Energy Poverty and Households' Reaction to Carbon Pricing: A Behavioral Model Using Belgian Data

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Abstract

This paper investigates the behavioral and welfare impacts of carbon pricing on energy-vulnerable households in Belgium. We focus on two distinct groups: energy poor (EP) households, who spend a large share of their income on energy, and hidden energy poor (hEP) households, who spend very little on energy, suggesting severe self-restriction. Leveraging eleven cross-sections of the Belgian Household Budget Survey, we estimate a Quadratic Almost Ideal Demand System with demographic controls to simulate household responses to energy price changes under the forthcoming EU ETS 2 reform. Our analysis shows that hEP households - despite their low observable energy use - suffer disproportionately high welfare losses. In contrast, EP households face higher tax burdens but experience comparatively smaller welfare impacts. Both groups display greater price sensitivity - particularly for heating fuels and transport - than the general population, with income emerging as the primary driver of this responsiveness. Logistic regression results further highlight key structural differences between EP and hEP households in terms of housing characteristics, heating systems, and regional location. These findings underscore the importance of integrating different vulnerability profiles into carbon pricing assessments, enabling the identification of horizontal equity concerns that are often overlooked in income-based analyses.

Keywords: Carbon Pricing, Energy Poverty, Demand System, Welfare Analysis

1. Introduction

In response to global warming, the European Union has committed to reducing greenhouse gas emissions by 55% by 2030 and achieving carbon neutrality by 2050. To help meet these targets, the Commission will introduce a new Emissions Trading Scheme for the road transport and building sectors (ETS 2). They accounted respectively for 23% and 14% of EU CO_2 emissions in 2021 (European Environment Agency, 2024). By requiring fuel suppliers to purchase emission allowances, ETS 2 is expected to increase fuel prices. Anticipating households behavioral reaction is therefore essential to understand its impact on their welfare and living standards. Public debates - most notably those sparked by the Yellow Vests movement in France - highlight how carbon pricing can have uneven effects across households. A substantial body of literature has integrated demand systems into microsimulation models to estimate responses to carbon pricing reforms. This stream of research broadly agrees that carbon taxes place a disproportionate burden on low-income households, who devote a larger share of their income to carbon-intensive energy goods (Douenne, 2020; Nikodinoska and Schröder, 2016; Tovar Reaños and Wölfing, 2018).

This article seeks to move beyond the standard conclusion that carbon pricing is regressive by offering an ex-ante behavioral welfare analysis rooted in the European policy framework, and by extending beyond traditional income-based classifications. A growing body of research stresses the importance of considering dimensions other than income when identifying households struggling to meet their energy needs (Okushima, 2017). This literature distinguishes between energy poor households—who spend a large share of their income on energy—and hidden energy poor households—who severely limit energy consumption to keep expenses low. In Belgium, 21.8% of households were affected by energy poverty in 2022 (Fondation Roi Baudouin, 2024), highlighting the urgency of recognizing and addressing the diversity within this vulnerable population to ensure a fair energy transition. Understanding how these groups respond to rising energy prices is essential for evaluating the distributional impacts of carbon taxation. Despite progress in identifying energy poverty, much of the existing literature on carbon pricing overlooks the specific burden it places on (hidden) energy poor households. Notably, behavioral microsimulation models rarely incorporate energy poverty indicators. Some exceptions exist: Berry (2019) underscores the need to consider energy-poor households, though her model relies on a simplified linear expenditure framework and focuses on revenue recycling. Charlier and Kahouli (2019) highlight heterogeneity in price responses and stress the distinction between energy and income poverty. More recently, Tovar Reaños and Lynch (2022) include energy poverty indicators in their analysis for Ireland but do not differentiate behavioral responses across household types. None of these studies fully account for the diversity within energy-poor groups. In fact, by including hidden energy poor households, we expand the identified energy-vulnerable population by roughly one third, significantly enhancing the scope of our policy analysis.

Building on this literature, our paper leverages eleven cross-sections of the Belgian Household Budget Survey (HBS) to conduct a behavioral microsimulation that explicitly incorporates energy poverty statuses into a welfare analysis of carbon pricing. We begin by reviewing the literature on energy vulnerability and its measurement to motivate our choice of indicators. We then offer a detailed descriptive analysis of the energy-vulnerable population in Belgium, showing how (hidden) energy poor differ not only from the general population but also from households with similar income levels. Moreover, we find substantial internal heterogeneity: key differentiating factors between energy poor and hidden energy poor households include region, dwelling type, and heating system. These insights are formalized through the estimation of two logistic regressions that identify the most salient determinants of both statuses. These variables are then embedded into a demographic specification of a Quadratic Almost Ideal Demand System (QUAIDS), allowing us to tailor behavioral responses to household characteristics and simulate demand adjustments in response to energy price increases. Our results point towards income as the dominant factor driving behavioral responses to carbon pricing, though some additional price-responsiveness is observed among hidden energy poor households. Importantly, our welfare analysis reveals that arithmetic tax burden measures overlook critical differences in vulnerability: hidden energy poor households, despite their low energy consumption, suffer disproportionately high welfare losses. In contrast, energy poor households display higher tax burdens but comparably lower welfare costs. These findings underscore the importance of complementing income-based and vertical equity metrics with horizontal welfare indicators that capture the non-linear utility of income and energy consumption within a carbon pricing framework.

Our contributions to the literature are fourfold. First, to our knowledge, this is the first study to conduct an econometric analysis of the socio-demographic determinants of hidden energy poverty, and the first to estimate the impact of carbon pricing on this specific population. By including hidden energy poor households, we significantly expand the scope of the vulnerable groups typically considered in policy analyses. Second, by embedding these determinants into a demographically-specified demand system, we are able to simulate differentiated behavioral responses across household types, yielding a more accurate picture of how energy vulnerability shapes reactions to energy price changes. Third, our ex-ante microsimulation approach offers fresh insights into the horizontal equity dimensions of green taxation, a concern that is often underexplored in policy design despite its importance for social acceptance. Finally, our work is among the very few to evaluate the expected distributional effects in Belgium of the forthcoming EU-ETS 2, thereby contributing to the empirical grounding of current policy debates.

In the remainder of this paper, Section 2 reviews the main concepts and measurement challenges related to energy poverty, with a particular focus on the Belgian context, and outlines our energy poverty indicators. Section 3 introduces the dataset, before presenting key descriptive statistics and the results of our econometric analysis of (hidden) energy poverty determinants. Section 4 details our demand system estimation, including the specification of the QUAIDS model, the estimation strategy, and elasticity results. Section 5 presents our welfare analysis of carbon pricing, based on a behavioral microsimulation of the forthcoming EU-ETS 2 reform, with a focus on the distributional impacts across income deciles and energy-vulnerable households. We conclude with a discussion of our findings and their implications for policy design.

2. The Energy Poverty Phenomenon

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 method of measurement. Over the past three decades, the literature has proposed five main approaches to measuring energy poverty: (i) expenditure-based indicators, (ii) subjective indicators based on household self-identification, (iii) minimum-income-standard-based indicators assessing the affordability of essential energy needs relative to a minimum standard of living, (iv) multidimensional composite indicators, and (v) indicators based on the modelling of households' required energy consumption. Subjective indicators are excluded due to their sensitivity to socio-cultural context and survey design (Waddams Price et al., 2012), while minimum-income-standard-based measures are typically suited for application at regional or sub-regional levels (Romero et al., 2018). Regarding multidimensional approaches, we follow Rademaekers et al. (2016) in advocating for the use of a selection of targeted indicators, rather than relying on a single composite metric, to better distinguish between different forms of energy poverty. Finally, we do not employ model-based indicators, as these require a wide range of assumptions, the existence of advanced engineering models, and extensive datasets (Ye et al., 2022). Therefore, we focus in this paper on expenditure-based measures for which we leverage detailed consumption data, allowing us to also estimate a demand system and evaluate households' behavioral responses to carbon pricing

Expenditure-based indicators are the most widely used approaches to identifying energy poverty and typically focus on households whose energy expenditure is disproportionately high relative to their income (hereafter referred to as *EP households*). A pioneering example is the 10% Fuel Poverty Ratio introduced by Boardman (1991), which defines a household as energy poor if its domestic energy costs amount to at least 10% of its income. Other widely used measures include the Low Income High Costs (LIHC) indicator proposed by

Hills (2011), which compares a household's energy expenditure with its disposable income, and the After Fuel Cost Approach, which identifies households as income poor after accounting for housing and energy costs. However, these 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 adjustments, which can lead to inconsistent household classifications and potential false positives (Legendre and Ricci, 2015; Moore, 2012). A more recent and prevalent 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). Meyer et al. (2018) further adapt the 2M indicator in their construction of an energy poverty barometer for Belgium, incorporating housing costs and 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: 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.[1] 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 relative energy expenditure does not reliably indicate whether energy needs are met, and therefore advocate for hEP measures based on absolute monetary thresholds rather than expenditure shares. Building on this rationale, Bagnoli and Bertoméu-Sánchez (2022) and Tovar Reaños et al. (2023) define hEP households as those whose energy expenditure falls below half the national median (M/2). Meyer et al. (2018) further refine this approach by incorporating equivalised disposable income and dwelling insulation, while Betto et al. (2020) adapt the M/2 measure to account for regional climate variability, reflecting the specific requirements of the Italian context.

[1] Yet, underconsumption of energy resulting in inadequate thermal comfort can have serious adverse effects on health, underscoring the need for policy intervention (Ormandy and Ezratty, 2012).

2.2. Measuring (hidden) Energy Poverty

In this study, we adopt the indicators developed by Meyer et al. (2018) to assess both the extent and depth of (hidden) energy poverty. These indicators build explicitly on the existing literature to capture the multifaceted nature of energy poverty and are tailored to the Belgian context. Moreover, the annual recalibration of thresholds inherent in these indicators allows them to reflect evolving socio-economic conditions. As detailed in the next section, our primary adjustment is the use of Household Budget Survey data in place of Statistics on Income and Living Conditions (SILC) data. While this choice offers greater precision in the breakdown of energy expenditures, it provides less detailed information on dwelling insulation in recent years. Nevertheless, our measures remain effective and consistent in capturing both phenomena.[2]

2.2.1. Energy Poverty (EP)

Our objective is to identify households that overspend on energy and to quantify the extent of this overspending. A household is classified as energy poor if its energy expenditure exceeds twice the median ratio of energy expenditure (EE) to disposable income net of housing costs.[3,4] To exclude more affluent households whose high energy spending may reflect lifestyle preferences rather than financial vulnerability, we restrict the analysis to households in the bottom half of the equivalised income distribution. The threshold is calculated as follows:

$$\text{EP threshold} = 2 \times \text{median}\left(\frac{\text{household energy expenditure}}{\text{household disposable income (exc. housing costs)}}\right) \tag{1}$$

Following standard practice in poverty research, the depth or severity of energy poverty is defined as the monetary gap between a household's actual energy expenditure and the EP threshold.

[2] As shown in Table B.1 in the Appendix, our (h)EP prevalence figures over time align closely with official Belgian statistics reported by the Fondation Roi Baudouin, including those presented in their latest report (2024). Moreover, our measures clearly distinguish between the two types of energy poverty, as households falling under both measures never represent more than 0.1% of the population.

[3] As noted by Meyer et al. (2018), housing costs are capped at a maximum of twice the median housing cost in order to isolate energy-related hardship from issues arising from excessively high housing expenses.

[4] Housing costs include rent for tenants and half of the imputed rent for homeowners with a mortgage, as imputed rent often overestimates actual mortgage payments.

2.2.2. Hidden Energy Poverty (hEP)

We also seek to identify households that underspend on energy and to quantify the extent to which their expenditures fall short of basic energy needs. The threshold for hEP targets households whose energy spending is insufficient to meet these needs compared to similar households. This absolute amount used for benchmarking is the mean of two medians: (i) the median absolute energy expenditure of households with the same number of members and (ii) the median absolute energy expenditure of households living in dwellings with the same number of rooms. To ensure accuracy, we again limit the analysis to households in the bottom half of the equivalised income distribution. In addition, to avoid misclassifying households that live in well-insulated dwellings—and thus have low energy needs—we exclude households in buildings classified as well-insulated.[5,6] The threshold hence represents a proxy for basic energy requirements[7] and is constructed as follows:

$$\text{hEP threshold} = \frac{\begin{array}{c}0.5 \cdot \text{median EE of all HH with similar size} + \\ 0.5 \cdot \text{median EE of all HH with similar dwelling}\end{array}}{2} \tag{2}$$

Adapting standard measures of poverty severity to the context of energy underconsumption, the depth of hidden energy poverty is defined as the monetary gap between a household's actual energy expenditure and the reference energy expenditure of comparable households (based on the average of the relevant medians). This metric captures the extent to which hEP households fall short of achieving a basic standard of energy comfort.

3. Data

3.1. The Household Budget Survey

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 biannually, with

[5]Our approach diverges from that of Meyer et al. (2018), who had access to additional variables concerning dwelling insulation for survey years after 2012. In line with Okushima (2017) for Japan and Betto et al. (2020) for Italy, we use a dwelling's construction year as a proxy for its insulation quality. Specifically, we define a dwelling as well-insulated if it was built after 1990, corresponding to the introduction of first major thermal insulation regulations in Belgium.

[6]Regarding electricity production through solar panels, Figure A.1 in the Appendix shows that this phenomenon was negligible before 2010 and surged only after 2017. Moreover, solar installations are more common in the upper half of the equivalised income distribution.

[7]Despite our methodological adjustments, the identification of hEP households remains imperfect. It may still capture households with atypical preferences, old but renovated dwellings, or specific energy needs. Therefore, it is more accurate to interpret households falling below the hEP threshold as being *at risk of hidden energy poverty*.

each cross-section surveying between 4,000 and 6,000 households. Although EU-SILC is also suitable for measuring energy poverty, Thomson et al. (2017) recommend using household energy expenditure data, as it offers the highest level of disaggregation available. Moreover, access to detailed household expenditure data is essential for robust demand system estimation, as discussed in the following section.

Our dataset includes over 40,000 households, each with detailed expenditure records, including spending on food and transport fuels (gasoline and diesel) during the survey period. Heating fuel (natural gas and heating oil) and electricity expenditures are derived from the most recently reported annual energy bill. Accordingly, when imputing prices using Statbel's[8] monthly Consumer Price Indices, we apply a six-month lag for 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 (*e.g.*, terraced house), and ownership of durable goods (*e.g.*, cars and appliances). We do not use data on durable goods expenditures, as these reflect investment decisions rather than routine consumption. However, we control for the stability of these expenditures over time, as shown in Figure A.2 in the Appendix.

3.2. Descriptive statistics

3.2.1. (hidden) Energy Poverty

We analyze the extent and composition of (hidden) energy poverty in Belgium using the indicators introduced in subsection 2.2. As shown in Table 3.1, energy-poor (EP) households are more prevalent in the sample than hidden energy-poor (hEP) households. However, including hEP households expands the population considered vulnerable to energy costs by approximately one third, underlining the importance of considering both groups. A clear income gradient is evident: the prevalence of both EP and hEP declines sharply across deciles. Notably, EP households tend to be more income-poor than hEP households. Table B.3 in the Appendix reports that 47% of EP households are At Risk of Poverty (AROP), compared to 37% of hEP households. Moreover, (h)EP households display deeper socio-economic vulnerability. As Table B.3 shows, 29% of EP households and 39% of hEP ones include a wage earner, compared to 62% of the general population. Educational attainment is also lower: over 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

[8] Belgium's National Statistical Agency, responsible for producing the HBS data.

(h)EP and the rest of the population: they are far more likely to be renters,[9] tend to live in smaller dwellings with fewer rooms, and a majority reside in buildings constructed before 1970. Regional patterns differ across the two groups: EP households are overrepresented in Wallonia, while hEP households are disproportionately concentrated in Brussels. Housing type and heating sources also vary: hEP households are more likely to live in flats but also to rely on solid fuels for heating, which may reflect structural constraints contributing to hidden energy poverty. Finally, demographic composition 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. Children are less frequently present in these households, suggesting differences in family structure that may intersect with vulnerability to energy poverty. While these descriptive statistics offer valuable insight into the socio-economic and housing profiles of energy-poor households, a fuller understanding of the determinants of (hidden) energy poverty requires formal econometric analysis, as developed in subsection 3.3.

Table 3.1: Share of (Hidden) Energy Poor Households by Income Decile

Income Decile	EP Share (%)	hEP Share (%)
1	41.0	30.7
2	26.1	22.5
3	15.9	17.8
4	10.3	15.7
5	6.7	13.2
Total Sample Rate	**13.6**	**4.62**

Note: EP = Energy Poverty, hEP = Hidden Energy Poverty. Shares represent the distribution across the bottom five income deciles. The final row reports the headcount rate for the total sample population.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

3.2.2. Price and Expenditure Patterns

As outlined in Subsection 4.1, the demand system is estimated over five composite consumption bundles. Identifying price elasticities reliably requires meaningful price variation over time. Figure 3.1 illustrates the evolution of consumer prices for each bundle, indexed to 2013 price levels. Energy-related goods exhibit substantial price volatility over the 2003–2016 period. This pronounced variation strengthens the identification of own-price and

[9] One possible concern is that (h)EP households consider expenditure on rents and expenditure on energy as substitutes (e.g., higher rents for better-insulated dwellings). However, as shown in Table B.2, the correlation between rent and energy expenditure is weakly negative, providing no strong evidence of such substitution.

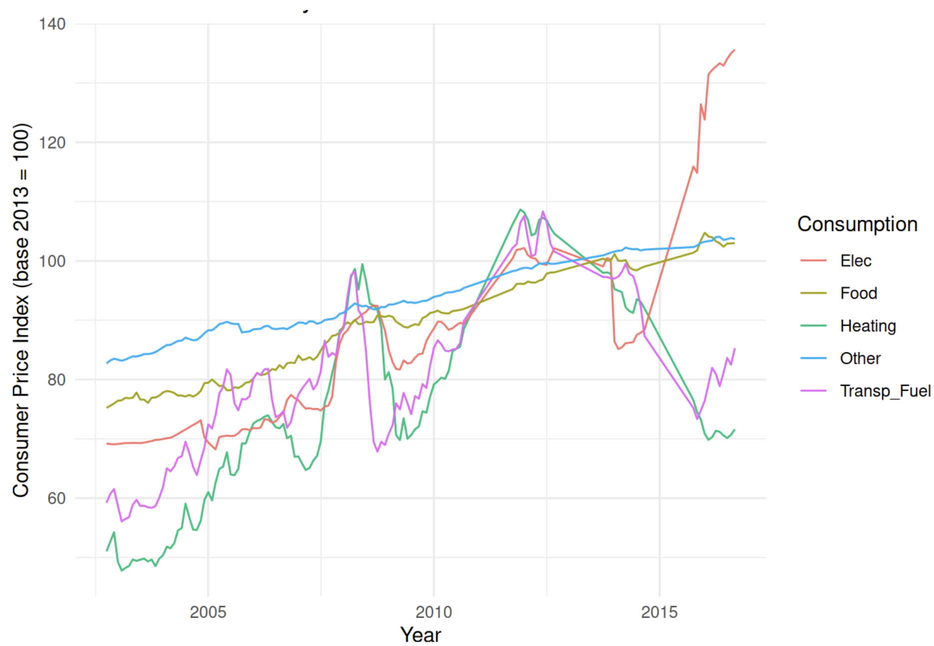


Figure 3.1: Real Price Variation for the Different Bundles of Goods
Source: Authors' calculations based on HBS data for Belgium (2003-2016).

cross-price elasticities for these categories. Figure 3.2 complements this by displaying trends in household expenditure shares, with a noticeable surge in energy spending around 2010. This dynamic coincides with peaks in energy price indices and highlights the importance of examining energy demand separately.

Figure 3.3a shows that overall expenditure shares devoted to the four consumption bundles decline as income increases. This pattern is primarily driven by a decrease in the budget shares allocated to food and electricity, while expenditure shares for heating and transport fuels show more muted or inconsistent trends across deciles. Figure 3.3b complements this by comparing expenditure patterns across energy poverty categories, as well as with the bottom half of the income distribution (both including and excluding energy-poor households). The figure confirms the core logic behind our classification: EP households are systematically identified as overspending on energy, while hEP households are characterized by unusually low energy spending. Additionally, hEP households allocate a relatively higher share of their budget to food, reinforcing the relevance of taking into account this bundle for potential substitution patterns. In contrast, EP households appear to spend relatively more on transport fuels, potentially reflecting greater mobility needs that could be explained by their presence in the more rural Wallonia.

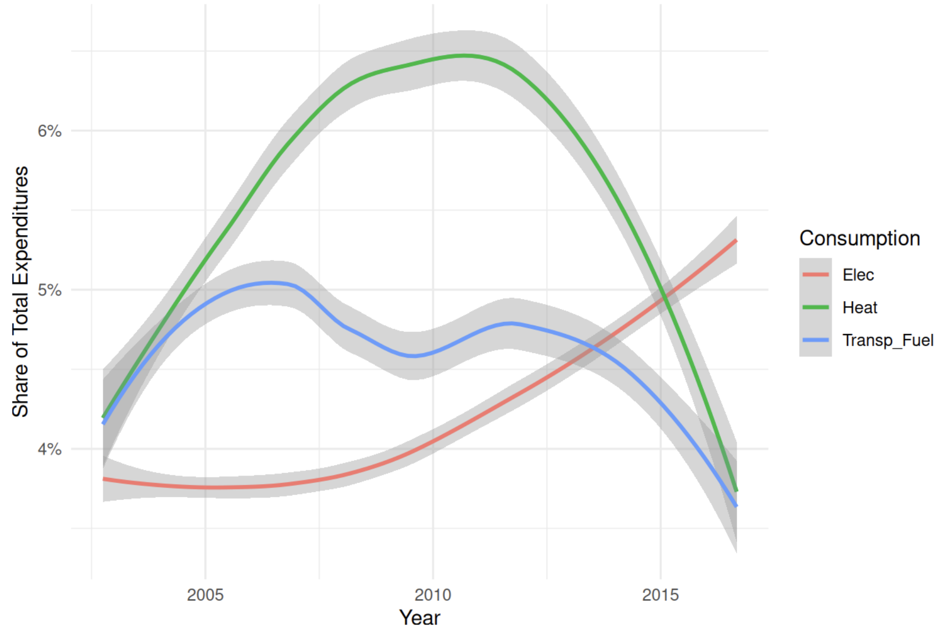
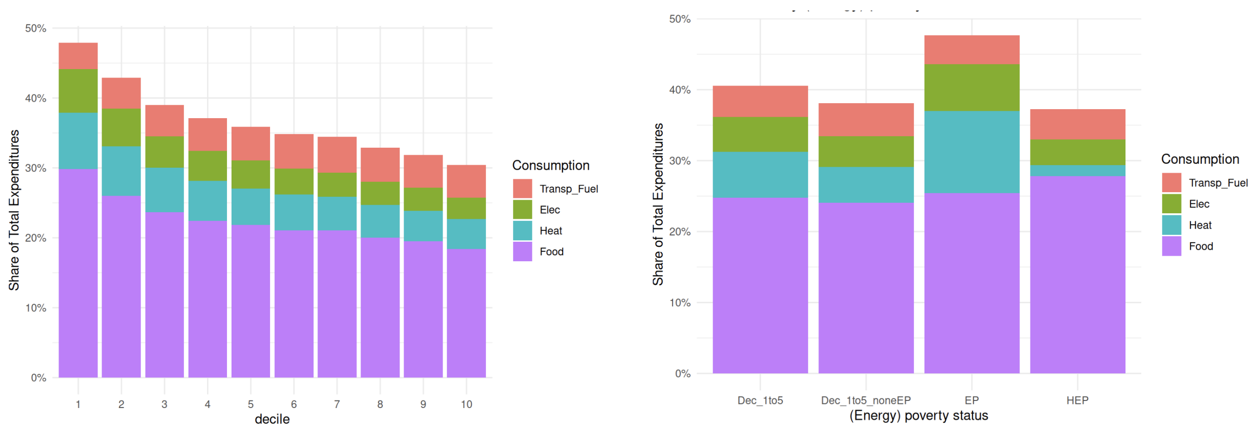


Figure 3.2: Evolution of All Population Expenditure Shares
Source: Authors' calculations based on HBS data for Belgium (2003-2016).



(a) Expenditure Shares by Income Decile

(b) Expenditure Shares by Category of the Population

Figure 3.3: Household Expenditure Shares by Income and Socio-demographic Group
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

3.3. The Determinants of (hidden) Energy Poverty

To analyse the socio-demographic determinants of (hidden) energy poverty, we employ a binary logit model. We assume the existence of an unobserved latent variable EP_i^* representing the propensity of household i to be energy poor. This latent variable is modeled as a function of the explanatory variables:

$$EP_i^* = X_i\beta + \varepsilon_i,$$

where X_i is a vector of observed covariates, β is a vector of coefficients to be estimated, and ε_i is an error term assumed to follow a logistic distribution. The coefficients β reflect the change in the log-odds of being energy poor for a one-unit increase in each covariate. For interpretability, we also report odds ratios, obtained by exponentiating the coefficients. An odds ratio greater than one implies an increased likelihood of being energy poor. The same specification is applied to model hidden energy poverty (hEP_i). To ensure comparability across households and to focus the analysis on the population most at risk, the models are estimated on a restricted sample comprising only households in the bottom half of the income distribution. This restriction allows the identification of the drivers of (hidden) energy poverty within a more homogeneous income group.[10]

To assess model robustness, we run the standard checks. Pseudo-R^2 values and Area Under the Curve statistics indicate satisfactory explanatory and discriminatory power for the EP model. In contrast, the hEP model performs less well.[11] Given the rarity of hidden energy poverty, we also estimated a complementary log-log specification, following Legendre and Ricci (2015), but results were largely unchanged.[12] This likely reflects the inherent difficulty of capturing the determinants of hidden energy poverty, which by nature involves behavioral and structural under-consumption patterns that are more complex and less easily explicable than "classic" energy poverty.

[10] Importantly, income is not included as an explanatory variable, as it directly enters the construction of the energy poverty indicators. Including income would therefore risk introducing endogeneity into the model. A similar logic explains the exclusion of construction year variables for the hEP logit.

[11] Variance Inflation Factor checks show no evidence of multicollinearity.

[12] The cloglog transformation is right-skewed and particularly suited for modeling rare events. Yet, the cloglog specification yielded results qualitatively similar to the logit, with only marginal changes in fit statistics.

Table 3.2: Logit Estimates for Energy Poverty (EP) and hidden Energy Poverty (hEP)

Variable	**EP**		**hEP**	
	Coef.	O.R.- 1	Coef.	O.R. - 1
Wage Earner	–0.91***	–60%	–0.08	–7%
No Education (ref. cat.)				
Primary Education	–0.15*	–14%	–0.05	–5%
Secondary Education	–0.18***	–16%	–0.15*	–14%
Tertiary Education	–0.30***	–26%	–0.03	–2%
Renter (ref. cat.)				
Owner with Loan	–1.31***	–73%	–0.17*	–15%
Owner without Loan	–1.59***	–80%	0.04	+4%
# Cars	–0.21***	–19%	–0.25***	–22%
HH Type: Couple Active (ref. cat.)				
Couple Retired	–0.54***	–41%	–0.16	–14%
Many Adults	–0.60***	–45%	–0.42***	–34%
Single Active	0.64***	+89%	0.25***	+28%
Single Retired	0.33***	+40%	0.08	+8%
# Children	–0.35***	–30%	–0.04	–4%
Region: Brussels (ref. cat.)				
Flanders	–0.00	0%	–0.78***	–54%
Wallonia	0.40***	+50%	–0.90***	–59%
Detached House (ref. cat.)				
Flat	–0.62***	–46%	0.85***	+133%
Terraced House	–0.44***	–36%	0.35***	+42%
Construction: After 2000 (ref.)				
Before 1970	0.32***	+38%	—	—
1970–1990	0.36***	+44%	—	—
# Rooms	0.16***	+18%	0.04	+4%
Heating System Type: Electricity (ref. cat.)				
Gas	0.22**	+24%	–0.54***	–42%
Oil	0.84***	+132%	–0.16	–15%
Other	–0.38	–31%	0.25	+28%
Solid	–0.04	–4%	1.17***	+224%
Time Controls				
Years After 2000	0.00	0%	–0.03*	–3%
Year 2008–09	0.03	+3%	–0.09	–9%
Years After 2011	–0.06	–6%	–0.34**	–29%
McFadden's R^2	0.171		0.084	

Note: Coefficients from logit regressions; OR = odds ratio interpreted as percentage change from baseline.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on HBS data for Belgium (2003–2016), bottom 5 deciles.

Table 3.2 reveals both shared and distinct determinants of (hidden) energy poverty. While many socio-demographic variables are significant in both models, coefficients for hEP tend to be smaller and less precisely estimated, reflecting the more diffuse nature of underconsumption. Three key dimensions 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, and those relying on oil-based heating. In contrast, hEP is more common in Brussels, and associated with flat dwellings and solid fuel heating systems. Some counterintuitive findings emerge with respect to what was observed in the descriptive statistics of subsection 3.2, such as the negative association between the number of children or retired household members and the likelihood of being (hidden) energy poor. Finally, all variables with statistically significant associations in either model are retained as candidate demographic controls in the subsequent behavioral model, ensuring the tailored estimation of (h)EP reactions to carbon pricing.

4. Demand System Estimation

In this section, we develop a behavioral model to estimate the price and income elasticities of household energy consumption. This model is designed to evaluate the extent to which households will be impacted by the policy reforms under consideration. Indeed, as the model is derived from theoretically consistent measures of utility, it allows for the computation of welfare metrics, as seen in section 5. To ensure consistency with the earlier sections of this study, we enrich our model with the socio-demographic variables driving (hidden) energy poverty.

4.1. Specification of the Demand System

4.1.1. The Quadratic Almost Ideal Demand System

Following common practice in the literature (Brännlund and Nordström, 2004; Douenne, 2020; Semet, 2024), we employ the Quadratic Almost Ideal Demand System (QUAIDS), as proposed 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 expenditures shares and income, commonly referred to as Engel curves. They are displayed for energy goods in the figure 4.1 below in a nonparametric form, reflecting the need for a quadratic specification. This model is particularly suitable for estimating elasticities while satisfying fundamental properties derived from neoclassical demand theory[13]. In addition,

[13]Homogeneity is imposed through the use of relative prices, while symmetry is enforced via the optimum minimum distance estimator (Blundell, 1988; Browning and Meghir, 1991). These properties are testable using likelihood-ratio tests, which compare restricted and unrestricted models. 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.

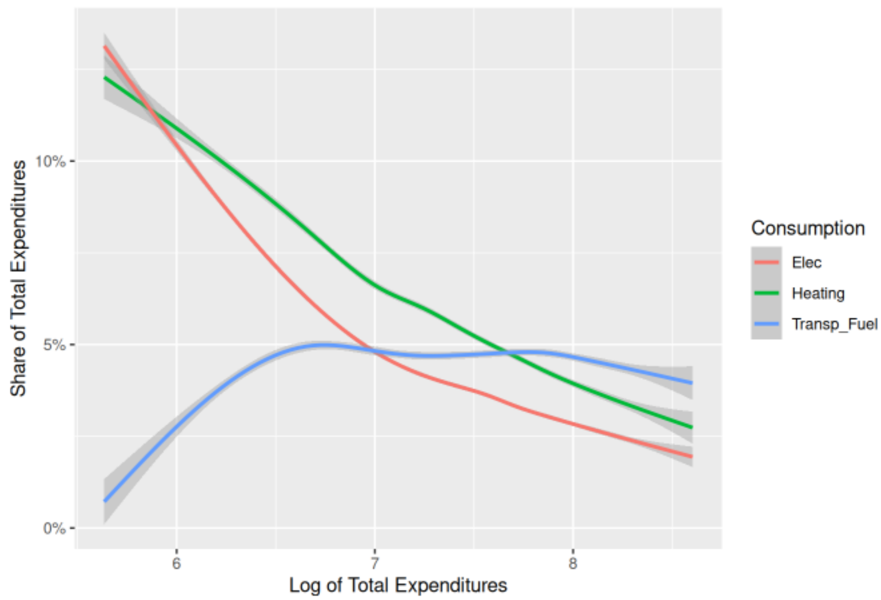


Figure 4.1: Engel curves for energy goods
Note: In demand system estimation, income is approximated by total expenditures, reflecting total budget allocation.

its flexibility in integrating demographic variables makes it suited to our analysis, as it allows key determinants of energy poverty to enter the specification of the model (see subsection 4.1.2). We present here the system of equations for QUAIDS without demographics. It is defined as follows and is solved using the Iterated Linear Least Squares (ILLS) estimator developed by Blundell and Robin (1999):

$$w_i = \alpha_i + \sum_{j=1}^{I} \gamma_{ij} \ln p_j + \beta_i \ln \frac{m}{a(\boldsymbol{p})} + \frac{\lambda_i}{b(\boldsymbol{p})} \ln \left(\frac{m}{a(\boldsymbol{p})} \right)^2 + u_i \tag{3}$$

where w_i is total expenditures' share spent on goods category i, p_j is the price index of goods bundle j and $\frac{m}{a(\boldsymbol{p})}$ are the real total expenditures. α_i, γ_{ij}, β_i and λ_i are parameters of interest, and u_i is the error term. $b(\boldsymbol{p})$ is the following price aggregator: $b(\boldsymbol{p}) = \prod p_i^{\beta_i}$

To implement this formula on our data, we must first choose the dependent variables, *i.e.*, the different goods categories based on which we construct the w_i. To be consistent with the analysis above, we consider separately transport (gasoline and diesel) and heating fuels (natural gas, liquid and solid fuels). In addition to that, we add food and electricity consumption as these categories present specific patterns of substitution/complementary with fuels. The remaining expenditures are listed under "other", with investments on durable goods excluded.[14] This gives a total of five categories ($I = 5$). Total nominal expenditures m are deflated by a general price index $a(\boldsymbol{p})$ whose choice is detailed here below. Demographic characteristics enter the equation by shifting the values of α_i as discussed in section 4.1.2.

Once variables are defined, parameter estimation proceeds via repeated OLS regressions of the first four equations of the system.[15] This iterative method accommodates the fact that parameters appear not only as coefficients but also within the translog price index used to define $a(\boldsymbol{p})$ (Deaton and Muellbauer, 1980):

$$\ln a(\boldsymbol{p}) = \alpha_0 + \sum_i \alpha_i \ln p_i + \frac{1}{2}\sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j \tag{4}$$

For the initial iteration, since the parameters are not yet valued, we approximate $a(\boldsymbol{p})$ using the *Stone Index* $\ln P_{Stone} = \sum w_i \ln p_i$. Subsequent iterations refine the estimates of parameters, along with $\ln a(\boldsymbol{p})$, until convergence is achieved. The final parameter values are used to compute total expenditure elasticities η_i and uncompensated (own- or cross-) price elasticities θ_{ij} by log-derivation of w_i:

$$\eta_i = 1 + \frac{\mu_i}{w_i} \tag{5}$$

with

$$\mu_i = \frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})} \ln \frac{m}{a(\boldsymbol{p})} \tag{6}$$

$$\Theta_{ij} = -\delta_{ij} + \frac{\mu_{ij}}{w_i} \tag{7}$$

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).

with

$$\mu_{ij} = \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i \left(\alpha_j + \sum_k \gamma_{kj} \ln p_k\right) - \frac{\lambda_i \beta_j}{b(\boldsymbol{p})} \left(\ln \frac{m}{a(\boldsymbol{p})}\right)^2 \tag{8}$$

[14] As we do not consider investments in durables explicitly, our elasticities might reflect some of these long term decisions. If a household facing high energy prices decided to invest in a cleaner heating system, thus reducing its energy consumption, this will translate into our elasticity estimates. We provide descriptive statistics about heating system switches in figure A.3 in the Appendix, showing the moderate increase in the adoption of natural gas in replacement of heating oil.

[15] The fifth equation is estimated ex-post by supposing additivity. The values of the parameters retrieved are independent of which equation is dropped from the estimation, as shown by Barten (1969).

4.1.2. Demographic Specification

Demographic characteristics are integrated into the model by making the intercept α_i household-specific (Lecocq and Robin, 2015): $\alpha_i^h = (\boldsymbol{\alpha\prime}_i)\boldsymbol{s}_h$ where $\boldsymbol{\alpha}_i$ is a vector of coefficients, and $\boldsymbol{s}_h$ represents socio-demographic variables. This method is known as the translating approach (Pollak and Wales, 1981) because it shifts the intercept value through the parameters (in $\boldsymbol{\alpha}_i$) associated to each characteristic (in $\boldsymbol{s}_h$). Ultimately, this allows better accounting of households' heterogeneity.

Based on the results from subsection 3.3, we calibrate the model using the following demographic variables: labor market status, education level, ownership status, mortgage repayment status, region, dwelling type, dwelling size (in rooms), presence of elderly members, household size, region.[16] Household income is used to instrument total expenditures using the instrumental variable techniques to account for potential endogeneity (Lecocq and Robin, 2015), while car and fossil heating system ownership are included to account for zero expenditure shares on transportation and heating fuels as explained in the next subsection.

Once parameters are obtained on the total sample, we obtain groups' specific reactions to prices (Baker et al., 1989; Blundell et al., 1993) by computing elasticities for different subgroups (*e.g.*, based on energy poverty statuses). To do so, elasticities are first projected for each household using model's estimates, and then averaged to obtain subsample means. This process makes the choice of demographics $\boldsymbol{s}_h$ key into tuning the demand system to reflect energy poverty determinants when computing households' behaviors.

4.1.3. Zero expenditure and estimation strategy

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 errors. While the one-month survey period of the Household Budget Survey (HBS) is generally sufficient to capture consumption patterns, some low-volume consumers may not purchase transport fuels within the survey window. However, this issue is mitigated by the fact that we mostly ill-capture relatively small consumers who fuel-up their tank only once in a while (such a behavior increases the probability of not reporting transport fuel expenditure during a whole month). Moreover, these errors cancel out as soon as we observe a sufficiently large pool of individuals, as it is

[16] We include two flags (starting from 2008 and 2012) to control for methodological changes in the Household Budget Survey. Besides, we did not retain construction year as it directly enters the definition of hEP households.

the case in our sample.

Secondly, car ownership determines 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.[17] To address this issue, we assume the ownership decision is taken *ex-ante* and we employ a Heckman-type two-step procedure (Labandeira *et al.*, 2022). Indeed, without that correction, these zero expenditures might be misclassified as optimal corner solutions rather than the result of ex-ante decision-making or constraints.[18] To avoid so, we first estimate a Probit regression of the ownership status (binary) over an enriched set of demographic variables for the entire sample. The resulting Inverse Mill's Ratio[19] is then included as a correction term in the QUAIDS equations of w_i. We apply a similar approach for heating fuels, as some households do not heat with gas or oil (8% to 18%, depending on the year). In the end, we pool both ownership statuses into one (owners of both a vehicle and a fossil heating system), and apply the Heckman correction once. Consequently, the final model is estimated on households owning both a vehicle and a fossil-fuel heating system.[20]

4.2. Elasticity Results

This subsection presents the (Marshallian) own-price elasticities and budget elasticities (relative to total expenditures). Budget elasticities directly contribute to the uncompensated price elasticities by informing us about the magnitude of the income effect, which comes along with the substitution between goods in Marshallian elasticities.[21]

[17] 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.

[18] Note that when vehicle owners do not report any transport fuel expenditures, this is still considered as a utility-maximizing behavior in our model (*e.g.*, absence of consumption in the face of high prices).

[19] Its inclusion corrects for the selection bias as shown by Heckman (1979).

[20] Doing so, we restrict our sample by approximately 25%.

[21] We can disentangle these effects by looking at compensated/Hicksian price elasticities. In appendix, you can find in Table B.5 all compensated cross-price elasticities, and in Table B.4 all uncompensated cross-price elasticities. When comparing both tables, we see that necessities like electricity and heating are mostly substitution-driven: people adjust consumption directly to price changes with little income effect. Transport fuels shows mostly substitution but slightly higher than domestic energy, reflecting more flexibility. Finally, Food has a balanced mix of both effects, aligning with its role as a necessary but partially adjustable good.

Table 4.1: Elasticities and Model Fit – Full Population

Consumption	Price Elasticity	Budget Elasticity	R^2
Food	-0.38^{**} *[-0.65 ; -0.11]*	0.87^{***} *[0.84 ; 0.90]*	0.30
Transport	-0.24^{***} *[-0.35 ; -0.13]*	0.79^{***} *[0.73 ; 0.86]*	0.13
Electricity	-0.72^{***} *[-0.86 ; -0.58]*	0.27^{***} *[0.22 ; 0.33]*	0.35
Heating	-0.10^{**} *[-0.18 ; -0.02]*	0.35^{***} *[0.29 ; 0.41]*	0.22
Other	-0.83^{***} *[-0.91 ; -0.74]*	1.18^{***} *[1.17 ; 1.19]*	0.45

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

Note: Uncompensated price and budget elasticities with 95% confidence intervals.

Source: Authors' calculations based on QUAIDS estimation using HBS data.

In Table 4.1, 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 –0.24 and –0.1. These low values suggest limited short-run substitutability or behavioral flexibility in these domains, which is consistent with their status as necessities or infrastructure-constrained expenditures. By contrast, electricity shows a much higher elasticity of –0.72, which may seem surprising at first given it also represents a form of domestic energy. However, this likely reflects greater adjustability in usage (e.g. lighting, appliances), compared to heating which is more rigid in the short run. The food elasticity (–0.38) lies in a mid-range, while "other goods" display the highest elasticity (–0.83), as expected for a more heterogeneous and discretionary category.

These patterns align with recent empirical findings. 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. More importantly, the general ranking across categories we observe is in line with the literature. Finally, the particularly low elasticity for heating fuels we observe (–0.1) is at the bottom of the range found in the literature, suggesting very limited short-run substitutability or adaptation capacity in this domain in our sample.

In Table 4.1, we also report the budget elasticities across consumption categories. All of them are strictly positive and below or close to 1, indicating that the goods are normal and that expenditure shares remain relatively stable as income increases; except domestic energies (electricity and heating) that clearly emerges as necessities with low budget elasticities. The elasticity for other goods is the highest at 1.18, confirming its status as the most income-sensitive category, likely encompassing many luxury or non-essential items. This is followed by food (0.87) and transport (0.79), which are necessities, in line with their essential nature.

These results are consistent with findings in 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), very close to 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 flexible, luxury-type expenditures. This confirms the validity of our model and aligns well with international evidence.

Table 4.2: Uncompensated Price Elasticities by Group and Consumption Category

Group	n	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All Population	33,699	-0.40	-0.24	-0.72	-0.09	-0.82
Deciles 1–3	7,899	-0.56	-0.39	-0.70	-0.19	-0.87
Deciles 1–5	14,825	-0.51	-0.34	-0.71	-0.16	-0.85
Deciles 6–10	18,874	-0.30	-0.15	-0.72	-0.02	-0.80
hidden Energy Poor	1,111	-0.65	-0.48	-0.77	-0.19	-0.93
Energy Poor	3,427	-0.58	-0.36	-0.76	-0.18	-0.89
Dec. 1–5, non EP	10,297	-0.47	-0.32	-0.69	-0.15	-0.82

Source: Authors' calculations based on QUAIDS estimation using HBS data.

In table 4.2, we break down uncompensated price elasticities by group. First, we concentrate on the income dimension with the three first deciles (poor households), the five first deciles (bottom half of the income distribution, and cutoff for energy poverty statuses), 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 whose elasticity remains high for all income groups. Looking at energy poverty statuses, we observe a similar pattern with hidden energy poor (hEP) being more price-sensitive than energy poor. Both of them report higher price elasticities than the rest of the population in the bottom half of the income distribution (Dec. 1–5, non EP). 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 poor households to which they mainly belong), hEP are particularly price-sensitive despite being richer that EP. We show in section 5 that these strong reactions to price variation come along with a non-negligible welfare cost.

Table 4.3: Budget Elasticities by Group and Consumption Category

Group	*n*	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All Population	33,699	0.88	0.78	0.30	0.39	1.17
Deciles 1–3	7,899	0.95	0.86	0.29	0.44	1.23
Deciles 1–5	14,825	0.94	0.84	0.30	0.43	1.19
Deciles 6–10	18,874	0.83	0.73	0.31	0.36	1.15
hidden Energy Poor	1,111	0.98	0.93	0.30	0.44	1.24
Energy Poor	3,427	0.96	0.77	0.28	0.38	1.23
Dec. 1–5, non EP	10,297	0.93	0.85	0.30	0.45	1.17

Source: Authors' calculations based on QUAIDS estimation using HBS data.

We then compare the results obtained before with the ones of table 4.3 reporting budget elasticities by group. The gradients in price elasticities is not that clearly reproduced here. Though poorer households show slightly higher budget elasticities than richer ones (except for electricity), differences in budget elasticities for (h)EP compared to same-income population (Dec. 1–5 non EP) are not striking. Therefore, the trends obtained in the uncompensated price elasticities should not be the sole result of differences in budget elasticities. Indeed, looking at Table B.6 in the Appendix, we see that vulnerable groups (low income, (hidden) energy poor) show stronger substitution patterns as well.

5. Welfare Analysis of Carbon Pricing

To assess the distributional and welfare impacts of carbon pricing, we adopt the compensating variation (CV) metric, following the methodology established by King (1983). This approach allows us to account for non-homothetic preferences, heterogeneous price elasticities, and realistic income-dependent substitution patterns. Unlike raw tax burden metrics, the CV captures the full welfare cost of price changes. As such, it provides a money-metric measure of welfare loss that is sensitive to both behavioral responses and differences in marginal utility across households. This is especially critical when analyzing vulnerable groups such as the energy poor and hidden energy poor. Using this framework, we are able to produce a more nuanced and policy-relevant analysis of carbon pricing reforms.

Formally, the CV is defined as:

$$CV = E(\mathbf{p_1}, u_0) - E(\mathbf{p_0}, u_0) \tag{9}$$

with

$$E(\mathbf{p}, u) = a(\mathbf{p}) \cdot \exp\left(\frac{u \cdot b(\mathbf{p})}{1 - \lambda \cdot u}\right) \tag{10}$$

where $E(p, u)$ represents the expenditure function derived here from QUAIDS, $\mathbf{p_0}$ and $\mathbf{p_1}$ are the pre- and post-tax price vectors, and u_0 is the initial utility level. Intuitively, the CV tells us how much additional income a household would need after the tax to maintain the same level of well-being as before the policy change. By definition, the level of expenditure at initial price and utility level $E(\mathbf{p_0}, u_0)$ is equal to total expenditures prior carbon pricing m. In our case, m is also used to retrieve u_0 using the indirect utility function (see 11). Once we obtain u_0, we plug its value into the expenditure function along with the new price vector $\mathbf{p_1}$ to obtain $E(\mathbf{p_1}, u_0)$. CV is then given by $E(\mathbf{p_1}, u_0) - m$ and is strictly positive in the case of additional taxation like carbon pricing.

$$\log u_0(\mathbf{p}, m) = \frac{1}{b(\mathbf{p})}\left[\log\left(\frac{m}{a(\mathbf{p})}\right) + \lambda\left(\log\left(\frac{m}{a(\mathbf{p})}\right)\right)^2\right] \tag{11}$$

For our policy analysis, we draw from the up-coming EU-ETS 2 by simulating the impact of a €45 carbon price (valued at 2016 price-levels), which results in a 17% increase in heating fuel prices and a 9.2% increase in transport fuel prices.[22] As the QUAIDS framework allows

[22]The relative price increase allows us to simulate carbon pricing adaptive to inflation with a carbon price

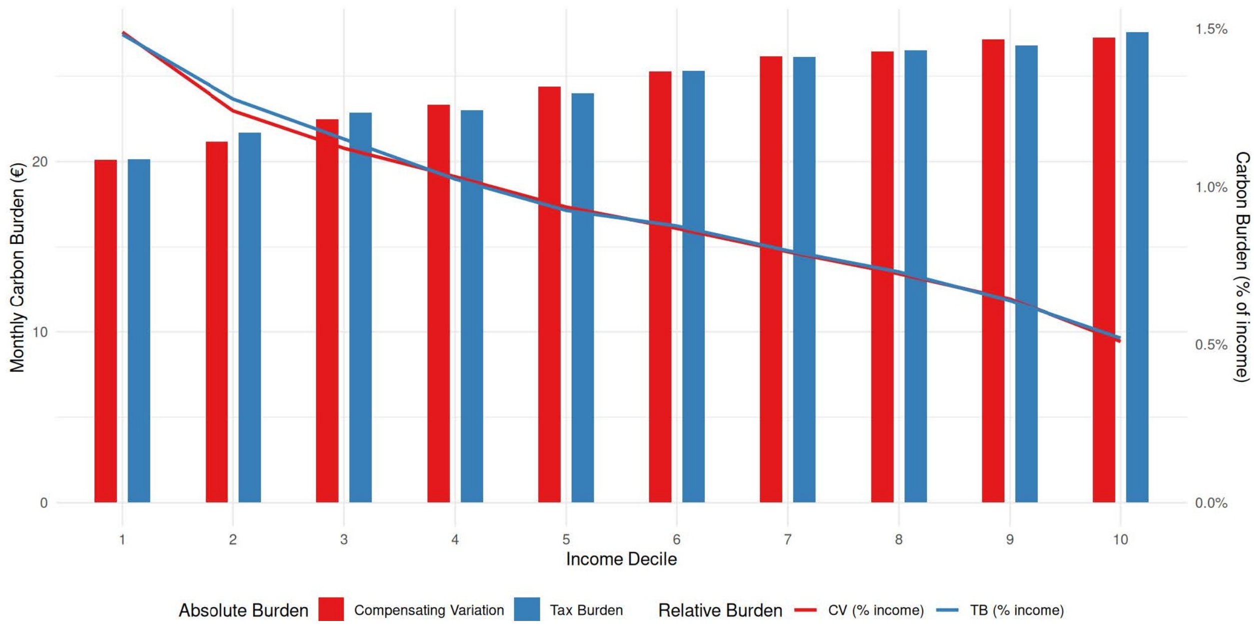


Figure 5.1: Tax Burden and Compensating Variation by Income Decile

us to compute household-specific welfare losses, capturing non-linear expenditure responses and income effects, we obtain individual CV that we compare with the computations of an arithmetic (non behavioral) tax burden.

First, we look at the comparison across the income distribution in Figure 5.1. We observe that both the tax burden and the compensating variation (CV) increase in absolute terms across income deciles, while exhibiting the usual regressive pattern when expressed relative to income. When comparing the tax burden with the CV across income groups, differences remain relatively limited, suggesting that in terms of aggregate monetary impact, both indicators yield similar patterns. Even though (substitution) behaviors adaptation could entail lower CV than TB on average, low price elasticities on heating and transport, coupled with moderate price increases, limit the behavioral effect encompassed in the CV measure.[23]

proportional to past price levels.

[23] With general population price elasticities of -0.24 and -0.10 for transport and heating fuels, the price increases of 9.2% and 17% result to average consumption drops of -2.21% and -1.7% respectively.

Table 5.1: Comparison of Compensating Variation and Tax Burden Across Groups

Group	CV (€/month)	TB (€/month)	CV (% Inc.)	TB (% Inc.)
All Population	–24.6	–24.6	–0.91	–0.91
Deciles 1–3	–21.4	–21.7	–1.26	–1.28
Deciles 1–5	–22.5	–22.5	–1.14	–1.14
Deciles 6–10	–26.4	–26.4	–0.71	–0.72
hidden Energy Poor	–18.6	–8.5	–1.10	–0.50
Energy Poor	–21.7	–30.3	–1.49	–1.98
Dec. 1 to 5, non-EP	–23.2	–21.4	–1.02	–0.93

Note: CV = Compensating Variation, TB = Tax Burden. Values in euros per month. Relative CV and TB are expressed as percentages of household disposable income.
Source: Authors' calculations based on QUAIDS simulations and policy scenario modelling.

However, when disaggregating the analysis along energy vulnerability dimensions, significant differences emerge between the magnitudes of TB and CV. Indeed, looking at Table 5.1, we observe large discrepancies between the two measures for (h)EP households. These differences are primarily driven by divergent expenditure profiles among EP and hEP households. EP households, who allocate a large share of their budget to energy, appear highly exposed in arithmetic tax burden terms, yet their CV is lower—a sign that behavioral adjustments (such as substitution or curtailment) partially mitigate welfare loss. In contrast, hEP households exhibit the opposite pattern: despite a relatively low tax burden due to their limited energy spending, their CV is notably higher. This discrepancy reflects a higher marginal utility of income and a constrained ability to substitute or absorb further energy price increases without utility loss.

These results underscore the analytical value of a welfare-based approach, which captures both non-linear income effects and heterogeneous behavioral responses. Relying solely on tax burden measures may thus underestimate the real incidence of carbon pricing for vulnerable groups, whereas compensating variation offers a more comprehensive metric of welfare impact. While EP households might appear as the biggest losers in the classical monetary framework, their loss is compensated by their ability to cope with higher energy prices. On the contrary, hEP households are already restraining on energy use and further price increases might impact them well beyond the sole monetary dimension. This results underpins the need to complement energy poverty metrics with the hidden energy poverty dimension, as this population might suffer proportionally more than their limited monetary loss from higher energy prices. Finally, enriching carbon pricing impact analyses with a focus on vulnerability profiles that go beyond income poverty allows to disentangle relevant horizontal distributive patterns that are otherwise neglected in vertical equity studies.

6. Discussion and Conclusion

This paper has explored the distributional implications of carbon pricing through a behavioral lens, with a particular focus on energy poor (EP) and hidden energy poor (hEP) households in Belgium. Leveraging a detailed household demand system estimation based on eleven years of household budget survey data, we have provided a welfare-based evaluation of the forthcoming EU-ETS 2 policy, disaggregated across income and energy vulnerability dimensions.

Traditional energy poverty metrics often fail to detect households that restrict their energy consumption below adequate levels due to financial constraints. Our analysis demonstrates that hEP households, though not visible in standard indicators, represent a substantial share of the vulnerable population—particularly within urban area—while EP households are more likely to be income poor and reside in less-densily populated areas. These distinct patterns underscore the importance of disaggregating energy poverty into its visible and hidden components. Logistic regression results confirm that Region, housing type, and heating systems are key differentiators between the two groups. Educational attainment and car ownership further stratify vulnerability, suggesting that energy poverty is embedded within broader socio-economic disadvantages.

Our demand estimates indicate that food, domestic energy and transport fuels are price inelastic, with transport and heating fuels showing the lowest responsiveness. Budget elasticities put electricity and heating as necessities, whereas food and transport have moderate income sensitivity. Lower-income and (hidden) energy poor households display higher price elasticities, particularly for food, transport, and heating fuels. The lower income of (h)EP households largely explains the differences in elasticities between them and other households. Nevertheless, hidden energy poor households exhibit greater sensitivity than energy poor households, despite having higher average incomes. These variations highlight the need to account for behavioral heterogeneity when evaluating carbon pricing effects on vulnerable populations.

Our results also emphasize the importance of moving beyond income-based metrics. While EP households face high tax burdens due to high energy expenditures, their welfare impact is comparably smaller. In contrast, hEP households, who appear less affected under arithmetic measures due to their low energy use, incur greater welfare losses. This divergence between tax burden and compensating variation highlights the limitations of conventional policy assessments and underscores the added value of a behavioral welfare approach.

These findings carry several policy implications. Carbon pricing must be accompanied by targeted compensation schemes that account not only for income, but also for vulnerability arising from housing conditions and behavioral constraints in energy use. Recognizing hidden energy poverty is particularly urgent: without intervention, these households may face welfare losses disproportionate to their observable energy consumption. Structural interventions such as building renovations and heating system upgrades are key to long-term resilience.

By bridging demand system estimation with energy poverty metrics, this paper contributes to the literature on the distributive effects of green taxation and introduces a novel approach for evaluating horizontal equity. Future work could refine vulnerability indicators, integrate more granular data on housing quality and energy needs, and simulate broader climate policy packages that combine carbon pricing with investment and redistribution. In doing so, it will be possible to craft climate policies that are not only environmentally efficient, but also just and politically acceptable.

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Appendix

A. Supplementary Figures

Source: Bilans régionaux (SPW DGO4, Bruxelles-Environnement, VITO) sur base des données de la CWaPE, Brugel et la VREG.

A partir de 2020, en l'absence des données des bilans régionaux, les données résultent d'hypothèses de Energie Commune, sur base des données de ELIA .

Figure .1: Historical electricity production from PV panels in Belgium

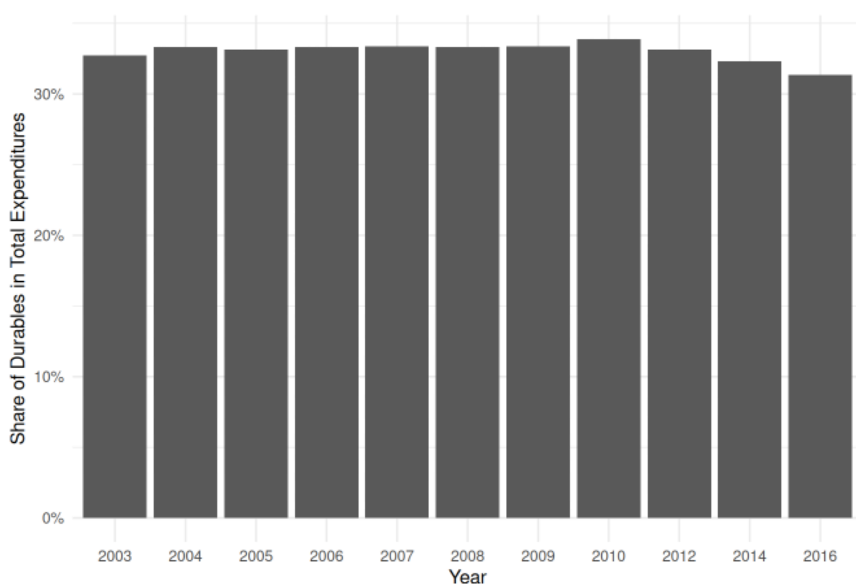

Figure .2: Evolution of Durables' Share in Total Expenditures

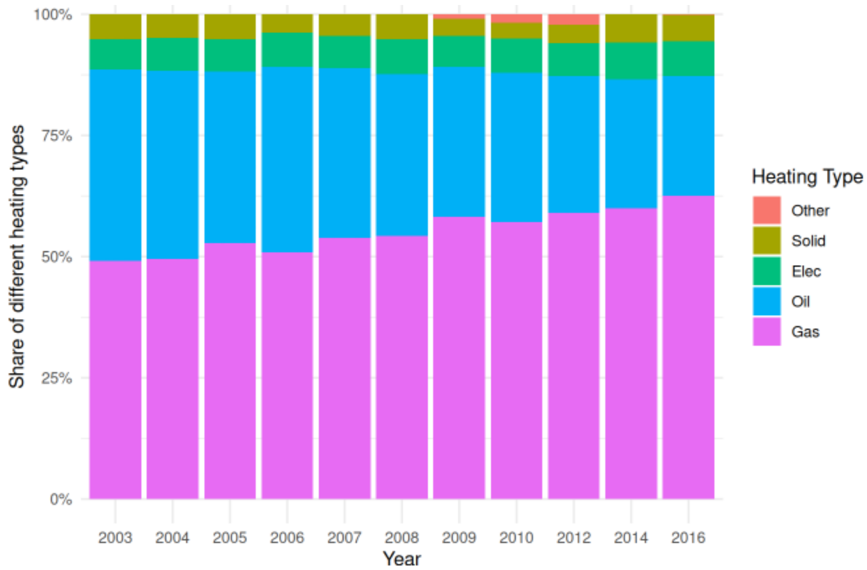

Figure .3: Evolution of Households Heating System Type

B. Supplementary Tables

Table .1: (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 .2: Correlation Between Rent, Energy, and Total Housing Costs

Variable Pair	**Correlation**	**95% CI**	**p-value**
Rent vs Energy Expenditure (absolute)	-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 .3: Household Socio-demographic Characteristics Across Categories of the Population

Characteristic	**All**	**D1–5**	**D1–3**	**EP**	**hEP**
Wage Earner Ref	62%	46%	38%	29%	39%
Education: No Education	7.2%	12%	15%	15%	14%
Education: Primary	13%	19%	21%	21%	20%
Education: Secondary	63%	59%	56%	55%	55%
Education: Tertiary	15%	8.0%	6.3%	6.7%	9.8%
Ownership: No	29%	41%	52%	62%	56%
Ownership: With Loan	36%	22%	16%	11%	14%
Ownership: Without Loan	34%	35%	31%	26%	28%
Number of Cars	1.04	0.89	0.78	0.69	0.66
Region: Brussels	10%	11%	13%	12%	26%
Region: Flanders	57%	52%	49%	43%	43%
Region: Wallonia	32%	35%	37%	44%	30%
House Type: Detached	53%	46%	41%	44%	29%
House Type: Flat	25%	30%	35%	36%	50%
House Type: Terraced	21%	23%	23%	19%	20%
Construction Year: After 1990	16%	11%	9.5%	7.5%	–
Construction Year: Before 1970	55%	59%	61%	61%	68%
Construction Year: 1970–1990	27%	28%	29%	31%	31%
Number of Rooms	5.94	5.72	5.55	5.50	5.29
Heating: Electric	6.9%	6.7%	6.4%	5.2%	8.2%
Heating: Gas	55%	55%	57%	51%	49%
Heating: Oil	32%	31%	29%	39%	28%
Heating: Other	0.5%	0.5%	0.5%	0.2%	0.7%
Heating: Solid	4.6%	5.6%	6.4%	4.5%	12.9%
HH Type: Couple Active	34%	25%	23%	17%	22%
HH Type: Couple Retired	17%	18%	18%	14%	14%
HH Type: Many Adults	12%	13%	12%	5.6%	6.9%
HH Type: Single Active	22%	25%	28%	37%	35%
HH Type: Single Retired	13%	17%	17%	25%	20%
Number of Children	56%	58%	60%	35%	49%
Older Person Present	32%	38%	38%	42%	36%
At Risk of Poverty (AROP)	12%	24%	41%	47%	37%
Single Parent Family	5.8%	8.8%	11%	10%	10%

Note: Percentages represent the share of households in each subgroup. Numeric variables (*e.g.*, rooms/cars) are presented as means.
Source: Authors' calculations using Belgian HBS data (2003–2016).

Table .4: Uncompensated Cross-Price Elasticities – Full Population

	Food	**Transport**	**Electricity**	**Heating**	**Other**
Food	-0.38^{**}	-0.29^{**}	0.45^{**}	0.14^{*}	-0.21^{***}
Transport	-0.08^{***}	-0.24^{***}	-0.22^{***}	0.14^{***}	-0.04^{***}
Electricity	0.05^{*}	-0.16^{***}	-0.72^{***}	-0.03	-0.02^{**}
Heating	0.01	0.11^{***}	-0.04	-0.10^{**}	-0.08^{***}
Other	-0.47^{***}	-0.22^{**}	0.26	-0.49^{***}	-0.83^{***}

Note: Own-price elasticities are on the diagonal. Stars indicate significance.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' calculations based on QUAIDS estimation using HBS data for Belgium.
Most cross-price effects are small but significant.
The positive cross-elasticity between Food and Electricity and between Transport and Heating suggests some substitutability or shared budget constraints.

Table .5: Compensated Cross-Price Elasticities – Full Population

	Food	**Transport**	**Electricity**	**Heating**	**Other**
Food	-0.19	-0.12	0.50^{***}	0.22^{***}	0.05
Transport	-0.03	-0.20^{***}	-0.20^{***}	0.16^{***}	0.03^{***}
Electricity	0.08^{***}	-0.13^{***}	-0.71^{***}	-0.02	0.03^{***}
Heating	0.06^{***}	0.16^{***}	-0.03	-0.08^{*}	-0.02^{**}
Other	0.08	0.29^{***}	0.43^{***}	-0.28^{***}	-0.09^{**}

Note: Own-price elasticities are on the diagonal. Stars indicate statistical significance.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' calculations based on QUAIDS estimation using HBS data for Belgium.
Electricity has strong substitution effects: it substitutes positively with food and other, and negatively with transport.
Heating substitutes with food and transport, and is complementary with other goods.
Own-price elasticities are still inelastic and mostly significant.

Table .6: Compensated Own-Price Elasticities by Group

Group	**Food**	**Transport**	**Electricity**	**Heating**	**Other**
All (full population)	-0.19	-0.19	-0.70	-0.06	-0.08
Deciles 1 to 3	-0.32	-0.32	-0.70	-0.17	-0.18
Deciles 1 to 5	-0.28	-0.28	-0.70	-0.14	-0.14
Deciles 6 to 10	-0.12	-0.12	-0.71	0.00	-0.04
Hidden Energy Poor (hEP)	-0.39	-0.51	-0.77	-0.18	-0.25
Energy Poor (EP)	-0.34	-0.29	-0.76	-0.15	-0.20
Dec. 1 to 5, Not (h)EP	-0.25	-0.26	-0.68	-0.13	-0.11

Note: Table reports compensated (Hicksian) own-price elasticities, which reflect substitution effects. More negative values indicate stronger substitution response to price changes. *Source:* Authors' calculations based on QUAIDS model using Belgian HBS data.