15	–0.11	–0.07
Many Adults	–0.75***	–0.78***	–0.43***	–0.42***	–0.50***	–0.52***
Single Active	0.63***	0.60***	0.30***	0.25***	0.37***	0.46***
Single Retired	0.49***	0.52***	0.11	0.08	0.24**	0.32***
# Children	–0.32***	–0.26***	–0.03	–0.04	–0.13***	–0.15***
Region: Brussels (ref. cat.)						
Flanders	–0.29***	–0.37***	–0.59***	–0.78***	–0.76***	–0.71***
Wallonia	–0.59***	–0.72***	–0.79***	–0.90***	–0.96***	–0.89***
Detached House (ref. cat.)						
Flat	1.23***	0.99***	0.94***	0.85***	0.31***	0.48***
Terraced House	0.32***	0.29***	0.24***	0.35***	0.21***	0.28***
Construction: After 2000 (ref.)						
Before 1970	–0.09*	–0.15**	–0.07	—	—	—
1970–1990	–0.19***	–0.24***	–0.18**	—	—	—
# Rooms	–0.19***	–0.24***	0.04*	0.04*	–0.03	–0.08***
Heating System: Electricity (ref. cat.)						
Gas	–0.46***	–0.62***	–0.72***	–0.54***	–0.55***	–0.50***
Oil	–0.35***	–0.53***	–0.42***	–0.16	–0.18*	0.00
Other	0.41*	0.02	0.18	0.25	0.20	0.00
Solid	1.09***	0.88***	0.91***	1.18***	1.13***	1.18***
Season: Winter (ref. cat.)						
Autumn	–0.09*	–0.15**	–0.17**	–0.16**	–0.12	–0.15**
Spring	0.04	–0.01	–0.10	–0.08	–0.04	–0.04
Summer	0.00	0.00	0.00	0.04	0.06	0.04
Time Controls						
Years After 2000	–0.02***	–0.02**	–0.03**	–0.03**	–0.03**	–0.04***
Year 2008–09	–0.05	–0.10	–0.06	–0.09	–0.07	–0.10
Years After 2011	–0.29***	–0.40***	–0.26**	–0.34***	–0.36***	–0.37***
Observations	44,207	21,200	21,200	21,200	21,200	21,200
McFadden's R^2	16.6%	16.2%	8.1%	8.4%	7.7%	9.2%
AIC	27,319	14,430	13,153	12,007	11,676	11,928

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on Belgian HBS data (2003–2016).

B.2 Reduced-form Equation for the Control–function (2SRI)

Following the 2SRI approach, we first estimate a logit regression of each status (EP_i and hEP_i) on the fitted probabilities $\widehat{(h)EP}_i$ obtained from augmented regressions similar to the ones in part 2.2.4.[69] Additionally, we use the set of socio-demographic controls used in the QUAIDS estimation. Equation (B.1) provides the fitted probabilities $\widehat{(h)EP}_i$, where $\Lambda(\cdot)$ is the logistic cumulative distribution function. Equation (B.2) is the reduced-form equation used to compute the residual $\widehat{\varepsilon}_i$ (first stage). In the QUAIDS, we include $(h)EP_i$ and $\hat{\varepsilon}_i$ as intercept shifters (second stage). We provide below the overall fit for the first stage and related contingency tables:[70]

$$\widehat{(h)EP}_i = \Lambda\big(\boldsymbol{x_i'}\beta\big)\,, \tag{B.1}$$

$$(h)EP_i = \alpha + \gamma\,\widehat{(h)EP}_i + controls + \varepsilon_i, \tag{B.2}$$

Table B.5: Fit of the reduced-form equations

	Energy Poverty	**hidden Energy Poverty**
McFadden R^2 from (B.2)	0.42	0.19

Table B.6: Energy Poverty — Predictions vs. Observed

	Predicted EP	**Predicted not EP**
Observed EP	65.1%	34.9%
Observed not EP	5.39%	94.6%

Table B.7: Hidden Energy Poverty — Predictions vs. Observed

	Predicted hEP	**Predicted not hEP**
Observed hEP	33.4%	66.6%
Observed not hEP	3.13%	96.9%

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

[69] Compared to part 2.2.4, we add all possible interactions between the models' variables, as well as income, for the sake of better fitted probabilities.

[70] The thresholds for predicting (h)EP statuses are set so that the number of predicted vulnerable households match the number of observed ones for each status.

B.3 Supplementary Tables

Additional descriptive statistics

Table B.8: (Hidden) Energy Poverty Rates and Depth Over the Years (%)

Year	EP Rate	EP Depth	hEP Rate	hEP Depth	Any EP Rate	Both EP Rate
2003	13.5	49.7	5.2	60.4	18.6	0.087
2004	14.3	55.3	6.7	62.9	20.9	0.051
2005	13.5	56.7	5.3	66.5	18.7	0.141
2006	13.4	65.8	5.2	77.4	18.3	0.199
2007	13.0	54.2	5.5	77.0	18.4	0.189
2008	13.5	69.9	5.0	81.2	18.4	0.114
2009	14.0	73.0	4.2	86.3	18.1	0.084
2010	14.3	67.0	4.7	82.8	18.9	0.028
2012	12.6	55.8	2.9	91.2	15.5	0.032
2014	13.5	57.0	4.2	84.1	17.7	0.000
2016	13.8	47.2	2.6	77.5	16.3	0.045

Note: EP = Energy Poverty, hEP = Hidden Energy Poverty. Rates are displayed in % and depth in €.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Table B.9: Correlation Between Rent, Energy, and Total Housing Costs

Variable Pair	Correlation	95% CI	p-value
Rent vs Energy Expenditure (abs.)	−0.111	[−0.120, −0.102]	$< 2.2 \times 10^{-16}$
Rent Share vs Energy Share	0.156	—	—
Rent Share vs Total Housing Share	0.949	—	—
Energy Share vs Total Housing Share	0.460	—	—

Note: The first row reports the Pearson correlation between absolute rent and energy expenditures, along with its 95% confidence interval and the p-value from a two-sided test. Remaining rows show Pearson correlations between expenditure shares. The low (but statistically significant) correlation of −0.111 suggests a weak inverse relationship between rent and energy expenses, indicating they are not close substitutes in household budgets. In contrast, budget shares for rent and energy are positively correlated (0.16), suggesting that households with high rent burdens often also face high energy burdens. Energy expenditure therefore appears to be a complementary - not substitutive - component of housing cost pressures, supporting the relevance of analyzing energy poverty separately.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Table B.10: Household Socio-demographic Characteristics Across Categories of the Population

Characteristic	All	D1–5	D1–3	EP	hEP
Wage Earner Ref	62.4%	46.6%	38.9%	29.3%	36.4%
Education: No Education	7.2%	12.2%	15.0%	15.6%	15.0%
Education: Primary	13.6%	19.9%	21.8%	21.8%	20.9%
Education: Secondary	63.7%	59.9%	56.9%	55.9%	54.8%
Education: Tertiary	15.5%	8.0%	6.3%	6.7%	9.3%
Ownership: No	29.0%	41.7%	52.2%	62.0%	57.2%
Ownership: With Loan	36.1%	22.7%	16.6%	11.5%	13.5%
Ownership: Without Loan	34.9%	35.6%	31.2%	26.5%	29.3%
Number of Cars	1.04	0.89	0.78	0.69	0.65
Region: Brussels	10.5%	11.6%	13.6%	12.0%	24.2%
Region: Flanders	57.1%	52.9%	49.1%	43.4%	44.5%
Region: Wallonia	32.4%	35.5%	37.3%	44.6%	31.3%
House Type: Detached	50.7%	44.1%	39.5%	41.7%	27.2%
House Type: Flat	28.3%	33.6%	38.2%	39.4%	54.0%
House Type: Terraced	21.1%	22.3%	22.4%	18.9%	18.8%
Construction Year: After 1990	16.8%	11.8%	9.5%	7.5%	–
Construction Year: Before 1970	55.8%	59.9%	61.2%	61.3%	68.3%
Construction Year: 1970–1990	27.4%	28.4%	29.3%	31.2%	31.7%
Number of Rooms	5.94	5.72	5.55	5.50	5.14
Heating: Electric	6.7%	6.2%	6.0%	4.8%	7.7%
Heating: Gas	55.2%	55.4%	56.9%	51.1%	49.3%
Heating: Oil	33.1%	32.1%	30.2%	39.4%	31.4%
Heating: Other	0.5%	0.4%	0.5%	0.3%	0.4%
Heating: Solid	4.6%	5.8%	6.4%	4.4%	11.2%
HH Type: Couple Active	34.1%	25.4%	23.6%	17.0%	18.6%
HH Type: Couple Retired	15.5%	18.9%	18.2%	14.4%	14.7%
HH Type: Many Adults	12.4%	13.1%	12.9%	5.6%	5.3%
HH Type: Single Active	25.7%	25.5%	28.2%	37.1%	38.4%
HH Type: Single Retired	12.2%	17.0%	17.1%	25.9%	22.9%
Number of Children	56.5%	58.2%	60.7%	35.5%	37.8%
Older Person Present	32.7%	38.9%	38.6%	42.2%	39.2%
At Risk of Poverty (AROP)	12.4%	24.7%	41.2%	47.9%	36.1%
Single Parent Family	5.8%	8.8%	11.0%	10.4%	9.7%

Note: Percentages represent the share of households in each subgroup. Numeric variables (*e.g.*, rooms/cars) are means.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Complementary econometric outputs

Table B.11: Logit Models for Energy Poverty from Reduced to Complete

Variable	EP–1	EP–2	EP–3	EP (Full)
Wage Earner (ref. person)	–0.91***	–0.86***	–0.91***	–0.91***
Education: No Education (ref.)				
Primary	–0.10*	–0.13**	–0.15**	–0.15**
Secondary	–0.19***	–0.18***	–0.19***	–0.18***
Tertiary	–0.32***	–0.27***	–0.30***	–0.30***
Tenure: Renter (ref.)				
Owner with Loan	–0.88***	–0.96***	–1.31***	–1.31***
Owner without Loan	–1.02***	–1.04***	–1.59***	–1.59***
# Cars	–0.03	–0.07**	–0.21***	–0.21***
HH Type: Couple Active (ref.)				
Couple Retired	–0.44***	–0.39***	–0.54***	–0.54***
Many Adults	–0.41***	–0.40***	–0.60***	–0.60***
Single Active	0.52***	0.53***	0.64***	0.64***
Single Retired	0.29***	0.33***	0.33***	0.34***
# Children	–0.24***	–0.25***	–0.35***	–0.35***
Region: Brussels (ref.)				
Flanders	—	0.21***	–0.00	–0.00
Wallonia	—	0.76***	0.40***	0.40***
Dwelling: Detached (ref.)				
Flat	—	—	–0.62***	–0.62***
Terraced House	—	—	–0.44***	–0.44***
Construction: After 2000 (ref.)				
Before 1970	—	—	0.32***	0.32***
1970–1990	—	—	0.37***	0.36***
# Rooms	—	—	0.16***	0.16***
Heating: Electricity (ref.)				
Gas	—	—	0.22***	0.22***
Oil	—	—	0.84***	0.84***
Other	—	—	–0.39	–0.38
Solid	—	—	–0.04	–0.04
Season: Winter (ref.)				
Autumn	—	—	—	0.04
Spring	—	—	—	0.06
Summer	—	—	—	0.09**
Time controls				
Years After 2000	—	—	—	0.00
Year 2008–09	—	—	—	0.03
Years After 2011	—	—	—	–0.06
Observations	21,200	21,200	21,200	21,200
McFadden's R^2	12.4%	13.6%	17.1%	17.1%
AIC	22,032	21,740	20,863	20,871

Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Authors' calculations based on Belgian HBS data (2003–2016).

Table B.12: Logit Models for Hidden Energy Poverty from Reduced to Complete

Variable	**hEP–1**	**hEP–2**	**hEP–3**	**hEP (Full)**
Wage Earner (ref. person)	–0.14*	–0.13*	–0.09	–0.07
Education: No Education (ref.)				
Primary	–0.04	–0.05	–0.03	–0.05
Secondary	–0.14*	–0.19**	–0.17*	–0.15*
Tertiary	0.18*	–0.00	0.04	–0.03
Tenure: Renter (ref.)				
Owner with Loan	–0.48***	–0.33***	–0.20*	–0.16*
Owner without Loan	–0.27***	–0.14*	0.02	0.03
# Cars	–0.41***	–0.28***	–0.25***	–0.25***
HH Type: Couple Active (ref.)				
Couple Retired	–0.25*	–0.21*	–0.16	–0.15
Many Adults	–0.39***	–0.43***	–0.41***	–0.42***
Single Active	0.19**	0.22**	0.22**	0.25***
Single Retired	–0.04	0.01	0.04	0.08
# Children	–0.02	–0.04	–0.03	–0.04
Region: Brussels (ref.)				
Flanders	—	–0.88***	–0.76***	–0.78***
Wallonia	—	–0.92***	–0.90***	–0.90***
Dwelling: Detached (ref.)				
Flat	—	—	0.84***	0.85***
Terraced House	—	—	0.37***	0.35***
# Rooms	—	—	0.04*	0.04*
Heating: Electricity (ref.)				
Gas	—	—	–0.55***	–0.54***
Oil	—	—	–0.11	–0.16
Other	—	—	0.09	0.25
Solid	—	—	1.19***	1.18***
Season: Winter (ref.)				
Autumn	—	—	—	–0.16*
Spring	—	—	—	–0.08
Summer	—	—	—	0.04
Time controls				
Years After 2000	—	—	—	–0.03*
Year 2008–09	—	—	—	–0.09
Years After 2011	—	—	—	–0.34**
Observations	21,200	21,200	21,200	21,200
McFadden's R^2	3.1%	4.4%	7.6%	8.4%
AIC	12,673	12,507	12,103	12,007

Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Authors' calculations based on Belgian HBS data (2003–2016).

Cross-price elasticities

Table B.13: Uncompensated Cross-Price Elasticities – Full Population

	Food	**Transport**	**Electricity**	**Heating**	**Other**
Food	-0.46^{***}	-0.29^{***}	0.44^{***}	0.07	-0.19^{***}
Transport	-0.08^{***}	-0.22^{***}	-0.17^{***}	0.12^{***}	-0.04^{***}
Electricity	0.05^{**}	-0.12^{***}	-0.66^{***}	-0.04^{**}	-0.02^{***}
Heating	0.00	0.12^{***}	-0.05	-0.16^{***}	-0.08^{***}
Other	-0.43^{***}	-0.30^{***}	0.04	-0.67^{***}	-0.77^{***}

Note: Own-price elasticities are on the diagonal. Most cross-price effects are small but significant. Positive links between Food and Electricity, and between Transport and Heating, suggest mild substitution or shared expenditure constraints.

Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Compensated price elasticities

We can isolate substitution effects by looking at compensated/Hicksian price elasticities. In Table B.14, we report compensated cross-price elasticities for the whole population, and in Table B.15 compensated own-price elasticities for different sub-groups.

Table B.14: Compensated Cross-Price Elasticities – Full Population

	Food	**Transport**	**Electricity**	**Heating**	**Other**
Food	-0.26^{**}	-0.11	0.53^{***}	0.21^{***}	0.05
Transport	-0.03	-0.17^{***}	-0.15^{***}	0.16^{***}	0.02^{**}
Electricity	0.08^{***}	-0.09^{***}	-0.65^{***}	-0.02	0.02^{**}
Heating	0.06^{***}	0.16^{***}	-0.03	-0.12^{***}	-0.02^{***}
Other	0.16	0.21^{**}	0.30^{**}	-0.23^{***}	-0.07

Note: Compensated (Hicksian) elasticities calculated at sample means. Own-price elasticities are on the diagonal.

Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

Interpretation: Electricity substitutes with food and other goods, and is complementary with transport. Heating substitutes with food and transport but complements other goods.

Table B.15: Compensated (Hicksian) Price Elasticities by Group and Consumption Category

Group	n	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All Population	33,269	−0.26**	−0.17***	−0.65***	−0.12***	−0.07
Deciles 1–3	7,728	-0.32***	-0.30***	-0.62***	-0.21***	-0.12**
Deciles 4–5	6,822	-0.28**	-0.21***	-0.65***	-0.15***	-0.08*
Deciles 6–10	18,719	-0.23*	-0.11**	-0.66***	-0.07*	-0.05
Deciles 1–5 (all)	14,550	-0.30**	-0.26***	-0.64***	-0.18***	-0.15**
Hidden Energy Poor	1,061	-0.39***	-0.30***	-1.14***	-0.40***	-0.13**
Energy Poor	3,342	-0.35**	-0.34***	-0.53***	-0.16***	-0.14**
Deciles 1–5, non-EP	10,150	-0.28**	-0.23***	-0.65***	-0.18***	-0.08**

Note: Compensated (Hicksian) elasticities calculated at subsample means.

Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Source: Authors' calculations based on HBS data for Belgium (2003–2016).

B.4 Supplementary Figures

Figure B.3: Evolution of Durables' Share in Total Expenditures

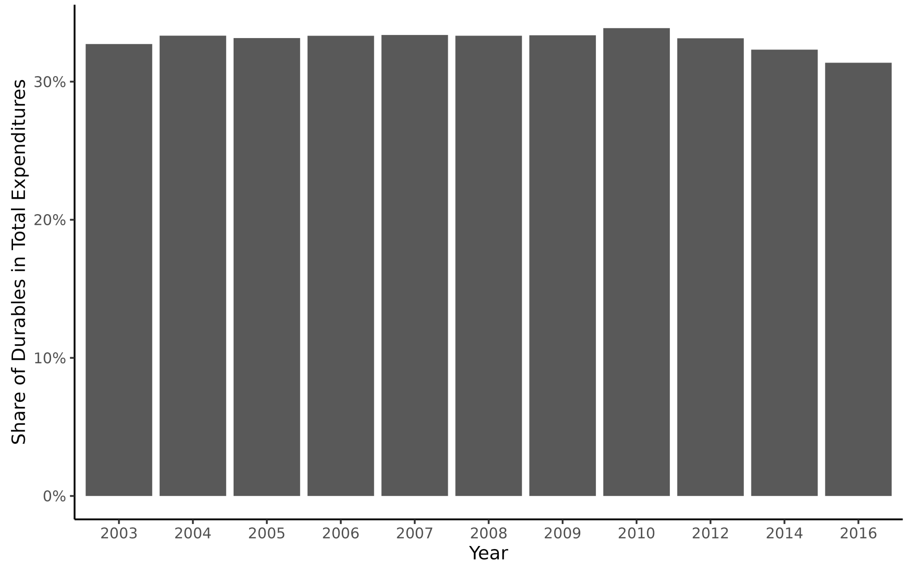
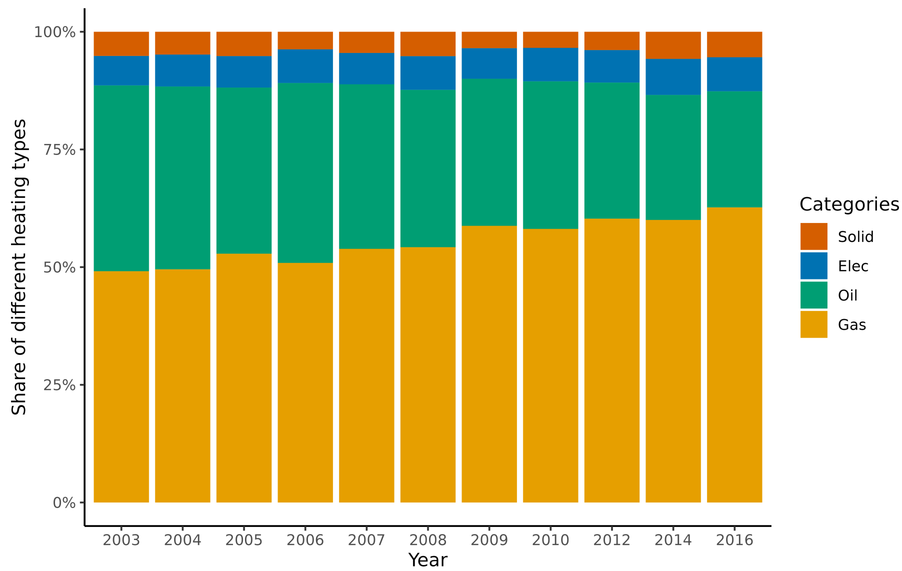


Figure B.4: Evolution of Households Heating System Type



C Appendix for Chapter 3

C.1 Descriptive Statistics and External Validity

Woonsurvey and Augmented Woonsurvey

In moving from Woonsurvey to the Augmented Woonsurvey, many observations are lost due to missing information on energy bills, reducing the sample from 2,973 to 1,332 dwellings. Table C.1 reports key descriptive statistics for the Augmented Woonsurvey and compares them with the original Woonsurvey; numbers in parentheses indicate the coverage rate, i.e., the share of observations with a non-missing entry for that variable category in Woonsurvey. Relative to the original sample, the retained sample contains (i) a somewhat higher share of houses (vs. apartments), (ii) a higher share of owner-occupiers, and (iii) a higher share of oil-heated households at the expense of gas-heated dwellings. By contrast, distributions are very similar across the two samples for envelope component performance, household income, total residential energy use, and CO_2 emissions.

To correct these composition shifts, we recalibrate the original survey weights (Woonsurvey) on the retained sample (Augmented Woonsurvey) using iterative post-stratification (raking), so that the weighted shares of dwelling type (house vs. apartment), owners (vs. tenants), and heating technology (electricity, gas, heat pump, solid fuels, oil) are closer to those observed in the full Woonsurvey. We report the so-obtained descriptive statistics under "Augm. WS (calibrated)". All other descriptive statistics and model outcomes in this paper are computed using these calibrated weights, which restores representativeness along these key margins while keeping weight dispersion moderate[71].

[71] Weight dispersion remains limited (max $\approx$ 5.6), and the effective sample size declines from 1,265 under the raw weights to 1,016 under the calibrated weights (about a 20% drop).

Table C.1: Treatment of Woonsurvey dataset

Variable	**WS 2018**	**Augm. WS**	**Augm. WS (cal.)**
Obs.	2973	1332	1332
Heating system			
Gas heating	71%	48%	72%
Oil/mazout	18%	35%	18%
Heat pumps	1.2%	1.7%	0.9%
Electric (other)	7.4%	11.4%	6.1%
Solid	2.5%	3.4%	2.5%
Envelope (U-values)			
U-floor (avg.)	1.65	1.61	1.61
U-roof (avg.)	0.85	0.76	0.81
U-walls (avg.)	0.92	0.90	0.93
U-window (avg.)	2.65	2.67	2.67
Energy consumption			
Gas (kWh/yr)	14 473	14 155	14 131
Oil (kWh/yr)	20 919	20 952	20 748
Solid (kWh/yr)	8 756	8 358	7 207
Fossil (avg., kWh/yr)	17 681	17 722	16 024
Elec (avg., kWh/yr)	4 143	4 170	3 692
Total (avg., kWh/yr)	18 763	19 879	18 733
Other			
Houses	74%	83%	77%
Owners	72%	82%	76%
HH income (avg., €)	2 713	2 815	2 825
Emissions (avg., tCO_2/yr)	3.36	3.79	3.48

Source: Own calculations based on Woonsurvey 2018.

Energy Performance Certificate

In the Augmented Woonsurvey, we impute theoretical energy consumption from responses collected in the original Woonsurvey. A key step is to infer, for each dwelling and each envelope component (walls, windows, roof, floor), a thermal performance level from the survey's reported year of construction and insulation quality (bad, intermediate, good). We then construct component-specific U-values following Gendebien et al. (2014), who distinguish five main construction periods and two insulation levels (bad, good). Since Woonsurvey includes an additional "intermediate" category, we set its U-value to the midpoint between the "bad" and "good" scenarios. For buildings constructed since 1990, we adjust the "bad" scenario from Gendebien et al. (2014) to satisfy the Flemish maximum U-values in force for the corresponding period (Vlaamse Overheid, 1991, 2018). These imputed U-values feed the heat-loss coefficients used to compute theoretical space-heating needs (and, by extension, total theoretical consumption). Full details of the theoretical-consumption calculation are provided in Section 2 of the Technical Report.

In Table C.2, we compare the distribution of EPC labels generated by our methodology with official statistics to assess consistency and external validity. In line with Table C.1, the aggregate theoretical consumption computed in the Augmented Woonsurvey closely matches what can be calculated from the original Woonsurvey. Nonetheless, relative to administrative EPC label statistics, discrepancies arise at the distributional tails: our imputation procedure yields no dwellings in EPC A and very few in EPC F, while over-representing EPC C and D. These differences plausibly reflect (i) the conversion of the "intermediate" insulation category to U-values by taking the midpoint between "bad" and "good," (ii) sample selection due to restricting to dwellings with complete billing data, and (iii) partial non-comparability with administrative series.

Table C.2: EPC label distribution by dwelling type. Shares in %.

Dwelling type	EPC label ($kWh/m^2 \cdot year$)	Flanders (SERV)	WS 2018	Augmented WS 2018
Apartment	A (0–100)	10	0	0
Apartment	B (101–200)	38	37.1	33.1
Apartment	C (201–300)	24	38.9	43.3
Apartment	D (301–400)	12	14.5	16.0
Apartment	E (401–500)	7	4.5	4.2
Apartment	F (>500)	9	5.0	3.5
House	A (0–100)	5	0	0
House	B (101–200)	10	19.7	19.5
House	C (201–300)	17	32.4	33.4
House	D (301–400)	17	25.5	25.2
House	E (401–500)	15	13.9	14.4
House	F (>500)	36	8.5	7.5

Note: Official EPC statistics for 2019 are retrieved from Sociaal Economische Raad van Vlaanderen (2019), which is based on approximately one million official EPC collected by the Flemish Agency of Climate and Energy (VEKA).
Source: Own calculations based on Woonsurvey 2018.

Distribution of Energy Performance Certificate

Table C.3 reports the cumulative distribution of EPC labels by household income group. The income-specific distributions obtained from the original Woonsurvey and from the Augmented Woonsurvey are very similar, supporting the distributive representativeness of our working sample. The table also confirms a clear gradient: lower-income households are disproportionately located in dwellings with poorer EPC ratings. This composition effect is central for the distributional incidence of the policies we study—most notably for standards—since households in inefficient homes are more likely to be compelled to renovate and thus face higher average burdens, which contributes to the observed regressivity of norms.

Table C.3: Cumulated EPC label distribution by income group

Income group	EPC label (kWh/m^2·year)	WS 2018 (cum. %)	Augm. Woonsurvey (cum. %)
Q1–Q2	A (0–100)	0.0	0.0
Q1–Q2	B (101–200)	16.4	15.1
Q1–Q2	C (201–300)	49.7	49.4
Q1–Q2	D (301–400)	74.8	75.2
Q1–Q2	E (401–500)	89.0	89.9
Q1–Q2	F (>500)	100.1	100.0
Q4–Q5	A (0–100)	0.0	0.0
Q4–Q5	B (101–200)	32.2	31.1
Q4–Q5	C (201–300)	65.7	66.1
Q4–Q5	D (301–400)	86.4	86.3
Q4–Q5	E (401–500)	95.8	96.7
Q4–Q5	F (>500)	100.0	100.0

Note: The table reports cumulated EPC label distributions for lower-income (Q1–Q2) and higher-income (Q4–Q5) households, comparing the Woonsurvey 2018 and the augmented Woonsurvey samples (shares in %).
Source: Own calculations based on Woonsurvey 2018.

CO_2 emissions

According to the Flemish greenhouse-gas inventory, residential direct combustion emissions amounted to 8.92 $MtCO_2$ in 2017 in Flanders (Vlaamse Milieumaatschappij, 2017). In the same year, the Flemish Region counted about 2.77 million private households (Statbel, 2017). This implies an average of approximately 3.22 tCO_2 per household per year. Note that this covers direct fuel combustion in dwellings; it excludes electricity (accounted for in power supply) and biogenic CO_2 from biomass.

As reported in Table C.1, average direct household emissions are 3.36 tCO_2 in Woonsurvey and 3.48 tCO_2 in the Augmented Woonsurvey corrected by reweighing, i.e., slightly above the inventory benchmark.

C.2 Additional results: Box plots

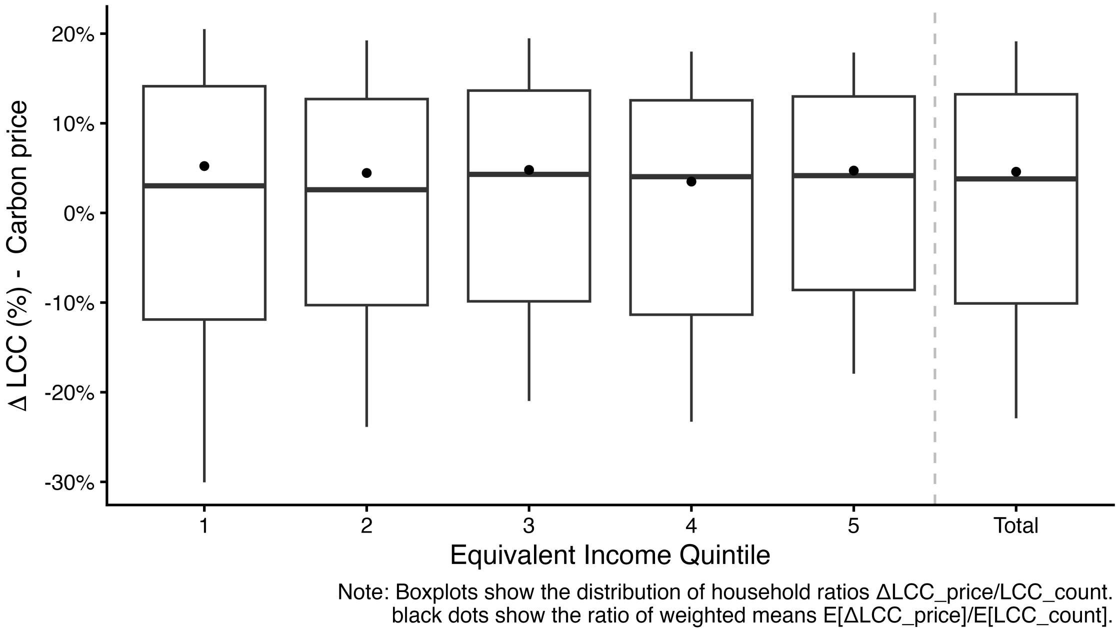
Figures C.1, C.2 and C.3 present different moments of the distribution of monetary impacts under the three policy scenarios, by income quintile. The boxplots display the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution. Monetary impacts are measured as the percentage change in life-cycle cost under each policy scenario relative to the no-policy counterfactual. The red dot indicates the mean effect.

The figures show that the median impact is close to zero across all income quintiles in both scenarios. In the norm scenario, the median effect is exactly zero, reflecting the fact that fewer than half of households within each quintile are constrained by the standard. In the carbon pricing scenario, the mean impact is relatively stable across quintiles and amounts to approximately 2%. By contrast, under the norm scenario, the mean increase in life-cycle cost is about 15% in the lowest income quintile and declines steadily as income rises. This pattern indicates that the norm scenario is regressive, and that it exacerbates vertical inequality.

Horizontal distributional impacts are also markedly more unequal under the norm scenario. The most affected households within each income quintile experience very large increases in life-cycle cost, particularly in the first two quintiles. In these groups, 10% of households face an increase in life-cycle cost exceeding 45%, which is twice as high as the corresponding threshold in the fifth quintile and more than three times higher than the 90th-percentile impact observed under carbon pricing, for any quintile.

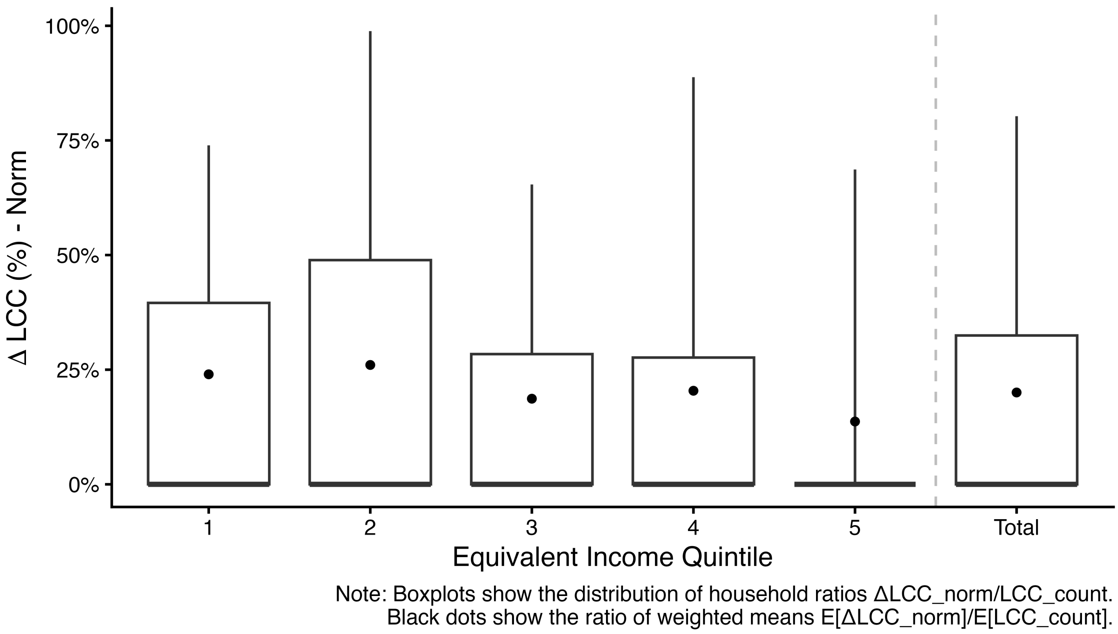
While there are no financial winners under the norm scenario, half of households experience a decrease in life-cycle cost under carbon pricing. These winners are households with below-average energy consumption, which receive more in lump-sum transfers than they pay in carbon taxes. For some households, the positive financial impact is substantial: more than 10% of households in each income quintile see their energy expenditures decline by more than 20%.

Figure C.1: Variation in LCC from the counterfactual - Carbon price scenario



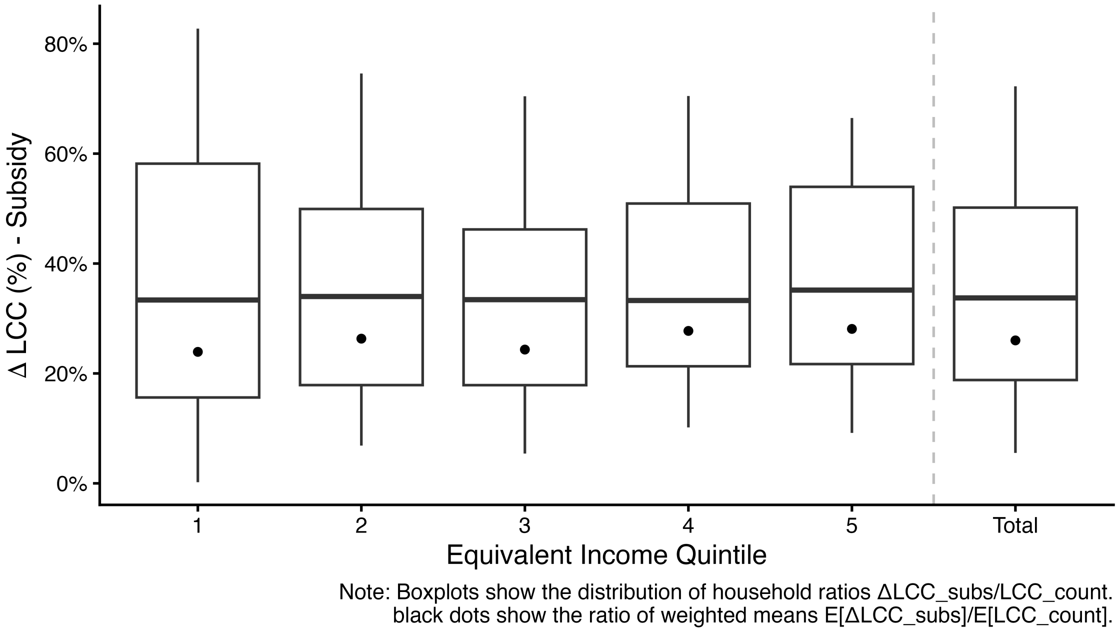
Source: Own calculations based on Woonsurvey 2018.

Figure C.2: Variation in LCC from the counterfactual - Norm scenario



Source: Own calculations based on Woonsurvey 2018.

Figure C.3: Variation in LCC from the counterfactual - Subsidy scenario



Source: Own calculations based on Woonsurvey 2018.