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

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Abstract

This paper examines how carbon pricing affects the welfare of energy vulnerable households in Belgium, distinguishing between energy poor (EP) households, who devote a large share of income to energy, and hidden energy poor (hEP) households, who severely restrict their consumption. Using eleven cross-sections of the Belgian Household Budget Survey (2003–2016), we characterise both groups through logistic regressions and estimate a demographically specified Quadratic Almost Ideal Demand System, developing a two-stage residual inclusion procedure to address the endogeneity of energy vulnerability status. The resulting group-specific price and budget elasticities are used to simulate the welfare impact of a carbon price on heating and transport fuels calibrated to the forthcoming EU ETS 2 (2028). Behavioural adjustments are heterogeneous: lower-income and energy vulnerable households exhibit higher fuel price elasticities than wealthier groups, with hEP households responding most strongly to price increases. The welfare analysis reveals that EP households face substantial carbon costs but comparatively modest welfare losses, whereas hEP households bear a disproportionate relative welfare burden despite their low expenditure-based exposure. These findings highlight horizontal equity concerns missed by income-based metrics and call for integrating energy vulnerability profiles and welfare measures into carbon pricing design.

Keywords: *Carbon Pricing, Energy Vulnerability, Demand System Estimation, Welfare Analysis*

JEL Classification: *D12, D63, H23, H31, Q41, Q48*

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1 Introduction

To meet its carbon-neutrality objectives, the European Union will introduce a new Emissions Trading Scheme (ETS 2) in 2028 encompassing the buildings and road-transport sectors. Together, these sectors accounted for 39% of EU CO_2 emissions in 2023 (European Environment Agency, 2025). 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 vulnerability—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 vulnerable in 2022 (Fondation Roi Baudouin, 2024). Identifying which households are affected, understanding the determinants of energy vulnerability, and anticipating their behavioural responses to carbon pricing are hence 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: Douenne (2020) shows that substantial variation in net burdens persists within income groups, even when carbon taxes are combined with targeted cash transfers; 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.[1] 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 of these studies goes beyond the classical expenditure-based energy poverty indicators 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 vulnerability 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) to detect households at risk of "hidden energy poverty" (severely

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

restricting 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[2] differ not only from the general population but also from households with similar income levels. These insights are formalised 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. 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 vulnerability groups. The aggregate results support the credibility of our demand system estimates, 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, while conventionally defined energy poor households respond no more strongly than the similar-income population, hidden energy poor households exhibit markedly higher price elasticities.

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.

Our contribution is threefold. First, we augment a demographic QUAIDS demand system with a two-stage residual inclusion procedure that controls for the endogeneity of energy vulnerability statuses. To our knowledge, this is the first application of such an approach within a demand system framework, allowing a more accurate estimation of price responses among essentially different energy vulnerable groups. Second, we adapt and extend the hidden energy poverty indicator of Meyer et al. (2018) to better capture energy underconsumption, and incorporate it alongside conventional measures into a demand system framework. This yields new empirical evidence on how demand elasticities and carbon price responses vary across energy vulnerability profiles, uncovering distributional patterns that

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

would be overlooked by analyses focusing solely on income or aggregate populations. Third, our policy analysis across the income and energy vulnerability dimensions reveals a misalignment between monetary exposure and welfare cost that carries direct implications for the design of equitable compensation schemes.

For the entirety of this research, we use 11 cross-sections of the Belgian Household Budget Survey (HBS), covering the years 2003 to 2010 annually and 2012 to 2016 biennially, with each cross-section surveying between 4,000 and 6,000 households.[3] 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, 2026), 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).

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. Section 5 concludes and draws out the main implications for policy.

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 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. Boardman 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

[3] 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).

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 (Burlinson et al., 2018)—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: 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.[4] 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), and 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 rela-

[4] 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).

tive to a minimum standard of living, (iii) multidimensional composite indicators, and (iv) indicators based on the modelling of households' required energy consumption. Subjective indicators are excluded from our analysis due to data constraints[5] 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. 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. 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 measures rather than a single composite index; in line with the approach adopted in the Belgian and French contexts (Meyer et al., 2018; ONPE & ADEME, 2025).

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, as they 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 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 data required for demand system estimation. Despite this change, the indicators remain robust and internally consistent in identifying both forms of energy vulnerability. As shown in Table C.1 in the Appendix, the magnitude of (h)EP prevalence follows the official Belgian statistics published by the *Fondation Roi Baudouin* (2024). 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 A.

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

2.2.1 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.[6,7] 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.[8] 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 reference expenditure implied by the EP threshold.

2.2.2 Indicator for Hidden Energy Poverty

Hidden energy poor households are households 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 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.[9] 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.[10]

[6] 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.

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

[8] Appendix A 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.

[9] 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.

[10] Appendix A 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.

The resulting threshold, which builds on the original M/2 logic, serves as a proxy for basic energy needs[11] 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.

2.3 Descriptive Statistics

Table 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).

We now analyse the extent and characteristics of (hidden) energy poverty in Belgium. As shown in Table 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

[11] 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.

by approximately one third, underlining the importance of considering both groups.[12] 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.

Both EP and hEP households exhibit deeper socio-economic vulnerability than the rest of the population.[13] As Table C.3 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,[14] tend to live in smaller dwellings with fewer rooms, and a majority reside in old buildings. Demographic composition also differs: both EP and hEP households are more likely to consist of single adults, either active or retired, are more often single-parent families, and contain fewer children.

While many of these characteristics are shared, the two groups diverge along several dimensions that are likely confounded in the descriptive comparisons above. Regional patterns differ markedly: 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. Because descriptive patterns alone cannot isolate the independent contribution of each factor, we complement these descriptive insights with a formal econometric study.

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

To formally identify the socio-demographic drivers of (hidden) energy poverty, we estimate two logit models, one for each energy vulnerability status. These regressions allow us to quantify how each covariate is associated with the odds of being (h)EP and serve a dual purpose: they characterise the distinct profiles of EP and hEP households, and they inform the selection of demographic controls for the demand system estimation.

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.

[12] 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.

[13] Appendix A.3 documents the corresponding patterns using alternative (h)EP metrics.

[14] 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 C.2, the correlation between rent and energy expenditure is weakly negative, providing no strong evidence of such substitution.

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, $(h)EP_i^*$):

$$(h)EP_i^* = \boldsymbol{x}_i'\beta + \varepsilon_i, \tag{2.4.1}$$

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.[15]

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[16]. The hEP model exhibits lower discriminatory power, which is expected given the lower prevalence and greater heterogeneity of the phenomenon. Hidden energy poverty combines behavioural and structural underconsumption patterns that are less systematically predicted by standard socio-demographic covariates than conventional energy poverty. As reported in Appendix A.4, a complementary log-log specification following Legendre and Ricci (2015) yielded qualitatively similar results.[17]

[15] 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 $\widehat{(h)EP_i} = \Lambda(\boldsymbol{x_i}'\hat{\beta})$.

[16] We also computed variance inflation factors, which showed no evidence of multicollinearity, see Appendix A.4.

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

Table 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%	
AUC	0.78		0.74	

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).

Table 2 reveals both shared and distinct determinants of each of the energy vulnerability statuses.[18] While several covariates are statistically significant in both models, the hEP estimates are more often

[18] Appendix A.4 reports and discusses similar econometric results using alternative (h)EP metrics. Appendix C.2 reports the coefficients of each model when going from the reduced form to the complete one; underlining the importance of dwelling-related variables.

imprecise, consistent with the weaker model fit discussed above. The regressions highlight the three key dimensions that differentiate the two forms of deprivation: heating technology, dwelling type, and region. EP is significantly more prevalent among households relying on oil-based heating, among those living in detached houses, and more prevalent in Wallonia. By contrast, hEP is significantly more prevalent among households relying on solid-fuel heating systems or living in flats, and is more common in Brussels. Some associations change sign relative to the descriptive patterns. For instance, the number of children and the presence of retired household members are negatively associated with both forms of energy vulnerability once other covariates are controlled for. These sign reversals likely reflect confounding in the unconditional comparisons rather than a direct causal link between these variables and energy poverty, and we interpret them with caution.

Our econometric analysis yields two inputs for the behavioural model: the set of significant covariates, which enter the demographic specification of the demand system, and the logistic framework itself, which is adapted to address the endogenous nature of an estimation using (hidden) energy poverty statuses. Both inputs allow for a more precise identification of energy consumption patterns and price responses to carbon pricing.

3 Demand System Estimation

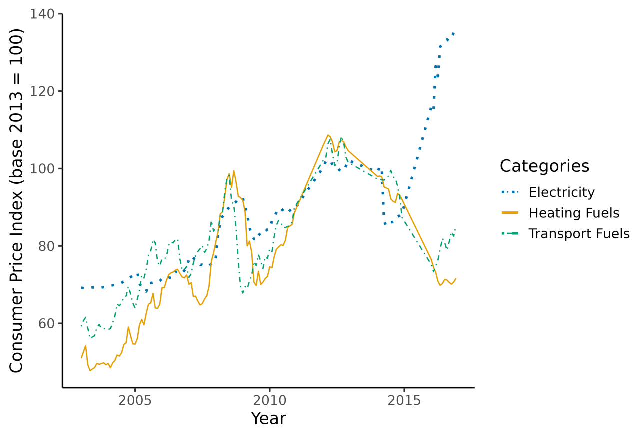
In this section, we estimate a demographic demand system to obtain price and budget elasticities of household energy consumption. We first present the general specification, then describe how (hidden) energy poverty statuses are incorporated and how their endogeneity is addressed. The resulting elasticities are reported for the overall population and disaggregated by income group and energy vulnerability status.

3.1 Price and Expenditure Patterns

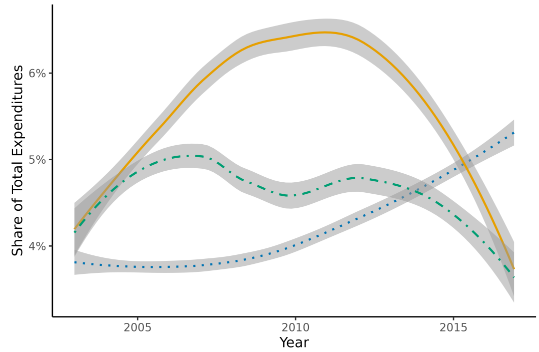
Identifying price elasticities reliably requires sufficient price variation over time. Figure 1a illustrates the evolution of consumer prices for energy-related goods, indexed to 2013 price levels. These prices exhibit substantial volatility over the 2003–2016 period, which strengthens the identification of price elasticities for these categories. Figure 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 1: Descriptive Figures for Energy Goods (2003-2016)

(a) Price Variation



(b) Evolution of Expenditure Shares

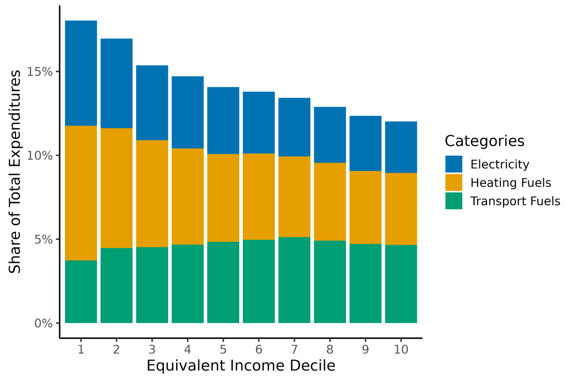


Notes: Smoothed trends across the population. The area in grey is the 95% confidence interval.

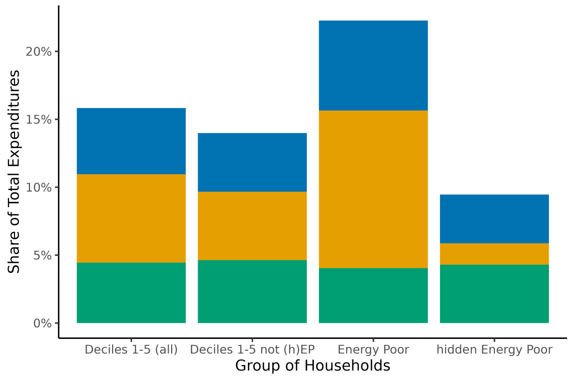
Source: Statbel (2026) and HBS data for Belgium (2003–2016).

Figure 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 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: Household Expenditure Shares by Income and Vulnerability Group



(a) Expenditure Shares by Income Decile



(b) Expenditure Shares by Household Groups

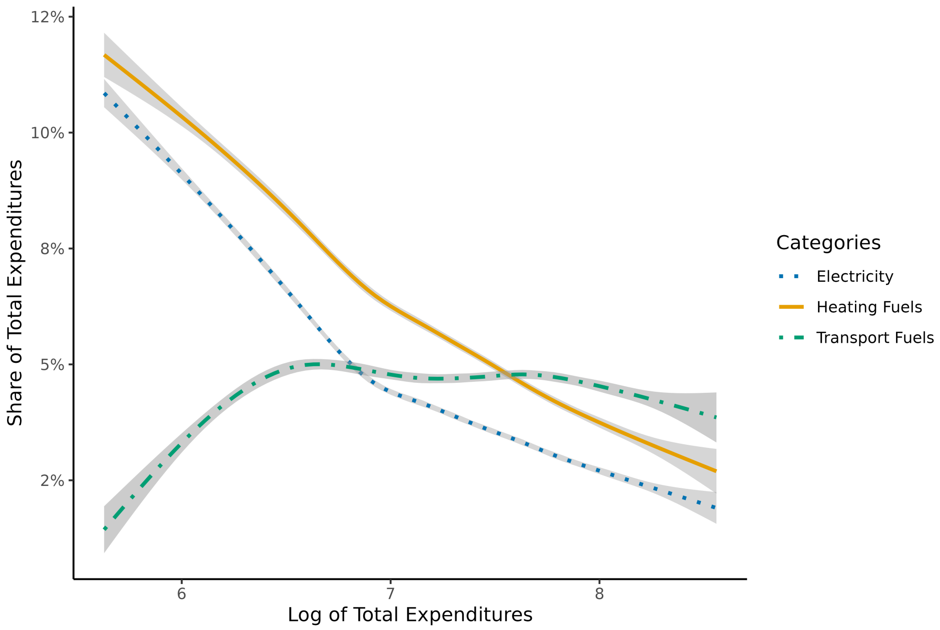
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

3.2 Specification of the Demand System

3.2.1 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

Figure 3: Engel curves for energy goods



Notes: In demand system estimation, income is approximated by total expenditures, reflecting total budget allocation. The area in grey is the 95% confidence interval.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

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 expenditures shares and budget, commonly referred to as Engel curves. In Figure 3, these are displayed for energy goods in a non-parametric form, reflecting the need for a quadratic specification. The model satisfies fundamental properties derived from neoclassical demand theory[19] and is flexible enough to integrate demographic variables, which allows key determinants of energy consumption to enter the system directly. It is defined as follows:

$$w_i^h = \alpha_i^h + \sum_{j=1}^{I} \gamma_{ij} \ln p_j + \beta_i \ln \frac{m}{a(\boldsymbol{p})} + \frac{\lambda_i}{b(\boldsymbol{p})} \ln \left(\frac{m}{a(\boldsymbol{p})} \right)^2 + u_i \tag{3.2.1}$$

where w_i^h is the share of total expenditures spent on good i by household h, α_i^h is the intercept, p_j is the price index of goods bundle j, and m are 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 price aggregators.[20] We define each term below.

[19] 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.

[20] 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.

Dependent variable. The expenditure share w_i^h is constructed over five consumption bundles: food, transport fuels (gasoline and diesel), electricity, heating fuels (natural gas, liquid and solid fuels), and a residual category "other"[21] regrouping remaining non-durable goods (we exclude investments in durables).[22] Food and electricity are included alongside fossil fuels because of their specific substitution patterns with domestic energy: the "heat or eat" dilemma points at a direct trade-off between heating and food expenditures (Bhattacharya et al., 2003; Zabel & Hendlin, 2025), while substitution between electricity and heating may arise when households switch from fossil-powered central heating to on-demand electric appliances. Including these categories also improves convergence and identification by adding signal through large, reliably observed budget shares and additional relative-price variation, while reducing the residual "other" aggregate that can otherwise absorb misspecification biases arising from failing weak separability conditions.[23]

Demographic heterogeneity. 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.[24]

Price effects. 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 bundles described above.

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

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

[22] We do not use data on durable-goods expenditures, as these reflect long-term investment decisions rather than day-to-day consumption. Nevertheless, we document the stability of durable expenditures over time in Figure D.1 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 D.2, which shows a moderate substitution from heating oil to natural gas.

[23] Aggregating a broad range of non-durable goods requires assuming weak separability between the explicitly modelled categories and the grouped items. Extracting major specific categories like food and electricity mitigates the risk of this condition failing by explicitly modelling their distinct cross-price dynamics.

[24] 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, a status later used to report group-specific elasticities.

$$\ln a(\boldsymbol{p}) = \alpha_0 + \sum_i \alpha_i^h \ln p_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j \tag{3.2.2}$$

Quadratic extension. The 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 (which is relevant to fit our data, see Figure 3). The price aggregator is defined as $b(\boldsymbol{p}) = \prod p_i^{\beta_i}$.

Estimation and elasticities. The parameter estimates are obtained by fitting the share equations (3.2.1) jointly as a nonlinear system.[25] After estimation, budget and price elasticities are obtained by log-differentiation of w_i^h with respect to total expenditure and prices. We first obtain μ_i and μ_{ij}:

$$\mu_i = \frac{\partial w_i^h}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})} \ln \frac{m}{a(\boldsymbol{p})} \tag{3.2.3}$$

$$\mu_{ij} = \frac{\partial w_i^h}{\partial \ln p_j} = \gamma_{ij} - \mu_i \left(\alpha_j + \sum_k \gamma_{kj} \ln p_k \right) - \frac{\lambda_i \beta_j}{b(\boldsymbol{p})} \left(\ln \frac{m}{a(\boldsymbol{p})} \right)^2 \tag{3.2.4}$$

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

$$\eta_i = 1 + \frac{\mu_i}{w_i^h} \tag{3.2.5}$$

$$\theta_{ij} = -\delta_{ij} + \frac{\mu_{ij}}{w_i^h} \tag{3.2.6}$$

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).

Group-specific elasticities are obtained following Baker et al. (1989) and Blundell et al. (1993) by evaluating equations 3.2.5 and 3.2.6 at the average values of prices, demographic variables, and total expenditures for each group. Because α_i^h enters the price index $a(\boldsymbol{p})$ directly, the demographic specification allows energy vulnerability statuses to shift households' estimated behavioural responses, which is the mechanism through which our demand system produces group-specific elasticities.

3.2.2 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

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

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 Section 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.[26] The first-stage regression is:

$$(h)EP_i = \alpha + \gamma\,\widehat{(h)EP}_i + controls + \varepsilon_i \tag{3.2.7}$$

where $(h)EP_i$ is the observed individual status and $\widehat{(h)EP}_i$ is obtained from equation 2.4.1. 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 3.2.1), 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) show that the two-stage predictor substitution (2SPS) might lead to inconsistent results and that 2SRI should be preferred.[27]

3.2.3 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 may 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 and are therefore recorded as non-consumers. The resulting measurement error is likely limited in magnitude, however, as the households most likely to be missed are infrequent, small-scale purchasers whose absence from the data has a modest effect on estimated expenditure shares.

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.[28] 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.[29] To address this issue, we

[26] Doing so, we construct our instrument as a linear prediction of exogenous parameters, using the determinants of (h)EP already identified in Section 2. As detailed in Appendix B, the instrument $\widehat{(h)EP}_i$ is generated from an augmented first-stage model that includes household income and covariate interactions. These variables provide exogenous variation to identify the vulnerability-status effects, as they are explicitly excluded from the second-stage QUAIDS demographic controls.

[27] 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.

[28] 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.

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

assume the ownership decision is taken *ex-ante* and we employ a Heckman-type two-step procedure in the spirit of West and Williams (2004) and 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-fuel 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).

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 C.4).

Table 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 spanning survey waves from 2003 to 2016).

Aggregate price elasticities. In Table 3, all consumption categories are price inelastic, with elasticities below one in absolute value. Transport and heating fuels display the lowest price responsiveness (–0.22 and –0.16, respectively), consistent with their necessity status. By contrast, electricity exhibits a notably higher elasticity (–0.66) compared to heating, which is more rigid in the short run. Food (–0.46) lies in the mid-range, while "other goods" display the highest elasticity (–0.77), as expected for a heterogeneous category that includes more price-elastic items. These estimates are consistent with the broader empirical literature. Our price elasticities are close to the short-run estimates reported in the meta-analysis of Labandeira et al. (2017), and comparable to those obtained with similar demand system approaches: Douenne (2020) finds uncompensated elasticities of –0.45 for transport and –0.2 for housing energies in France; Semet (2024) reports –0.3 for food and –0.2 for home energy; and our electricity elasticity is close to those in Labandeira et al. (2022) for Mexico (–0.67 to –0.71) and Nikodinoska and Schröder (2016) for Germany (–0.81).[30] The low elasticity for heating fuels (–0.16) suggests very limited substitutability or adaptation capacity for heating consumption in the Belgian context.

Aggregate budget elasticities. The budget elasticities visible in Table 3 are strictly positive and close to one for most categories, indicating that expenditure shares remain relatively stable as budgets expand. The exceptions are domestic energies (electricity and heating), which clearly emerge as necessities with smaller budget elasticities, and "other goods" (1.11), which is the most income-sensitive category. These estimates display a classical Engel pattern and are broadly in line with comparable studies.[31]

Table 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 (h)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).

Price elasticities by group. Table 4 disaggregates uncompensated price elasticities by income group and energy vulnerability status. The upper panel focuses on the income dimension, distinguishing the three lowest deciles (where most (h)EP households are found), deciles 4 and 5 (completing the bottom half of the distribution, i.e., the population at risk of energy vulnerability), and the upper half (deciles 6 to 10). A clear gradient emerges: lower-income households exhibit stronger price responses, except for electricity and "other goods" for which elasticities remain similar across income groups.

The lower panel reveals the central finding of this section. Hidden energy poor households are roughly

[30] The demand system methodology appears to consistently yield higher electricity price elasticities (in absolute terms) than other estimation methods (Labandeira et al., 2017).

[31] For instance, Semet (2024) reports a budget elasticity of 0.8 for food; Douenne (2020) finds values around 0.5 for housing energy; Labandeira et al. (2022) reports 0.27 for electricity; and Nikodinoska and Schröder (2016) reports 0.5 for electricity and 0.8 for transport fuels.

twice as sensitive to domestic energy price variations as other categories. For food and transport fuels, both EP and hEP households show higher price elasticities than the rest of the population. Income appears as the main factor explaining the difference between EP households and the general population: their elasticities are close to those of households at similar income levels. By contrast, hEP households are markedly more responsive to domestic energy prices despite being slightly richer on average than EP households. This finding is central to understanding their underconsumption status: it suggests that these households react to price increases by cutting back on heating and electricity rather than on other necessities such as food or transport fuels, pointing to a strong and specific restriction pattern in domestic energy consumption.

Table 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).

Budget elasticities by group. Table 5 reports budget elasticities by group. Poorer households show slightly higher budget elasticities than richer ones (except for electricity), but the income gradient is less pronounced than for price elasticities. Differences between (h)EP households and the similar-income population (deciles 1–5, non (h)EP) are modest, except for heating: EP households display lower budget elasticities for domestic energy than hEP households, particularly for heating fuels. Yet, the patterns observed in the uncompensated price elasticities are not the sole result of differences in budget elasticities. Indeed, looking at Table C.8 in the Appendix, we see that all groups also exhibit significant substitution patterns.

Overall, despite sharing many characteristics with income poor households, EP and hEP households exhibit distinct energy consumption patterns. EP households are constrained by high domestic energy expenditure and show limited adaptation to price and budget variations. By contrast, hEP households severely underconsume energy and react strongly to both price and budget changes, particularly for domestic energy goods. These distinct behavioural patterns make distinguishing the two groups essential for the policy simulation that follows.

4 Analysis of Carbon Pricing Impact

4.1 Monetary Welfare Approach

In this policy analysis, we simulate the effect of a carbon price on transport and heating fuels (€180/tCO_2 expressed at 2016 HBS price levels), assuming full pass-through to consumer prices. This corresponds to a 68% increase in heating fuel prices and a 37% increase in transport fuel prices.[32] 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 is defined as $TB = \Delta p \times Q_1$, where Q_1 denotes post-reform quantities,[33] and $\Delta p = (p_1 - p_0)$ the corresponding price increase due to carbon pricing. The Equivalent Variation (EV) is defined following King (1983):

$$EV = m - E(\mathbf{p_0}, u_1) \tag{4.1.1}$$

with the underlying QUAIDS expenditure function:

$$E(\mathbf{p_0}, u_1) = a(\mathbf{p_0}) \cdot \exp\left(\frac{u_1 \cdot b(\mathbf{p_0})}{1 - \lambda(\mathbf{p_0}) \cdot u_1}\right) \tag{4.1.2}$$

and the indirect utility function:

$$\log u_1(\mathbf{p_1}, m) = \frac{1}{b(\mathbf{p_1})}\left[\log\left(\frac{m}{a(\mathbf{p_1})}\right) + \lambda(\mathbf{p_1})\left(\log\left(\frac{m}{a(\mathbf{p_1})}\right)\right)^2\right] \tag{4.1.3}$$

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 3.2.1, 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 4.1.3, plug it into equation 4.1.2 to obtain $E(\mathbf{p_0}, u_1)$, and then compute EV using equation 4.1.1. With our sign convention, the EV is reported as a positive welfare loss under a price increase.[34]

Intuitively, TB is the extra amount paid for carbon pricing based on after-tax fuel quantities, abstracting from utility losses and the cost of substituting toward other goods. 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, and includes the welfare cost of adapting to new prices. In that way, 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

[32] Using relative price changes allows us to simulate carbon pricing consistently over time, with the carbon price scaled to past price levels.
[33] Q_1 are model-predicted quantities obtained using the behaviours estimated in the previous section.
[34] We could analogously report the compensating variation $CV = E(\mathbf{p_1}, u_0) - m$, which takes as arguments post-tax prices and pre-tax utility; we computed the CV and obtained similar results. 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.

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.

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 relative 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.[35]

4.2 Results of the Policy Analysis

First, we compare outcomes across the income distribution in Figure 4. 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. As a benchmark, under a uniform lump-sum redistribution of all revenues, lower-income households would be net winners on average as they contribute less in absolute terms than the per-household transfer they would receive. 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[36] and does not vary substantially across the income distribution.[37]

Second, we disaggregate the analysis by energy vulnerability status. In addition to the TB and the EV, we report in Table 6 the deadweight loss ($DWL = EV - TB$) and the average excess burden ($AEB = 100 \cdot DWL/TB$). These measures quantify the efficiency cost of carbon pricing in absolute and relative terms, and relate to the concept of the marginal cost of public funds (except that our AEB measure is computed at the average rather than the marginal level).

[35] For instance, see Berry (2019) on whether revenue-recycling policies can address energy poverty. Regarding policy responses more broadly, Makridou et al. (2024) emphasise that addressing energy vulnerability requires a mix of complementary policy instruments reflecting its multidimensional nature, rather than a one-size-fits-all approach.

[36] 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.

[37] 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 4: Tax Burden and Equivalent Variation by Income Decile

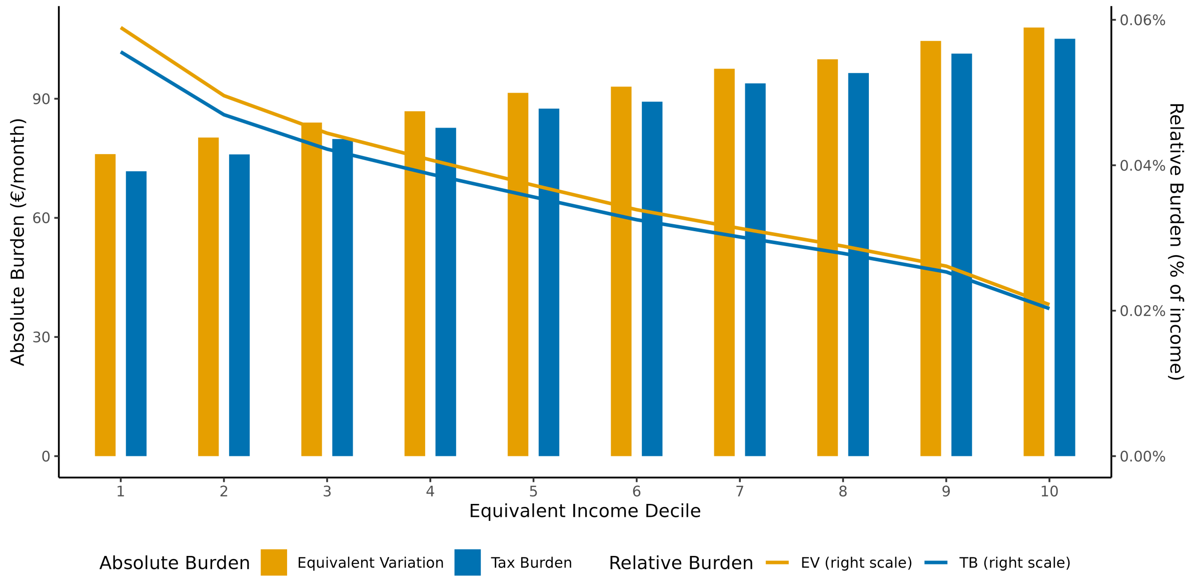


Table 6: Comparison of Equivalent Variation and Tax Burden Across Groups

	€/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. The Deadweight Loss (DWL) measures the efficiency loss from the tax beyond the revenue it raises and the Average Excess Burden is the DWL per euro of tax revenue. Monetary values are in constant 2016 euros per household per month.
Source: Authors' calculations based on HBS data for Belgium (2003–2016).

The results reveal 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 this DWL is expressed relative to the TB, the resulting AEB is moderate: the welfare cost of raising one euro of carbon tax revenue from EP households is only 4.5 cents above the revenue collected. This suggests that the efficiency cost of taxing their energy consumption remains contained and may leave room for compensating them at a moderate societal cost. The picture for hEP households is markedly different. Because they spend little on energy, their TB and EV are lower in absolute terms, and their DWL is smaller than that of EP households. Their AEB, however, is roughly twice the population average, and collecting revenues from a group with such restricted expenditure incurs a disproportionately high welfare cost per euro raised. Hence, the group least visible in the tax base is the group whose consumption is most disturbed by the policy. The misalignment between expenditure-based exposure and relative welfare cost across the two groups underscores the need for differentiated policy responses.

5 Conclusion

This paper has examined the distributional and welfare effects of carbon pricing on heating and transport fuels in Belgium. We estimated a demographically specified QUAIDS demand system with a two-stage residual inclusion treatment of endogenous energy vulnerability statuses. This approach allowed both behavioural responses and welfare impacts to be assessed separately for energy poverty (EP, households overspending on domestic energy) and hidden energy poverty (hEP, households restricting their domestic energy consumption). Three findings stand out. First, hidden energy poverty captures a substantial share of energy vulnerable households that conventional expenditure-based indicators miss, roughly one third more than classical energy poverty alone. Second, hEP households exhibit markedly higher price elasticities for domestic energy than other groups, including similar-income or EP ones. Third, a welfare-based assessment reveals that hEP households bear a disproportionate welfare burden relative to their low tax exposure, while EP households experience lower relative welfare losses compared to their high nominal carbon cost.

The policy implications differ across the two groups. For EP households, the welfare cost of raising one euro of carbon tax revenue remains moderate. This indicates that targeted transfers could offset their welfare losses at a relatively limited social cost, making direct compensation a viable instrument. However, their strong dependence on fossil fuels points to a degree of lock-in into carbon-intensive consumption patterns, likely sustained by financial constraints that limit investment in cleaner durables or home retrofits. Subsidies and other accompanying measures, such as easier access to credit or government-guaranteed loans for energy-efficiency investments, appear particularly relevant for this group. For hEP households, the policy challenge is different: their restricted energy use leaves little room for further adjustment without reducing heating and electricity consumption below adequate levels. Hence, additional price increases may generate relative welfare losses substantially larger than suggested by their tax burden. This discrepancy illustrates the value of welfare-based incidence analysis, which reveals vulnerabilities that standard measures understate when households self-restrict their consumption. More broadly, it underscores the need to complement conventional energy poverty indicators with hidden energy poverty metrics, with direct implications for the Social Climate Fund and similar compensation instruments accompanying ETS 2. An equitable allocation should incorporate energy vulnerability profiles and take welfare losses into account, rather than rely on income or observed energy expenditure alone. This concern has only grown since energy vulnerability issues have gained renewed attention in Europe following the 2021–2022 energy crisis, during which rising fossil fuel prices substantially increased the energy cost burden faced by European households (Guan et al., 2023).

Several limitations of our analysis suggest avenues for further work. First, although ETS 2 covers transport fuels, our energy vulnerability indicators focus on domestic energy use; extending the framework to encompass transport poverty represents a natural and policy-relevant direction for future research (see, e.g., Alonso-Epelde et al. (2023) for a recent HBS-based framework). Second, our identification of hidden energy poverty rests on expenditure-based proxies and remains imperfect, as the relevant notion of energy need is inherently unobserved. Merging HBS data with EU-SILC and/or detailed housing information would allow us to combine the expenditure detail required for demand system estimation with information central to robust energy vulnerability identification. Third, our cross-sectional setting precludes a dynamic analysis; panel data would enable us to examine the persistence of underconsumption over time, complementing recent evidence on energy poverty dynamics in European contexts (Drescher & Janzen, 2021). Beyond these data and methodological extensions, the mechanisms driving self-restriction among hEP households, whether financial constraints, behavioural factors, or housing-related lock-ins, remain incompletely understood and warrant dedicated investigation. Finally, the framework developed here is transferable to other EU countries with comparable household budget data, supporting comparative analyses of distributional impacts as ETS 2 implementation approaches.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Daniel Coppens d'Eeckenbrugge: Conceptualization, Methodology, Software, Formal analysis, Data curation, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing. **Audric De Bevere:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Data availability

The household microdata used in this study come from the Belgian Household Budget Survey and are confidential. The authors accessed these data under agreement with Statbel (Statistics Belgium) and are not permitted to redistribute them; the data can be obtained directly from Statbel subject to its access conditions. The analysis code is available from the authors upon reasonable request.

Appendices

A 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.

A.1 Descriptive statistics on energy vulnerability

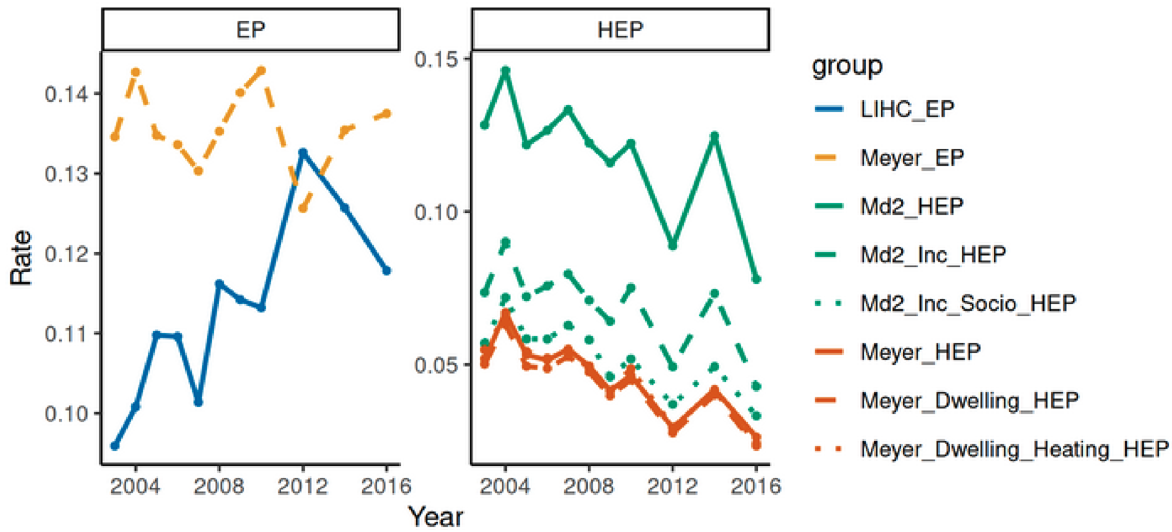
Table A.1 reports the prevalence and average depth of energy vulnerability across indicators, and Figure A.1 shows how the vulnerable populations evolve over time.

Table A.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 A.1: Energy vulnerable populations over time by indicator.

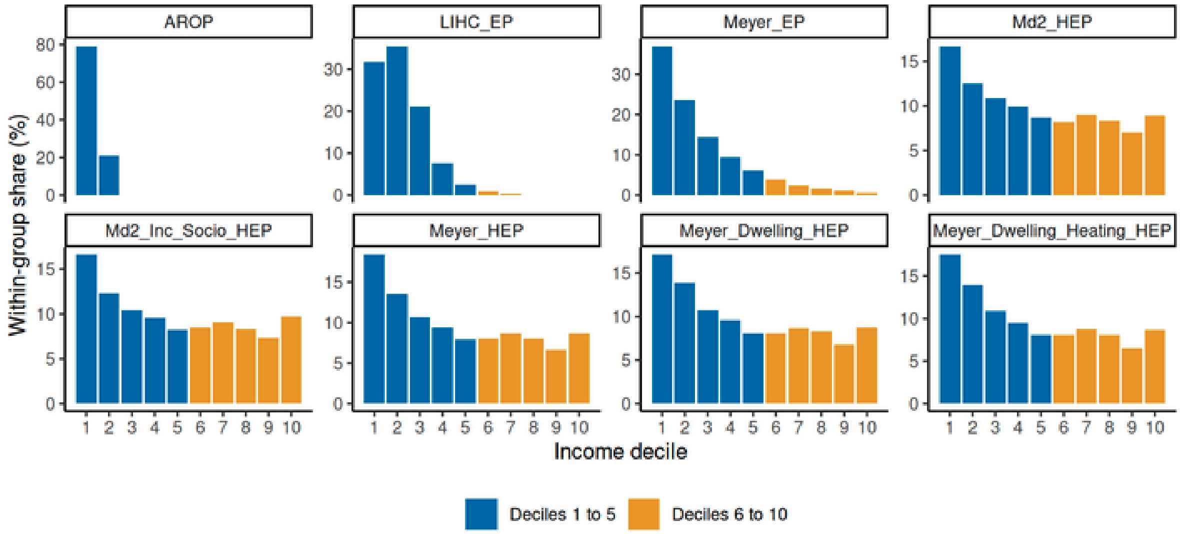


Source: Authors' calculations based on HBS data for Belgium (2003–2016).

A.2 Importance of the exclusion rule for high-income households

Figure A.2 shows how the vulnerable groups are distributed across income deciles with and without the income exclusion threshold.

Figure A.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).

A.3 Socio-economic descriptive statistics with the different indicators

Table A.2 reports socio-demographic characteristics across subgroups for the different indicators.

Table A.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 Dwelling–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%
Children Present	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).

A.4 Robustness checks for the econometrics results

We report logit estimates for alternative energy poverty indicators (Table A.3) and alternative hidden energy poverty indicators (Table A.4), the associated variance inflation factors (Table A.5), and a complementary log-log specification for hidden energy poverty (Table A.6).

Table A.3: Logit Estimates for Alternative 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 A.4: Logit Estimates for Alternative 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 Type: 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).

Table A.5: Variance Inflation Factors for Energy Poverty (EP) and Hidden Energy Poverty (hEP) Specifications

Variable	**EP**	**hEP**
Wage Earner	1.29	1.30
Education	1.02	1.03
Ownership	1.23	1.22
# Cars	1.18	1.19
HH Type	1.12	1.13
# Children	1.19	1.19
Region	1.09	1.11
Dwelling Type	1.23	1.23
Construction Year	1.03	—
# Rooms	1.32	1.32
Heating Type	1.04	1.04
Season	1.00	1.00
Years After 2000	2.12	1.99
Year 2008–09	1.17	1.17
Years After 2011	2.21	2.04
Maximum	2.21	2.04

Note: Reported values correspond to the adjusted generalised variance inflation factor $\text{GVIF}^{1/(2Df)}$.

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

Table A.6: Complementary Log-log Specification for Hidden Energy Poverty (hEP)

Variable	**Coef.**
Wage Earner	–0.07
No Education (ref. cat.)	
Primary Education	–0.05
Secondary Education	–0.14*
Tertiary Education	–0.02
Renter (ref. cat.)	
Owner with Loan	–0.14
Owner without Loan	0.05
# Cars	–0.23***
HH Type: Couple Active (ref. cat.)	
Couple Retired	–0.15
Many Adults	–0.40***
Single Active	0.23***
Single Retired	0.08
# Children	–0.03
Region: Brussels (ref. cat.)	
Flanders	–0.69***
Wallonia	–0.80***
Detached House (ref. cat.)	
Flat	0.80***
Terraced House	0.34***
# Rooms	0.04
Heating System Type: Electricity (ref. cat.)	
Gas	–0.49***
Oil	–0.13
Other	0.26
Solid	1.07***
Time Controls	
Years After 2000	–0.03*
Year 2008–09	–0.09
Years After 2011	–0.33**
Mean of dependent variable	4.6%
McFadden's R^2	8.4%

Note: The table reports coefficients from a complementary log-log specification using the same covariates as the baseline hidden energy poverty logit model.

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

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

B 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 2.4.[38] 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 (Table B.1) and related contingency tables (Tables B.2 and B.3):[39]

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

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

Table B.1: Fit of the reduced-form equations

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

Note: McFadden R^2 summarises the in-sample fit.

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

Table B.2: Energy Poverty — Predictions vs. Observed

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

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

Table B.3: 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).

[38] Compared to part 2.4, we add all possible interactions between the models' variables, as well as income, for the sake of better fitted probabilities.

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

C Supplementary Tables

C.1 Additional descriptive statistics

Table C.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 C.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 C.3: 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).

C.2 Complementary econometric outputs

Tables C.4 and C.5 report the logit models for energy poverty and hidden energy poverty from the reduced to the complete specification.

Table C.4: 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 C.5: 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).

C.3 Cross-price elasticities

Table C.6 reports the uncompensated cross-price elasticities for the full population.

Table C.6: 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).

C.4 Compensated price elasticities

We can isolate substitution effects by looking at compensated/Hicksian price elasticities. In Table C.7, we report compensated cross-price elasticities for the whole population, and in Table C.8 compensated own-price elasticities for different sub-groups.

Table C.7: 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 C.8: 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).

D Supplementary Figures

Figure D.1: Evolution of Durables' Share in Total Expenditures

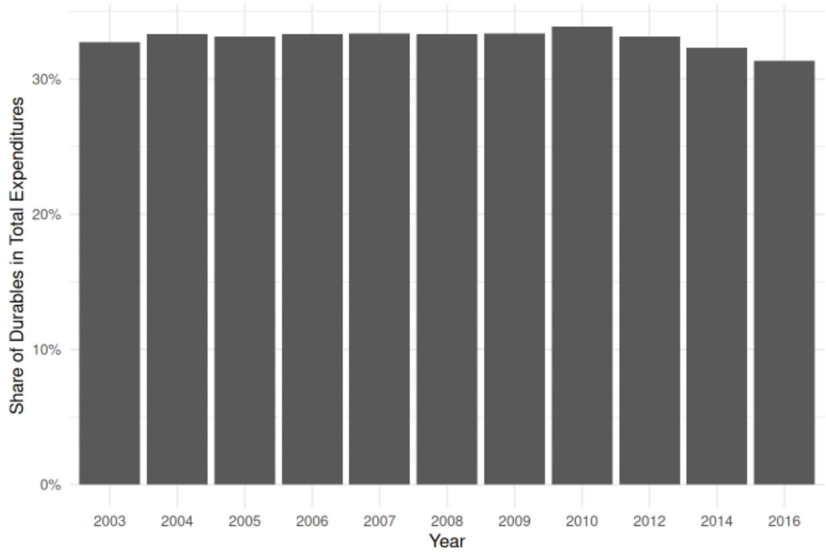


Figure D.2: Evolution of Households Heating System Type