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Is energy poverty characterized by a gender and migration bias? Microdata evidence from the Netherlands

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ABSTRACT

We assess the increasingly prevalent assertion that energy poverty in high-income countries disproportionately affects women and households with a migration background. Much of the existing evidence supporting this claim is non-causal and often fails to disentangle the effects of income. To address these limitations, we apply both descriptive statistical methods and a two-stage logistic regression analysis to comprehensive, high-quality administrative microdata covering nearly 90 % of Dutch households. We examine how gender, migration background, income, and housing characteristics interact to shape energy poverty outcomes. Our key finding is that what initially appears as a gender or migration bias in energy poverty statistics is, in fact, primarily a reflection of income disparities across these demographic groups. Beyond income, our results also highlight the importance of spatial, institutional, and behavioral factors in shaping vulnerability. In particular, we find that the relatively high energy quality of social housing in the Netherlands mitigates the risk that women and migrants—despite a gender and migration pay gap—end up in energy poverty. We also identify differences in energy poverty subtypes: women are more exposed to combinedenergy poverty (energy-inefficient housing and high energy costs), while men are more likely to exhibit hidden energy poverty (energy-inefficient housing but low energy costs). These findings underscore the importance of addressing structural inequalities in income and housing beyond the energy domain when designing effective policies to reduce energy poverty. A just and inclusive energy transition will therefore depend on addressing the broader socio-economic and institutional conditions that underlie energy poverty.

1. Introduction

In this study we use Dutch household-level microdata to assess the increasingly prevalent assertion that energy poverty in high-income countries disproportionately affects women and households with a migration background [1–10]. Energy poverty in the Global North refers to the difficulties faced by a minority of households in meeting their energy needs, typically due to the combination of low incomes, high energy costs, and/or poor energy efficiency of their dwellings [11–16]. The adverse effects of energy poverty extend beyond financial hardship to include impacts on health, social inclusion, and overall quality of life [17–19]. Recent energy price increases have exacerbated these challenges, highlighting the growing vulnerability of households in energy poverty and prompting renewed attention from policy makers and researchers alike.

Energy poverty is at odds with the pursuit of an inclusive and just transition to low-carbon economies and societies, which aim to benefit all individuals and leave no one behind [20]. Furthermore, policies designed to facilitate energy transitions—such as carbon pricing or fossil fuel subsidy reform—have the potential to exacerbate energy poverty, especially if households face higher energy costs and struggle to transition away from fossil fuel dependency [21]. Energy poverty is a pressing issue, given that an estimated 41 million Europeans (9.3 % of the population) were unable to keep their homes adequately warm in 2022 [22]. As a result, the European Union has committed to combating energy poverty through structural and targeted measures aimed at addressing its root causes [1,23].

Within this context, understanding any gender or migration bias in

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the incidence of energy poverty is crucial, as such disparities could inform the design of more effective and targeted policies. Prior research shows that energy poverty disproportionately affects women and migrant households. Gendered income inequalities, occupational segregation, and a greater prevalence of part-time work among women limit household resources and increase vulnerability to high energy costs [24,25]. Migrant households are often overrepresented in low-income brackets and more likely to reside in poorly insulated or rental housing, which restricts their capacity to invest in energy efficiency improvements [26,27]. These structural disadvantages explain why both groups face a heightened risk of energy poverty. There is ample recognition in the literature that policies targeting energy poverty through an income lens alone are insufficient (see e.g. [28]). Effective energy poverty policy requires a multidimensional targeting approach that integrates income, housing conditions, and social characteristics. Only by recognizing and addressing the complex interplay between these factors can policies be designed to accurately identify and support those most at risk, including women and migrant households.

Convincing empirical evidence linking gender and migration status to the incidence of energy poverty alongside income-based explanations remains scarce, especially outside the United States. Such evidence requires foremost proper identification of households' gender and migration characteristics as independent determinants of energy poverty incidence beyond their indirect effect through income poverty, given the existence of gender and migration pay gaps as well as income-correlated and ethnicity-based housing segregation [29–34]. Most studies that argue that women and migrant households are disproportionately affected by energy poverty, however, rely on statistical correlations rather than causal analyses—some notable exceptions notwithstanding [2]. Furthermore, much evidence rests on a single-dimensional approach that focusses on either gender or migration rather than on the multiple intersecting characteristics that render individuals (or households) part of a specific minority group (e.g. female first-generation migrants that are primary earner), and this is known to matter [35,36]. Also, in most studies to date, energy poverty measurement relies on merged household-level survey data that is based on statistical matching and conditional random imputations across different sources, which entails potential biases arising from disparate survey methodologies or sample populations [37–40].

Against this background, we exploit the availability of comprehensive sets of high-quality administrative data for The Netherlands, both at the household and individual level, to examine the complex interplay between gender, migration background and income in determining the incidence of energy poverty. We adopt the microdata-driven Dutch energy poverty monitoring framework of Statistics Netherlands and used by the Dutch government [41,42], that defines energy poor households as those household that combine low income with either high energy costs and/or low energetic housing quality. Our dataset includes 88 % of all Dutch households in 2020 and offers detailed information on energy poverty incidence, energy use and costs, housing characteristics, household income, and individual-level demographic details such as gender and migration background. We employ a series of regression models on these data to quantify the contribution of gender and migration background to energy poverty incidence, while correcting for income and other variables. We run our regression on two datasets – one at the household level (using characteristics of the primary earner) and one at the individual level (including all members) – to test whether gender and migration background beyond the primary earner affect energy poverty incidence. The novelty of our study lies in the combination of a comprehensive and consistent set of administrative data, a precisely defined energy poverty metric that is used in official Dutch policy, and a rigorous quantitative methodology.

The remainder of our manuscript is organized as follows: In Section 2 we describe our data in more detail and provide descriptive statistics of several variables in our dataset. In Section 3, we perform a two-stage logistic regression analysis to develop a nuanced understanding of intersecting household characteristics in relation to energy poverty, and to quantify the genuine contribution of gender and migration background to energy poverty incidence. In Section 4 we analyze in detail how gender and migration characteristics are distributed across key predictors of energy poverty vulnerability. In Section 5 we present our main conclusions and discuss the policy implications of our finding.

2. Data and descriptive quantitative analysis

2.1. Data: definitions, preparation and samples

We draw all our data from the microdata database of Statistics Netherlands (CBS). For the purpose of our analysis, we merged several CBS microdata subsets. The basis is formed by the official Dutch energy poverty monitor dataset for the year 2020, which reports various indicators of energy poverty along with additional socio-economic household and home characteristics, such as (source of) income, household type, housing tenure, construction year and location. The energy poverty monitor is in turn based on the 'Woonbase', a housing register developed by CBS in cooperation with the Ministry of the Interior and Kingdom Relations (BZK). Woonbase integrates detailed administrative records on individuals, households, and dwellings, including who lived in which dwelling, with whom, and under what housing conditions during the reporting year [43–45]. This dataset includes nearly 7 million records, representing 88 % of all households in the Netherlands. In this study we complement these data with a dataset that contains individual-level information on age, gender and migration background for each household member. We collected data for all household members, allowing for dual analysis at the individual level (all household members) and the household level (only the primary earner of a household). In the following paragraphs we elaborate on the features that were used for our analyses.

At the time during which our research was conducted, the energy poverty monitor only contained data for the years 2019 and 2020. After verifying that our main conclusions were robust for both years, we decided to focus the analysis on the most recent available dataset, i.e. for the year 2020. While the COVID-19 pandemic may temporarily have affected energy use or income levels for some households, given our focus on long-term vulnerabilities and structural inequalities, our findings remain relevant for current and future conditions.

Following the Dutch energy poverty monitoring framework [41], we define and measure energy poverty in terms of low income (LI) in combination with either high energy costs (HE) and/or low energetic housing quality (LEK) – subsequently referred to as *LIHELEK*. This definition is grounded in the capability-based affordability framework that underlies most energy poverty frameworks in high-income countries, in which energy poverty is operationalized as a household's inability to afford socially- and materially-necessitated energy services, where income is the binding resource constraint [11–16]. Note that the acronym *LIHELEK* refers to the intersection of low income (*LI*) households who face either high energy costs (*HE*), low energetic housing quality (*LEK*), or both. Hence, *LIHELEK* does not require that all three conditions be met to classify a household as energy poor. In our analysis we also make separate use of the various subsets of energy poverty indicators (i.e. *LI*, *HE* and *LEK*); in particular, we define the indicator *HELEK* as the combination of either high energy costs (HE) and/or low energy housing quality (LEK). This approach identifies three different subtypes of energy poverty, representing three different ways in which energy poverty manifests:

1. *HE & LEK:* Households facing both high energy costs and poor housing quality. In these cases, high energy costs are often driven by the low energetic efficiency of the home.
2. *HE & not-LEK*: Households with high energy costs despite living in relatively energy-efficient homes. This may result from high energy

needs or usage unrelated to housing quality, such as specific health needs.

3. *Not-HE & LEK*: Households living in energy-inefficient homes but with low energy costs, possibly due to under-consumption. This situation is often described as “hidden energy poverty” [46,51].

Note that households with a low income that experience neither *HE* nor *LEK* (*not-HE & not-LEK*) are not considered energy poor. Conversely, households without a low income are not classified as energy-poor within the Dutch framework, as the affordability of energy costs constitutes its primary focus. Nonetheless, the framework acknowledges that higher-income households may still encounter energy-related hardship, for example when residing in poorly insulated rental dwellings that landlords are unwilling to retrofit. This aspect of energy poverty is not considered in our analysis, as potential gender and migration biases are most directly associated with the affordability dimension. Including economically unconstrained HE/LEK households would then bias estimates toward high consumption without deprivation, diluting construct validity and complicating interpretation of affordability-linked mechanisms (including labor-market and housing-market sorting). Restricting the sample to resource-constrained households thus reduces noise, improves internal validity, and follows established practice in distributional energy-insecurity research.

We measure income as *standardized income*, defined as a household’s disposable income adjusted for the household composition (size), plus a correction term that accounts for a household’s financial capital, which is calculated by annuitizing households’ financial assets. Our definition low income (*LI*) is binary and based on a standardized threshold of ‘social minimum’ developed by Statistics Netherlands and widely used in Dutch policy making, which is adjusted for the household composition (size). Both the data on household’s disposable income and low income are provided in the Dutch energy poverty monitor [43]. *Standardized income* is identical for all members of a household, as is the binary variable *LI*.

Energy costs entail costs for both gas and electricity, defined as the product of annual consumption levels and the average end-user rates, measured over the year and the various providers. These costs are also adjusted for household composition. Following the definition adopted in the official Dutch energy poverty monitor, we set the threshold for high energy costs as the median energy bill (adjusted for household composition) for an average energy label C house in 2019 [43].

Energetic housing quality is defined as the energy efficiency of a dwelling. While official energy labels are, in principle, the ideal metric for assessing energy efficiency, their practical utility is limited in the Netherlands. As of 2023, approximately 40 % of dwellings lack an official energy label, and many existing labels are outdated and no longer accurately reflect the current condition of the property. To address these limitations, Statistics Netherlands (CBS) therefore employs a regression-based prediction model to estimate the theoretical energy consumption of all dwellings. This model is built on a dataset for the year 2019 and combines available energy label data with information on actual energy consumption at the household level, information on dwelling characteristics (e.g., type, floor area, construction year), the presence of solar panels, and household demographics such as size and income. The CBS model yields a normalized theoretical energy consumption for all buildings. CBS then identifies houses with low energetic quality (LEK) as those which have actual consumption levels (in any year) above the median theoretical consumption across the Dutch housing stock in 2019. This corresponds approximately to dwellings with an energy efficiency label of D or lower on the standard A–G scale [43].

Following definitions of Statistics Netherlands (CBS), in this study a person with a migration background in terms is defined as a person who was born outside of the Netherlands (individuals with a first generation migration background; referred to as *1GNL*) or a person born in the Netherlands to at least one non-Dutch-born parent (individuals with a second generation migration background; referred as *2GNL*) [47]. In our analyses these persons are distinguished from those without a migration background (born in the Netherlands to Dutch-born parents (referred to as *NL*). In addition the variable *country of origin* is defined as the country or region where someone is born or in case of an individual with a second-generation migration background as the country or region where the parents are born. We followed the categorization of CBS for this variable: the Netherlands, Asia, Europe, Turkey/Morocco/Suriname (TMS) and Other. Turkey, Morocco and Suriname are grouped together because many households with a migration background in the Netherlands have connections to one of these three countries.

Finally, we control in our analyses for a series of other factors that might contribute to energy poverty risk, including: age, source of income (pension, welfare benefit, paid employment), type of house (apartments, terraced houses, corner houses and (semi-)detached houses), housing tenure (homeowner, private rent and social housing), household type (couple with kids, couple without kids, single-parent household or single-person household), house size (m^2), standardized income of a household (euro), construction year of the house and urbanisation gradient (highly urban to rural, as measured by CBS on a categorical scale from 1 to 5, with class 1 to 3 classified by us as *urban* and 4 to 5 as *rural*).

In order to construct insightful regression models in Section 3, we carefully selected those variables in our dataset that are most likely to have a significant impact on energy poverty. We based the identification of these predictors on extensive exploratory data analysis and literature review. As part of the feature selection process, we addressed two key issues: multicollinearity among variables and the presence of outliers. Upon examining the correlation among the variables considered, one predictor (*age group*) was excluded. Notably, the age groups *65–80* and *80+* exhibited high correlation with the *pension* category of *income type*. Because of this, and since other age groups seemed to lack predictive power, *age group* was excluded as a predictor. In addition, from the feature *construction year* (numerical) a categorical variable *construction year category* has been created, which classifies residences based on their construction year into three categories: *old* (before 1950), *intermediate* (1950–2000), and *new* (2000−2020). This classification is motivated by two considerations: policy relevance and data reliability. From a policy perspective, these periods reflect significant changes in Dutch building codes and energy performance regulations. Homes built before 1950 typically follow pre-war construction standards and lack insulation [11]. The period from 1950 to 2000 captures the post-war building boom, during which energy efficiency gradually improved but remained largely unregulated [48]. Around 2000, newly constructed dwellings were increasingly subject to modern energy performance requirements, such as the introduction and subsequent tightening of the Energy Performance Coefficient (EPC) system in 1995 [49]. From a data reliability perspective, the construction year is often imprecisely recorded in administrative data for older buildings or missing [43]. Treating construction year as a continuous numerical variable could therefore introduce measurement error and allow outliers to skew the analysis. Moreover, such an approach would impose a linear relationship between building age and energy poverty, which is not theoretically justified, given that improvements in energy efficiency largely occurred in regulatory steps rather than through gradual change.[1] Tables A.6 and A.7 in Annex 2 provide a comprehensive overview of the final set of features selected in our analysis, and their roles in the regression models

[1] One may still argue that building technology (both with regard to building envelope as well as house appliances) has significantly evolved between 1950 and 2000, hence a finer subdivision of construction year categories would be desirable. In the context of the present analysis, however, such a finer categorization (based on changes in building standards – in 1965, 1992, 2003 and 2012 – that have brought significant improvements in house insulation) does not lead to additional insights. This is demonstrated in Fig. A.4 in the Annex.

presented in this paper.

Further data preparation involved creating two separate datasets: one at the household level and one at the individual level. The household dataset restricts personal characteristics like gender and migration background to a household's primary earner, while the individual dataset also specifies these features for the other household members. Given that energy poverty is measured at the household level (i.e. all members of a household are energy poor or not), the two separate datasets allow us to assess whether gender and migration background of individual household members play a role in energy poverty incidence beyond the gender and migration background of the primary earner in a household. After cleaning the dataset by removing missing values and outliers, the final household-level dataset comprises 6,898,824 records out of about 8 million Dutch households, of which 999,393 are households with a low income (14 %); the individual-level dataset comprises 15,450,630 records, of which 1,762,988 are individuals that have a low income (11 %).

Finally, besides analyzing the dataset at the household and individual level, we also compare results between the full sample and a subsample of only low-income households as part of our identification strategy in the regression analysis presented in Section 3 (i.e., we use a two-stage regression approach). Within the full sample, we define energy poor households (*LIHELEK*) as those households that combine a low income (*LI*) with high energy costs (*HE*) and/or low energetic housing quality (*LEK*) – as previously mentioned. This stage 1 model serves as a benchmark: we test the effect of gender and migration background on energy poverty, without controlling for income. With the stage 2 model we aim to identify the role of a potential income gap in driving energy poverty prevalence among women and migrant households. We therefore define a low-income sample in which we compare energy poor and non-energy poor households. Energy poor households in this subsample of low-income households are then defined as those with high energy costs (*HE*) and/or low energetic housing quality (*LEK*), i.e. the same subsample of energy poor households as in the full sample. Non-energy poor households then are those with a low-income but no high energy costs and/or low energetic housing quality. Stage 1 is thus deliberately specified as an unadjusted benchmark model, estimated for the full population, to document how gender- and migration-linked disparities in energy poverty appear prior to income adjustment. Stage 2 then narrows the analysis to the low-income risk set and controls for standardized income, enabling us to test whether gender and migration gradients persist above and beyond correlated income effects. Framed this way, the statistical bias present in Stage 1 is not treated as causal evidence, but rather as an analytically informative descriptive signal. If disparities observed in Stage 1 disappear after income control in Stage 2, this indicates that full-population inequalities are largely income-driven; If they persist within the low-income risk set, this suggests that gender and migration factors (e.g., housing-market sorting by gender/migration status) contribute independently to energy-poverty exposure (i.e. beyond income differences).

2.2. Descriptive analysis: gender and migration bias in energy poverty incidence

Tables 1, 2 and 3 and Fig. 1 present the main characteristics of our data. Table 1 shows that overall energy poverty incidence in the Netherlands in 2020 was 6.4 % at the household level and 4.9 % at the individual level. The higher percentage at the household level suggests that smaller households are more likely to be energy poor. Within the sample of households with a low income, energy poverty incidence was 44.0 % and 43.2 % at the household and individual level, respectively.

Table 2 provides a further characterization of our data by showing the median and interquartile ranges (IQR) for numerical features across the entire dataset and the energy-poor subgroup, both at the household and individual level. Consistently with our energy poverty definition, Table 2 shows that, as compared to the entire population, energy poor households and individuals have a substantially lower annual standardized income and live in smaller and older houses, while age differences are negligible.

Table 1
Energy poverty incidence.

	Sample size	Energy poverty incidence	
		#	%
Household-level dataset			
All households	6,898,824	439,254	6.4 %
Households with a low income (LI)	999,393	439,254	44.0 %
Individual-level dataset			
Individuals from all households	15,450,630	761,220	4.9 %
Individuals from households with a low income (LI)	1,762,988	761,220	43.2 %

In search of a possible gender and migration bias in energy poverty prevalence, we visualize in Fig. 1 the distribution of gender and ethnicity features in our different samples. At the household level, the stacked bar graphs clearly show a greater representation of women and individuals with a migration background (both first and second generation) in the energy-poor household sample relative to the entire dataset, suggesting evident biases related to gender and migration status at first sight. However, the very same bias is also prevalent in the sample with a low income as compared to the entire dataset, casting doubt at a broader gender and migration bias beyond the impact of low-income on energy poverty incidence. At the individual level—where the dataset includes all household members—the same bias pattern is observed across the different samples, although somewhat less pronounced. This is exactly why this study uses a two-stage regression approach exploiting variation in different samples of our data to see whether the observed gender and migration bias in energy poverty prevalence from descriptive statistics remains to exist after controlling for different channels of impact, most notably income.

Table 3 presents energy poverty prevalence across key gender and migration categories of households in our sample. Consistent with Fig. 1, the full sample data (left-hand side of Table 3) initially suggests a clear gender disparity at the household level: 12.4 % of female-headed households experience energy poverty, compared to 4.4 % of male-headed households, with an overall incidence of 6.4 %. Similarly, a migration-related disparity appears evident, with 13.0 % of foreign-born household heads classified as energy-poor, compared to 5.3 % among native-born household heads. When measured at the individual level, the incidence rates are slightly lower and the differences more modest, but the overall pattern remains consistent. However, these apparent biases disappear within the low-income subsample (right-hand side of Table 3). In fact, the data show a slight reversal: female-headed households and individuals with a migration background within the low-income group are somewhat less likely to face high energy costs or reside in energy-inefficient dwellings. This suggests again that the observed disparities in the full sample are mainly driven by income differences rather than by gender or migration status per se.

Furthermore, other microdata categories show that, within the full sample, energy poverty incidence is relatively high among single-person and single-parent households, as well as among households that rent in the social housing sector, live in older dwellings, reside in high-density urban areas, or depend on social assistance as their primary income source – some of which are highly correlated with low income. In the low-income subsample, however, the pattern shifts. Energy poverty—measured in terms of high energy costs (HE) and/or low energy efficiency of the dwelling (LEK)—is more prevalent among households whose primary income comes from employment, who are homeowners

Table 2
Median and interquartile range (IQR) of numerical variables for all and energy poor households, at household and individual level.

Household level	Unit	All households (6,898,824)		Energy poor households (439,254)	
		Median	IQR	Median	IQR
Standardized income	€	29,804	21,711–39,327	15,980	14,537–17,297
Age primary earner	Years	55	41–68	57	42–70
Accommodation area	m^2	107	83–136	87	68–106
Construction year	Year	1975	1958–1993	1965	1950–1976

Individual level	Unit	All individuals (15,450,630)		Energy poor individuals (761,220)	
		Median	IQR	Median	IQR
Standardized income (household)	€	31,626	23,306–41,049	15,697	14,476–17,264
Age individual household members	Years	51	40–63	51	39–65
Accommodation area	m^2	115	92–147	91	74–110
Construction year	Year	1976	1958–1994	1965	1950–1975

Table 3
Energy poverty incidence for gender and migration categories.

Category	Full sample (All households) Energy poverty incidence (LIHELEK)				Low income sample (Households with a low income) Energy poverty incidence (HELEK)			
	Household level[a]		Individual level		Household level[a]		Individual level	
	#	%	#	%	#	%	#	%
Households	439,254	6.4 %	761,220	4.9 %	439,254	44.0 %	761,220	43.2 %
Gender								
Women	212,582	12.4 %	423,726	5.4 %	212,582	43.6 %	423,726	42.9 %
Men	226,672	4.4 %	337,494	4.4 %	226,672	44.2 %	337,494	43.5 %
Born in the Netherlands								
Born in the Netherlands	319,115	5.3 %	567,330	4.1 %	319,115	46.2 %	567,330	45.0 %
Not born in the Netherlands	120,135	13.0 %	193,890	11.3 %	120,135	38.9 %	193,890	38.5 %
Migration background								
No migration background	281,569	5.2 %	446,232	3.7 %	281,569	46.8 %	446,232	47.6 %
First-generation migration background	120,139	13.0 %	193,890	11.3 %	120,139	38.9 %	193,890	38.5 %
Second-generation migration background	37,546	7.3 %	121,098	7.1 %	37,546	42.2 %	121,098	37.5 %
Country of Origin								
Country of origin: Netherlands	281,569	5.2 %	446,232	3.7 %	281,569	46.8 %	446,232	47.6 %
Country of origin: Turkey/Morocco/Surinam	52,227	13.2 %	101,439	10.1 %	52,227	37.3 %	101,439	34.9 %
Country of origin: Asia	27,193	15.7 %	70,496	14.1 %	27,193	35.3 %	70,496	35.9 %
Country of origin: Europe (not NL)	37,862	8.1 %	66,545	6.4 %	37,862	47.1 %	66,545	46.9 %
Country of origin: Other	40,403	10.1 %	76,508	8.8 %	40,403	40.2 %	76,508	38.8 %

[a] Measured at level of household head (i.e. primary earner).

or tenants in the private rental sector, and who live in (semi-)detached houses or rural areas.[2] These differences highlight the complex and context-specific nature of energy poverty drivers within different income groups. Together, the findings from these simple descriptive quantitative analyses underscore the relevance of an intersectional analysis and the importance to carefully unravel the various interacting home and household characteristics when identifying socio-demographic drivers in energy poverty. This is the topic of the next section.

3. Regression analysis

3.1. Set-up

In this section we perform a two-stage logistic regression analysis to develop a nuanced understanding of intersecting household characteristics in relation to energy poverty, and whether gender and migration background have distinct effects when income is accounted for. We use logistic regression for our analysis because energy poverty is represented in our dataset as a binary variable – a household or individual is either energy-poor or not. All regressions were performed in Python (version 3.11.6) using the *statsmodels* package.

As schematically depicted in Fig. 2, we devised a two-stages regression approach. This allows us to distinguish between the overall impact of *gender* and *migration background* on energy poverty (Stage 1)—including the gender and migration pay gap—and their specific effect on the likelihood of facing high energy costs and/or living in a low-energetic-quality home among households with a low income (Stage 2) – excluding the bias through the income gap. This helps to clarify whether *gender* and *migration background* influence energy poverty primarily through income disparities. Stage 1 regressions utilize the full dataset, with as dependent variable energy poverty defined as having a low income (*LI*) in combination with either high energy costs (*HE*) and/or low energetic housing quality dwelling (*LEK*): *LIHELEK*. At Stage 1 we aim to test whether women and individuals with a migration background show higher odds to be energy poor than men or individuals with no migration background. Subsequently in Stage 2, the analysis focuses on the subsample of households with a low income (hence, this sample also includes households with a low income that are not energy poor), with as dependent variable energy poverty defined as having high energy costs (*HE*) and/or low energetic housing quality dwelling (*LEK*) – in short: *HELEK*. Stage 2 models enable the inclusion of standardized income as an independent variable, thereby avoiding the issue of quasi-separation that would arise in Stage 1 models, where a portion of the observations could be perfectly predicted by including income as an

[2] For a complete overview of how household and dwelling characteristics relate to energy poverty, see Table A.1 in Annex 1.

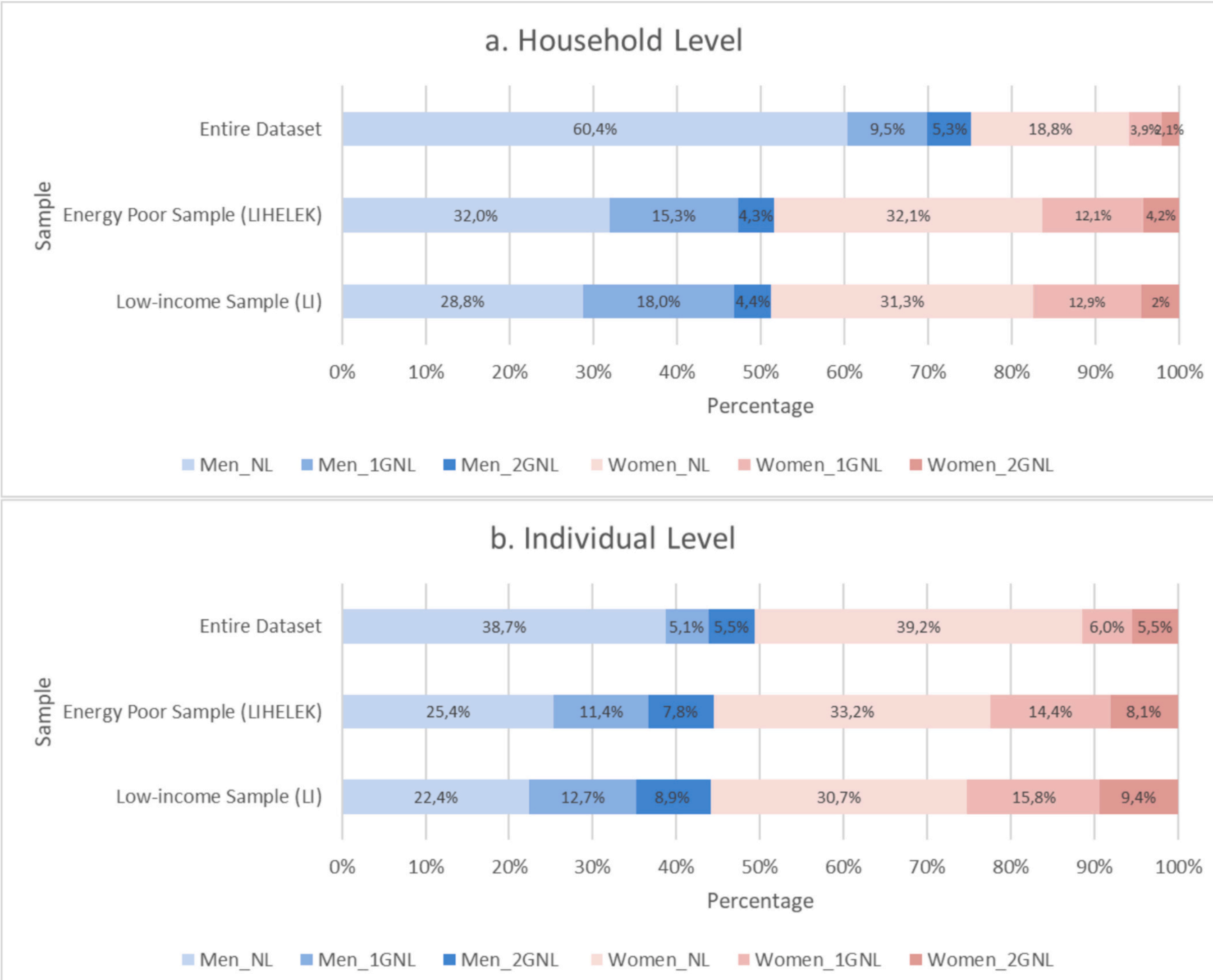

Fig. 1. Gender and migration based subgroup ratios within different samples at the household (a) and individual level (b).

independent variable, due to the fact that the *LIHELEK* indicator is based on income. With stage 2 we examine whether women or individuals with a migration background with a low income have higher chances to be energy poor compared to men or individuals with no migration background with a low income.

Within each stage, we first estimate a compact regression model using the individual-level dataset, in which the independent variables are *gender*, *migration background*, *primary earner status*, and their interaction terms. This initial model provides insight into the overall gender and migration biases in energy poverty. Subsequently, we estimate a complex model that incorporates a larger set of independent variables, with the aim to correct for other possible effects concerning energy poverty. Tables A.6 and A.7 in Annex 2 show an overview of the dependent and independent variables included in the compact and complex regression models for Stages 1 and 2. The complex model is evaluated both at the individual and at the household level.

Regression pre-processing included addressing data imbalance related to energy poverty, as only 6.4 % of all households are classified as energy poor. This imbalance could lead to models being biased toward the majority class (households not experiencing energy poverty). Logistic regression models were applied to both the imbalanced dataset and several balanced datasets, created through random undersampling, random oversampling, and Synthetic Minority Over-sampling Technique (SMOTE) to inform decisions regarding data balancing. After evaluating the outcomes of these various techniques, we opted for random oversampling of the minority class (households experiencing energy poverty), as this approach provides a good compromise between performance and computation time. Balancing the data to achieve a 50–50 distribution between energy poor and not energy poor was chosen to equally address factors influencing both the likelihood of experiencing energy poverty and the absence of energy poverty.

For each regression we applied stratified sampling to divide the balanced dataset based on the dependent variable (energy poor vs. not energy poor) to preserve the distribution of these two categories, allocating two-third of the data to the training set and the remaining one-third to the test set. The model underwent training using the designated training set, and its predictive performance was evaluated using the test set. The logistic regression model was built using the maximum likelihood estimation method. The classification threshold was set at 0.5 for the test set. The predictive performance of the logistic regression model was evaluated using various metrics on the test set, including accuracy, precision, sensitivity, specificity, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) [50]. Following successful model training and evaluation, logistic regression was performed on the entire balanced dataset to obtain the final model coefficients. Odds Ratios (ORs) were calculated for each coefficient,

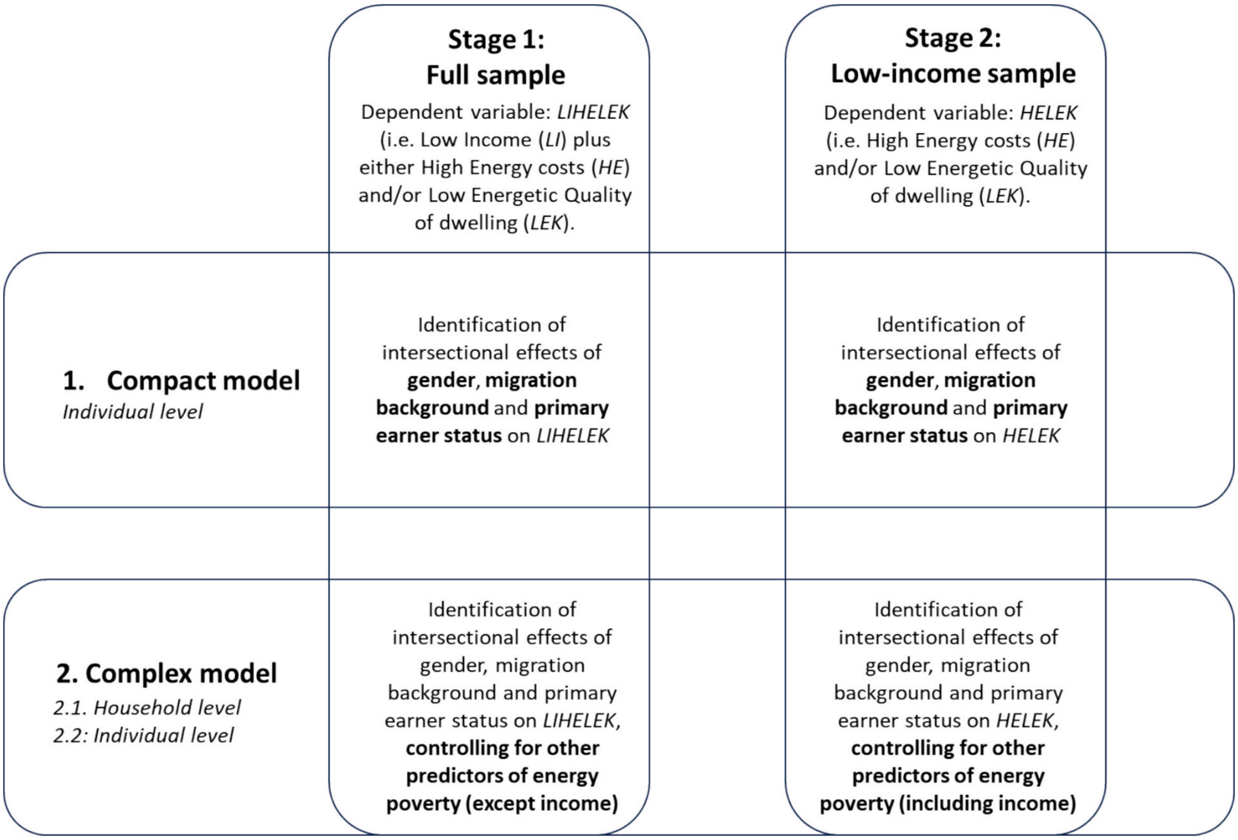

Fig. 2. Structure of logistic regression framework.

providing insights into the impact of independent variables on the odds of the binary outcome. For each categorical feature, ORs were calculated relative to a reference group. In addition, corresponding 95 %-confidence intervals (95 %-CIs) and *p*-values are obtained for each coefficient. The Likelihood Ratio Test (LRT) was executed for comparing model fit between different models and the Wald Test was performed for testing the significance of coefficients within the model.

3.2. Stage 1

3.2.1. Compact model

In our Stage 1 compact model we regress, for the full sample at the individual level, the *LIHELEK* energy poverty indicator on a limited series of independent variables and their interaction terms, as follows:

$$\begin{aligned}\text{Logit}(\textit{Energy Poverty}) = {} & \beta_0 + \beta_1(\textit{Woman}) + \beta_2(1\textit{GNL}) + \beta_3(2\textit{GNL}) \\ & + \beta_4(\textit{PrimaryEarner}) + \beta_5(\textit{Woman\_1GNL}) \\ & + \beta_6(\textit{Woman\_2GNL}) \\ & + \beta_7(\textit{Woman\_PririmaryEarner}) \\ & + \beta_8(1\textit{GNL\_PririmaryEarner}) \\ & + \beta_9(2\textit{GNL\_PririmaryEarner}) \\ & + \beta_{10}(\textit{Woman\_1GNL\_PririmaryEarner}) \\ & + \beta_{11}(\textit{Woman\_2GNL\_PririmaryEarner}).\end{aligned} \tag{1}$$

The reference group for the variable *gender* is defined as *men*, for *migration background* it is individuals without a migration background (*NL*), and for *Primary earner status* it is *NonPrimaryEarner*. We then can calculate the ORs from the values for the coefficients β_i, as obtained through the regression analysis. We calculate these ORs for the various independent variables and interaction terms, but also for specific subgroups, relative to the reference group (i.e. men without a migration background that are not primary earner). We do as follows:

$$OR_{SG} = exp\left(\sum_{i \in SG} \widehat{b}_i\right), \tag{2}$$

where the index i runs over all estimated regression coefficients $\widehat{b}_i$ corresponding to the variables and interaction terms that define the subgroup *SG*. This means the summation includes only those coefficients relevant for the subgroup under consideration. For example, to compute the OR for women with a first-generation migration background who are primary earners relative to men without a migration background who are not primary earnerprimary earners, the index i will run through values 1, 2, 4, 5, 7, 8 and 10 (see Eq. (1)).

Fig. 3, panel (a), presents the ORs and 95 %-CIs in forest plot format, resulting from the logistic regression model of Eq. (1) (numerical details are provided in Tables A.8 and A.9 in Annex 2). It is important to note that ORs are displayed at a logarithmic scale, where values above 1 indicate increased odds, and values below 1 indicate reduced odds of experiencing energy poverty. Due to the relatively small size of the 95 %-CIs, they are not visually discernible in the figure. The inclusion of interaction terms among predictors enables an evaluation of whether the effect of one predictor on the outcome varies across levels of other predictors. The values in Fig. 3, panel (a), shows that first-generation migrants (*1GNL*) have the highest odds of being energy poor, followed by female individuals that are primary earners (the interaction term *Women_PrimaryEarner*) and second-generation migrants (*2GNL*).

Fig. 3, panel (b) shows the ORs for various subgroups calculated according to Eq. (2). The results show that subgroups with a migration background are at greater risk of energy poverty compared to those without a migration background, with subgroups from first-generation migration background generally displaying higher odds than the subgroups from second-generation migration background. For example, among primary earners, the OR for men without a migration

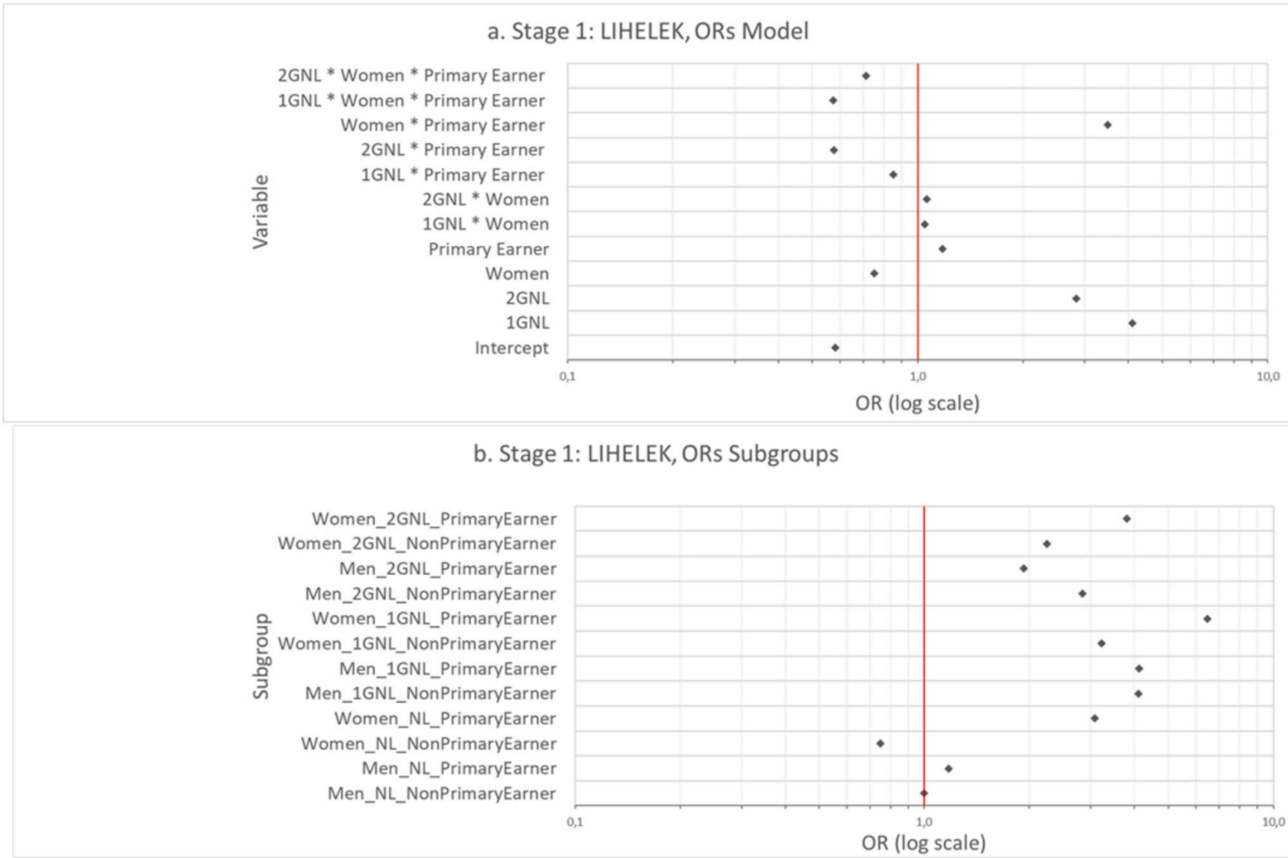

Fig. 3. Odd ratios from the compact model in Stage 1, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

background is 1.18, whereas men with a first-generation migration background exhibit an OR of 4.12, and men with a second-generation migration background feature an OR of 1.92.

Additionally, gender disparities are evident, as women that are primary earner consistently exhibit higher ORs than men that are primary earner across all migration background categories. For instance, women without a migration background who are primary earners have an OR of 3.08 compared to 1.18 for their male counterparts. These disparities underscore the intersectional influence of gender and migration background on energy poverty. Notably, households in which the primary earner is a woman with a first-generation migration background are at the greatest risk, with an OR of 6.48—indicating a 6.48-fold increase in the likelihood of experiencing energy poverty compared to the reference group.

For women, being the primary earner significantly increases the odds to face energy poverty risk. For instance, among women with a first-generation migration background, those who are primary earners exhibit an OR twice as high as that of those who are not primary earners (6.48 vs 3.22, respectively). In sum, these findings show that both migration background and primary earner status interact with gender to shape vulnerability to energy poverty.

3.2.2. Complex model

As noted before, next to the 'compact model' of Eq. (1) we run a 'complex model' to correct for the effect of possible predictors of energy poverty that may be correlated with gender and migration background. We do so by controlling for several explanatory variables (X) to our compact model, as follows:

$$\begin{aligned}\text{Logit}(\textit{Energy Poverty}) = & \beta_0 + \beta_1(\textit{Woman}) + \beta_2(1\textit{GNL}) + \beta_3(2\textit{GNL}) \\ & + \beta_4(\textit{Woman}_{1GNL}) + \beta_5(\textit{Woman}_{2GNL}) \\ & + \sum_{j \in Controls} \beta_j(X_j).\end{aligned} \tag{3}$$

The index j runs over a set of control variables, namely (with the reference categories indicated between brackets for categorical variables): *accommodation area*, *house type* (*apartment*), *homeownership status* (*homeowner*), *income type* (*work*), *urbanisation gradient* (*category 2*), *household type* (*couple without children*), and *construction year* (*intermediate*). We perform this more complex regression analysis both at the household and at the individual level. A comparison of the predictive performance (Table 4) between the compact model of Stage 1 and the more complex model presented here indicates that incorporating additional predictors improves the model's predictive capacity.

Because of space limitations, we present in Fig. 4, panel (a), only the household-level results (as identified by the primary earner of each household), as these summarize the main results and insights. Detailed results for the individual-level dataset are available in Tables A.10, A.11, A.12 and Fig. A.2 in Annex 2. Fig. 4, panel (a), presents the forest plot for

Table 4
Predictive performance metrics compact and complex model in Stage 1.

Household level	Compact model	Complex model
Performance metric	Score	Score
Accuracy	0,65	0,80
Precision	0,66	0,79
Sensitivity	0,62	0,84
Specificity	0,68	0,77
F-1 score	0,64	0,81
AUC-ROC	0,65	0,80

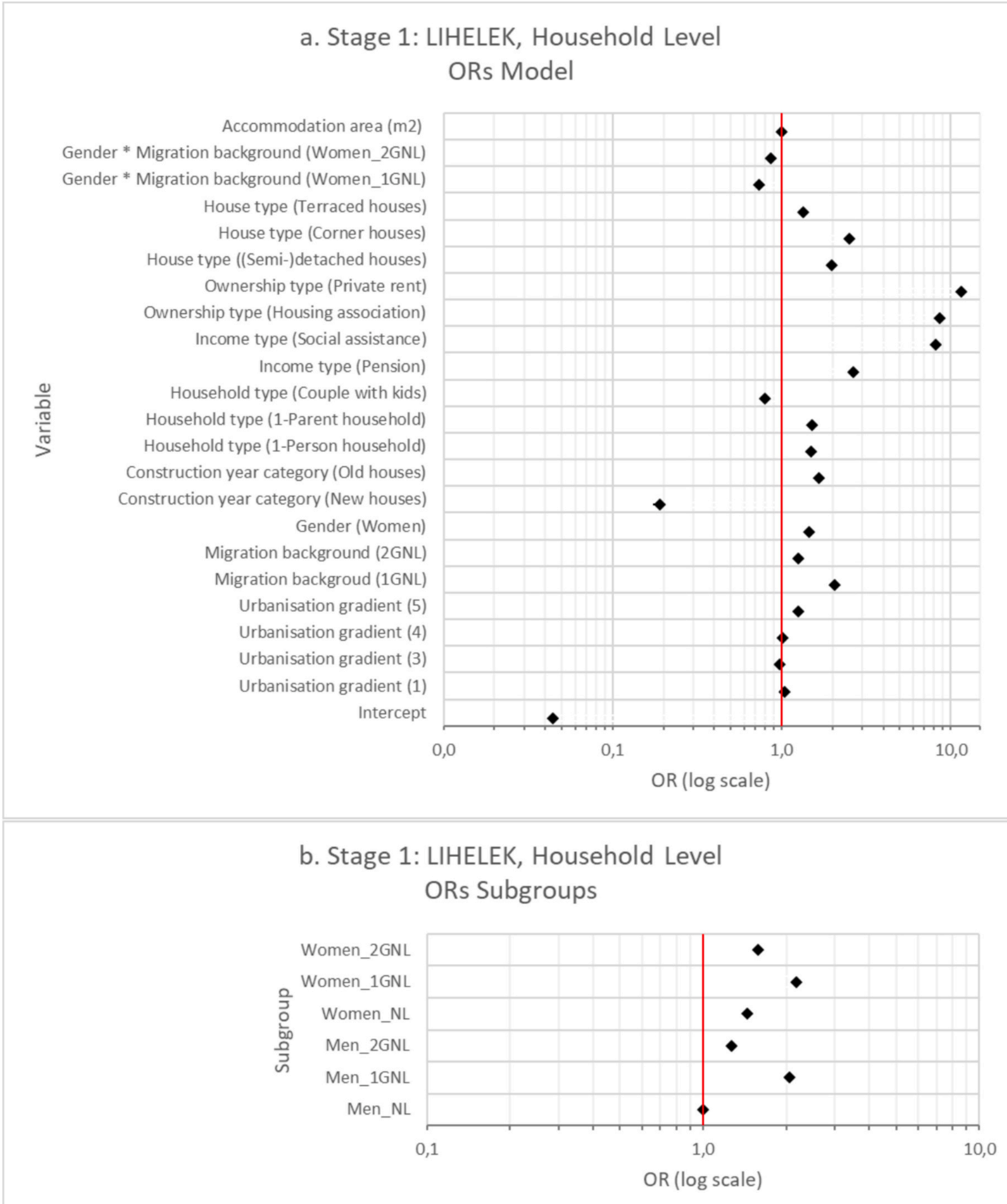

Fig. 4. Odd ratios from the complex model in Stage 1 at the household level, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

the complex logistic regression model corresponding to Stage 1. The results show that, compared to other predictors in the model, *gender* and *migration background* are now associated with relatively low ORs, indicating that these variables are not among the strongest predictors of energy poverty once we control the regression for other predictors of energy poverty. The most influential predictors for energy poverty include *ownership type* and *income type*. Households in commercially rented accommodations and social housing properties have ORs of 8.56 and 11.53, respectively, while those relying on social assistance or pensions exhibit ORs of 8.21 and 2.56, respectively. These factors are strongly correlated with income. Another significant predictor is the construction year category of the dwelling. Households in homes constructed in 2000–2020 (*new houses*) are associated with substantially lower odds of living in energy poverty (OR = 0.19) compared to those built between 1950 and 2000 (*intermediate houses*) (Fig. 4, panel a).

Panel (b) in Fig. 4 displays again the ORs for several subgroups, derived from the coefficients of the logistic regression model shown in panel (a) according to Eq. (2); again we use men without a migration background as the reference group. For more detail on numerical results of the underlying regression, including ORs, 95 %-CIs, and *p*-values, we refer to Tables A.10 and A.11 in Annex 2. The odds ratios (ORs) in Fig. 4, panel (b), demonstrate that after adjusting for the aforementioned additional predictors of energy poverty, the relationships between gender, migration background, and energy poverty as identified by the compact model (see Fig. 3, panel (b)) remain consistent. More specifically, we find again that households with a migration background, particularly first-generation migrants, as well as households led by women—particularly women with a first-generation migration background—have higher odds of living in energy poverty.

The analysis in Stage 2 allows us to separate the effect of income from that of gender and migration background on energy poverty status. In doing so, we explictly account for the fact that women and households with a migration background are often disproportionately represented in low-income groups [32–34].

3.3. Stage 2

In Stage 2 we narrow the focus of our analysis to low-income households, with the aim to identifying whether and to what extent gender and migration background characteristics among low-income individuals and households increase the risk of having high energy costs and/or a low energy-efficiency dwelling. The regression analyses in Stage 2 follows the same structure as Stage 1.

3.3.1. Compact model

Again, we start with a compact individual-level regression model, identical to Eq. (1), except that the dependent energy poverty variable is now defined in terms of high energy costs (HE) and/or a low energy-efficiency dwelling (LEK) – in short: HELEK – without the low-income (LI) criteria because the sample in Stage 2 is restricted to low-income individuals and households only. The reference groups remain the same as in Stage 1 and comparable forest plots are generated for analysis.

Fig. 5, panel (a), presents the forest plot with ORs and 95 %-CIs derived from the compact logistic regression model of Stage 2. Fig. 5, panel (b), again displays the calculated ORs for various subgroups relative to the reference group, using Eq. (2). The exact ORs, 95 %-CI and p-values can be found in Tables A.13 and A.14 in Annex 2. From Fig. 5, panel (b), it can be seen that the lowest OR obtained is for the category women with a second-generation migration background who are not primary earners (OR = 0.54). Notably, both male and female individuals without a migration background, irrespective of being a primary earner, exhibit higher odds of having energy costs and/or a house with low energetic quality (i.e. being energy poor according to the *HELEK* indicator) compared to their counterparts with a migration background. Among primary earners, people with a second-generation migration background display higher odds than people with a first-generation migration background, whereas the reverse pattern is observed for non-primary earners. For example, among primary earners, men without a migration background have an OR of 0.96, compared to men with a first-generation migration background (OR = 0.60) and men with a second-generation migration background (OR = 0.70).

The variation in ORs across migration background categories is more pronounced than the relatively modest differences observed between genders. However, across all migration backgrounds, within the low-income group, men are slightly more likely than women to be energy poor, regardless of primary earner status, except for people with a first-generation migration background who are primary earners.

A comparison between Stages 1 and 2 thus reveals a shift in patterns. In the compact model of Stage 1 (Fig. 3, panel b), women and households with a migration background displayed higher odds of experiencing energy poverty compared to men and those without a migration background. In Stage 2, however, when the low-income component of energy poverty is accounted for, the remaining bias reverses.

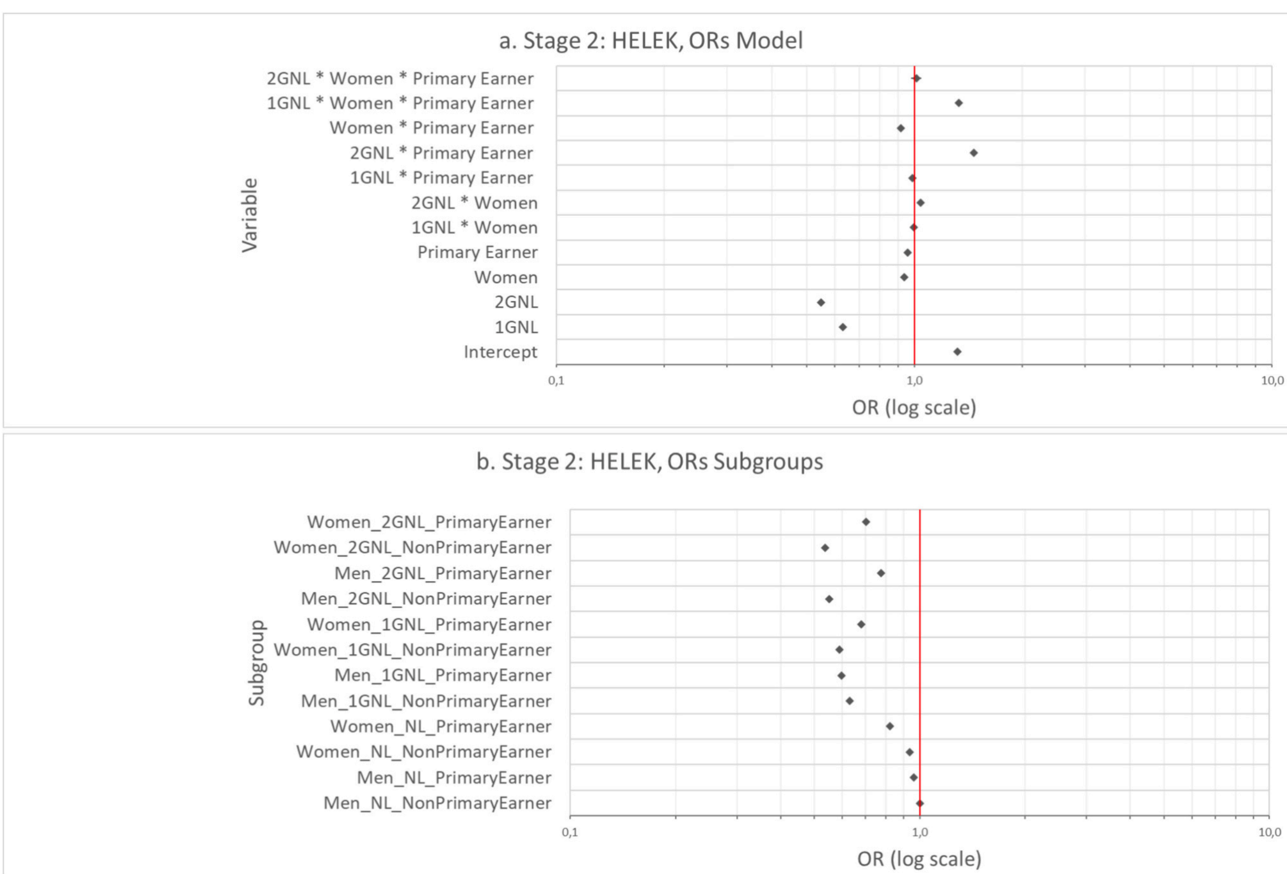

Fig. 5. Odd ratios from the compact model in Stage 2, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

Specifically, within the population of households with a low income, households with a migration background show lower odds of being categorized as being energy poor compared to those without a migration background (Fig. 5, panel b).

3.3.2. Complex model

Finally, we run the Stage 2 version of the complex logistic regression model (Eq. (3)), utilizing the household-level dataset. The reference groups for the variables remain consistent with those established in Stage 1. Like in Stage 1, the complex model not only takes into account the gender and migration characteristics of the compact model, but incorporates all relevant predictors (*household type, house type, income type, accommodation area, construction year category*), along with the interaction between *gender* and *migration background*. In addition, and in

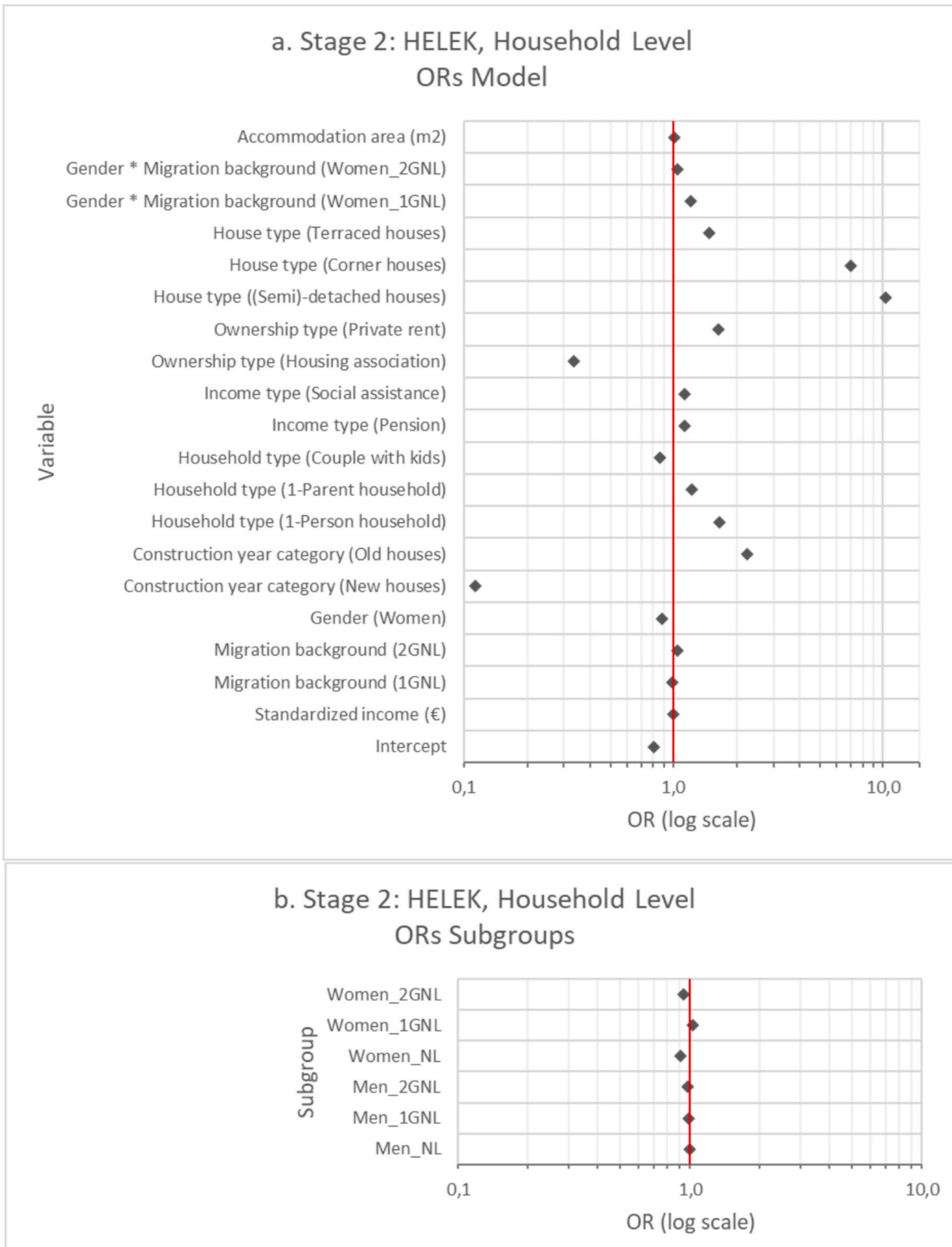

Fig. 6. Odd ratios from the complex model in Stage 2 at the household level, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

contrast to the complex model Stage 1, the complex model of Stage 2 also includes *standardized income* as independent variable, in order to be able to control explicitly for the interaction of income with gender and migration characteristics.

Fig. 6, panel (a), presents the forest plot with ORs and 95 %-CIs derived from the compact logistic regression model of Stage 2. Fig. 6, panel (b), again displays the calculated ORs for various subgroups relative to the reference group, using Eq. (2). The exact ORs, 95 %-CI, *p*-

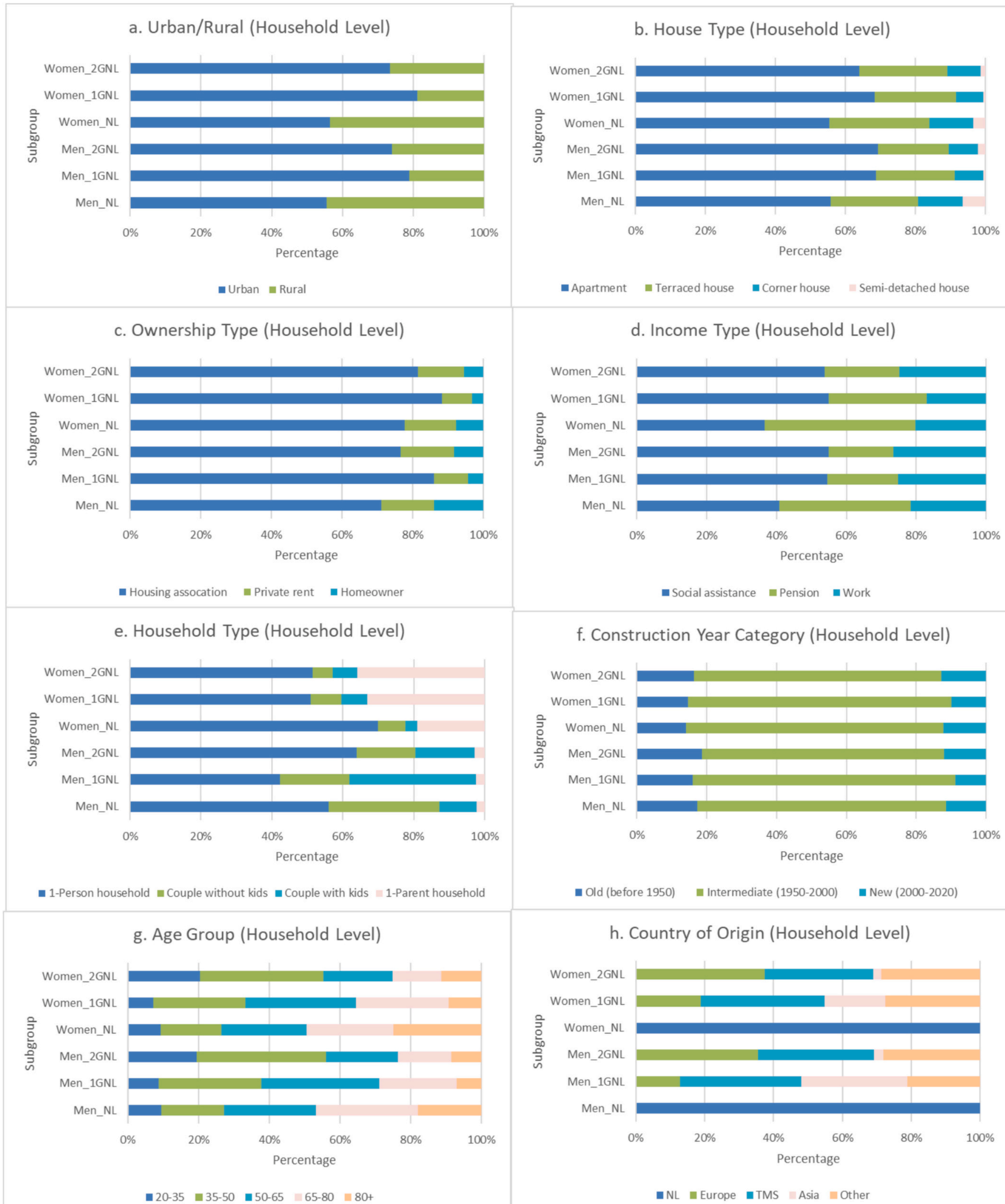

Fig. 7. Distribution feature categories in gender and migration background based subgroups within the low-income sample on the household level.

values and predictive performance metrics can be found in Tables A.15, A.16 and A.17 in Annex 2. Comparable results for the individual-level dataset are provided in the Fig. A.3 in Annex 2. A comparison of the predictive performance metrics for the compact model from Stage 2 with those of the more complex model reveals a similar improvement as observed in Stage 1 in all predictive scores upon the inclusion of the additional predictors (see Table A.10 in Annex 2). Finally, Table A.18 in Annex 2 outlines the likelihood ratio test performed to compare the full model (Fig. 6, panel b) with a restricted model that excludes the *gender* and *migration background* variables, as well as their interaction terms. Specifically, the inclusion of *gender* and *migration background* significantly enhances the model's fit, as evidenced by the LRT statistics (Table A.18 in Annex 2).

From Fig. 6, panel (a), it can be seen that, in general, variables associated with *gender* and *migration background* appear to play a relatively minor role in predicting energy poverty, as their ORs are close to 1. Notably, the predictor *1GNL* (first-generation migration background) is not statistically different from 1 (Table A.12 in Annex 2), an intriguing finding that suggests the previously observed lower odds of energy poverty within the subgroup of men with a low-income and first-generation migration background (Fig. 5, panel a) disappear when additional covariates are included. Fig. 6, panel (b), confirms these findings as the ORs for specific gender and migration subgroups are all very close to 1.

Fig. 6, panel (a), identifies *house type*, as primary predictor of energy poverty in the low-income sample; more specifically *(semi-)detached houses* exhibits an OR of 10.37, while *corner houses* have an OR of 7.03. Moreover, *construction year category* appears to significantly influence the likelihood of energy poverty, as newly built houses (2000–2020) have a notably lower OR (0.11), while older houses (before 1950) have a higher OR (2.25). Residing in a social housing dwelling is associated with significantly lower odds of energy poverty, as evidenced by an OR of 0.34. *Household type* also emerges as an important determinant, with one-person households and single-parent households demonstrating higher odds of experiencing energy poverty (ORs of 1.67 and 1.22, respectively), while couples with children exhibit lower odds (OR = 0.86).

In conclusion, when income is controlled for alongside other key predictors of energy poverty, the impact of gender and migration disparities on energy poverty prevalence is minimal compared to factors such as *house type, ownership type,* and *construction year category*. To further understand the underlying dynamics, in the next Section we provide a more in-depth descriptive quantitative analysis of the characteristics of intersectional gender and migration background subgroups with low income.

4. Characteristics of gender and migration background subgroups

The results from Stage 2 of the logistic regression analysis suggest that several characteristics—particularly *ownership type*, *house type*, and *construction year*—are significant predictors of energy poverty within the population of households with a low income, as also observed in other studies (see e.g. [41,42,46]. In this section, we examine characteristics across subgroups defined by the intersection of *gender* and *migration background*, aiming to deepen our understanding of variations in vulnerability to energy poverty within these subgroups of the low-income segment.

In Fig. 7 we present the distribution of household-level characteristics across the identified subgroups. A comparable figure at the individual level is provided in Annex 1 (Fig. A.1), with detailed percentages and counts available in Tables A.2 and A.3, and numerical subgroup characteristics in Table A.4.

As shown in Fig. 7, panel (a), households without a migration background are more likely to reside in rural areas. For example, among men, 44.5 % without a migration background live rurally, compared to 21.1 % with a first-generation and 26.1 % with a second-generation migration background. This spatial distribution is mirrored in dwelling type (panel b), where households without a migration background are more likely to occupy (semi-)detached houses, particularly men (6.0 %) compared to women (3.2 %). In contrast, households with a migration background—especially first-generation—are more frequently found in apartments, social housing, and in urban areas. This may partly explain why low-income households with a migration background are less likely to experience high energy costs or reside in low energy-efficiency houses, compared to their counterparts without a migration background. Apartments in urban areas tend to benefit from the urban heat island effect, which raises ambient temperatures and can reduce heating demand in winter. Compared to detached or semi-detached houses, apartments, especially those in multi-unit buildings, generally lose less heat because they share walls, floors, and ceilings with adjacent units, reducing the external surface area exposed to the cold. This means that households in apartments in urban areas may face lower energy costs, thereby reducing their exposure to energy poverty. However, apartment residents, particularly in social housing or private rent, can have limited control over heating systems and building-level energy upgrades, which can still heighten vulnerability to energy poverty if the building is poorly maintained or inefficient.

Housing tenure also varies substantially (panel c). Men, regardless of migration background, are generally more likely to own a home or rent commercially than women. Specifically, men without a migration background exhibit higher rates of homeownership (14 %) or commercial renting (14.8 %) compared to their counterparts with a migration background. Women with a first-generation migration background are most likely to live in housing corporation dwellings (88.3 %) and are the least likely to own a home (3.1 %) or rent privately (8.6 %) compared to all other groups. Homeowners can invest in energy efficiency themselves but face higher upfront costs, while tenants in social housing or private rent depend on landlords for upgrades, limiting their ability to lower energy bills and increasing energy poverty risk. In terms of income source (panel d), women with low incomes, particularly those without a migration background, more often rely on pensions (up to 41.3 %). In contrast, men, especially those with a second-generation migration background, more frequently derive income from employment (showing the lowest pension reliance at 18.5 %). Households with a migration background are relatively more dependent on social assistance. Households that rely on fixed or low benefits like pensions or social assistance often face tight budgets with little flexibility. This makes it harder to absorb high or rising energy bills, increasing their exposure to energy poverty. Employed individuals may be more resilient, but low-wage or unstable jobs still present risks, especially if energy costs spike. Household composition also varies significantly (panel e). Women, especially with a second generation migration background, are most likely to head single-parent households, with a rate of 36 %, compared to under 3 % for men across all migration backgrounds. Women without a migration background are most likely to live alone (70 %), the highest percentage among all groups, whereas men are more often in couple households, with or without children. Couples with children are most prevalent among first-generation migrants (35.7 %), while couples without children are most common among households without a migration background (31.2 %). Single-parent and single-person households tend to have higher energy usage per capita due to less opportunity to share fixed energy needs such as heating and appliances. In contrast, couples can benefit from economies of scale in energy use, which reduces their per capita consumption and associated energy poverty risk.

The distribution of construction year categories varies slightly across the different groups (panel f). Men consistently live more often in older homes than women across all migration backgrounds. Men with a second generation migration background are most likely to live in old houses (18.7 %), followed by men without a migration background (17.4 %), while women without a migration background have the lowest share in this category (14.1 %). Old houses are typically less energy-efficient, which may increase exposure to energy poverty, especially for those lacking resources to invest in renovations. Conversely, particularly women with a second generation migration background (12.8 %) and without migration background (12.3 %) are more likely to live in newer homes (built after 2000), which are typically more energy-efficient, significantly reducing the exposure to energy poverty.

In our regression models we did not include household head age and country of origin as predictors, as these variables did not show significant prediction power. Nevertheless, we show the distribution of these two variables in, respectively, panels g and h of Fig. 7, in order to provide additional contextual information about the heterogeneity of low income households. Panel g reveals that both men and women without a migration background have a relatively higher share of older individuals (65+), particularly women. Among women without a migration background, 22.7 % are aged 65–80 and 19.7 % are 80 or older; for men, these figures are 21.1 % and 13.6 %, respectively. These older age groups are highly correlated with the *pension* category of the income type variable (panel d), which is included in our regressions and captures much of the age-related effect on energy poverty risk. Panel h shows the distribution of country of origin among individuals with a migration background. Most first-generation migrants come from Turkey, Suriname, or Morocco (35.2 % of men and 36.0 % of women), or from Asia (30.8 % of men and 17.6 % of women). Among second-generation migrants, the largest group has European origins (35.5 % of men and 37.4 % of women), followed by Turkey, Suriname, or Morocco. While these background characteristics were not analyzed in relation to energy poverty here, they may offer valuable insights for future research.

Next, in Fig. 8, we present the distribution of these subtypes of energy poverty within the low-income sample, categorized by *gender*, *migration background*, and *housing tenure*. Exact percentages are detailed in Table A.5 in Annex 1.

Fig. 8 illustrates notable patterns at the intersection of gender, migration background, housing tenure, and energy poverty subtypes. Across all homeownership types, it is evident that among household residing in houses with poor energy efficiency, men are more likely than women to mitigate high energy costs when living in poorly insulated dwellings (classified as *not-HE & LEK*), likely by reducing energy usage. In contrast, women are more frequently affected by high energy costs in combination with low energetic housing quality (*HE & LEK*), suggesting a higher exposure to full-blown energy poverty. For instance, among homeowners without a migration background, 26.6 % of men fall into the *not-HE & LEK* subtype, compared to 23.2 % of women. Conversely, 40.1 % of men experience the *HE & LEK* subtype, whereas this figure rises to 44.6 % among women. Moreover, women with a first generation migration background appear disproportionately represented in the HE & not-LEK category—experiencing high energy costs despite residing in relatively energy-efficient homes—indicating vulnerability unrelated to housing quality alone. The data also reveal that households without a migration background are more likely to live in low-energy-efficiency homes, particularly in the private rental and homeownership sectors, compared to those with a migration background. Interestingly, households with a migration background—both private renters and homeowners—tend to manage their energy costs more effectively, even when residing in less efficient homes.

Another key observation is that households in social housing are less likely to experience energy poverty driven by poor housing quality, compared to private renters or homeowners. Instead, they are more likely to fall into the HE & not-LEK category—suggesting that high energy costs in this group may stem from factors unrelated to the buildings energy efficiency, such as household composition, energy needs, or pricing structures. Furthermore, private renters are disproportionately affected by the not-HE & LEK subtype, which may signal 'hidden energy poverty'—where households reduce their energy use below adequate levels to avoid unaffordable bills. This group faces additional financial vulnerability due to higher average rent levels in the private sector, increasing the overall housing cost burden.

5. Discussion & conclusion

This study set out to critically assess the increasingly prevalent claim that energy poverty in high-income countries, such as the Netherlands, is characterized by a gender and migration bias. Drawing on a unique and comprehensive dataset of Dutch administrative microdata, covering nearly 90 % of all households, we employed an intersectional approach combining descriptive statistics with a two-stage logistic regression framework. This allowed us to disentangle the influence of gender, migration background, income, and housing characteristics on energy poverty incidence, defined in line with the Dutch energy poverty monitor as low income in combination with either high energy costs or poor housing energy efficiency.

Our analysis shows that households led by women with a first-generation migration background face the highest odds of being energy poor, highlighting how gender, migration background, and primary earner status interact in ways that compound vulnerability. Our key finding is that what initially appears as a gender or migration bias in energy poverty statistics is, in fact, primarily a reflection of income disparities across these demographic groups. In other words, the over-representation of women and households with a migration background among energy-poor households is largely explained by their high prevalence of a low income. Beyond income, our results also highlight the significance of spatial, institutional, and behavioral factors in shaping gender- and migration-related variation in energy poverty. Housing location and tenure, building type, and energy-use strategies all interact with demographic characteristics, contributing to diverse vulnerability profiles that are not captured by income alone.

We found that while women and households with a migration background appear overrepresented among energy-poor households in the full population of Dutch households, this overrepresentation among energy-poor households largely disappears once we restrict our analysis to households with a low income. Our regression results further confirm that in the low income sample, once income is held constant, gender and migration background play a relatively modest role compared to other predictors. Housing tenure, dwelling type, and construction year emerged as dominant explanatory variables.

These results highlight that the elevated risk of energy poverty among women and migrant households is rooted in broader structural income inequalities. The persistent gender pay gap, which remains around 12–13 % in the Netherlands and mirrors the EU average [52–54], continues to limit women's financial resilience. Immigrants also earn less than native workers even in equivalent jobs, with recent empirical research finding an average gap of 15 % in the Netherlands and up to 25 % for workers from Africa and the Middle East [55]. These disadvantages intersect with household composition: women are disproportionately represented among single-parent households, which make up nearly 13 % of households with children in the EU and typically face greater financial constraints [56,57]. Using microdata by Statistics Netherlands, recent research by CPB Netherlands Bureau for Economic Policy Analysis shows that mothers' earnings fall by 46 % after childbirth while fathers' earnings remain unaffected, reinforcing long-term gendered income disparities [58]. Our regression analysis confirms this pattern, showing that single-parent households and those where a woman is the primary earner are significantly more likely to be energy poor. These findings underline that energy poverty cannot be understood in isolation, but must be situated in wider debates on gender and migration pay gaps and the socioeconomic vulnerability of single-parent families. For policy, this implies that interventions should not only target energy efficiency and affordability, but also address underlying structural inequalities that amplify vulnerability to energy poverty.

Importantly, we also found that households with a low income in commercially rented dwellings and own homes are significantly more

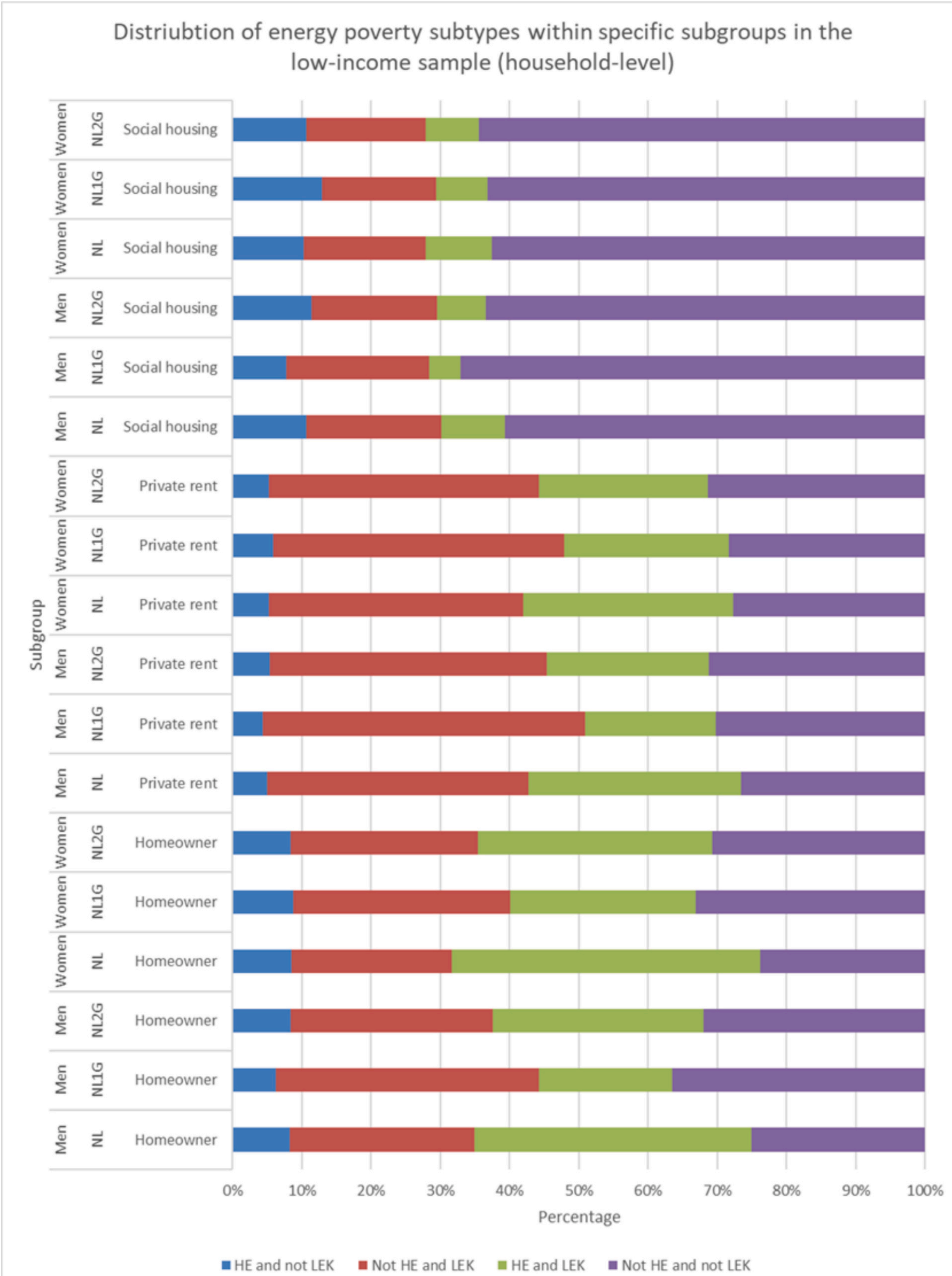

Fig. 8. HELEK division into subtypes of energy poverty in the low-income sample per subgroup based on gender, migration background and ownership type.

likely to experience energy poverty than households that rent in the social housing sector. This is primarily due to lower average energetic housing quality in the commercially rented and privately owned dwellings. Social housing in The Netherlands, by contrast, often provides relatively better insulation and energy efficiency [59], due to targeted public investment and regulation, thereby mitigating energy poverty risk despite residents' low incomes. In other words, we find that the relatively high energy quality of social housing in the Netherlands mitigates the risk that women and migrants end up in energy poverty because of a gender and migration pay gap.

Interestingly, we also found evidence of gender- and migration-related variation in how households may respond to energy poverty pressures. For example, our data suggest that women—especially those with a migration background—are relatively more likely to face the 'full-blown' energy poverty condition of simultaneously high energy costs and low energy efficiency, whereas men are more likely to show signs of 'hidden energy poverty' by under-consuming energy to avoid high bills. These behavioral responses, in combination with housing types and tenure, point to the complexity of how energy poverty manifests and how it should be addressed.

These results underscore the importance of intersectionality in energy poverty research. A one-dimensional focus on either gender or migration risks overlooking the complex interaction of these and other factors that shape vulnerability to energy poverty. Our study also illustrates the value of using high-resolution administrative microdata for such analysis, allowing for robust insights that can guide targeted policy interventions.

Inevitably, our study is subject to several limitations. First of all, an important limitation of our analysis relates to the measurement of energy poverty. We adopt the LIHELEK definition used in the CBS Energy Poverty Monitor, which includes the LEK (Low Energetic Quality) indicator as a proxy for poor housing conditions. The LEK measure is not based on direct energy performance data, but is estimated through a model. This modeling approach is necessary because up-to-date energy label data is not consistently available for all dwellings in the Netherlands. As a result, our identification of energy-poor households, based in part on this estimation, may be subject to measurement error, adding uncertainty to our findings.

Additionally, energy poverty is defined as a binary feature in this research, although in reality energy poverty is a nuanced issue that operates along a spectrum. For example, we only looked into households with a low-income defined by a certain threshold. Although the gender and migration bias in terms of housing quality and energy costs doesn't seem to appear in the low-income sample, there might be such a bias among households with a higher income, just above this threshold.

Moreover, we used data from 2020, a year marked by the COVID-19 pandemic, which may have temporarily affected energy consumption patterns and household incomes (e.g., due to remote work or economic disruptions). Further research should explore whether and how energy poverty patterns during the pandemic differ from non-pandemic periods, and what implications these differences may have for understanding long-term vulnerabilities. Although the use of large datasets helps us to conduct generalizable insight for the Dutch population, we are aware of the fact that intercategorical intersectionality may oversimplify the experiences of individuals with different gender and migration backgrounds. With the current analysis we assume a uniformity within these categories, while in reality, experiences can differ widely based on factors such as nationality, immigration history, or integration into society. This approach risks overlooking how gender roles and migration experiences are shaped by varying social, cultural, and political contexts. Moreover, existing research highlights that energy poverty is not only experienced differently across social groups, but also coped with in distinct and gendered ways [60]. Dedicated qualitative case studies are needed to get to a more nuanced understanding of intersectional identities, which are beyond the scope of our data-driven analysis.

Furthermore, endogeneity is always a potential concern in this type of research. While we had access to a wide range of household and housing characteristics for our analyses, there remains a possibility that an important predictor is missing. For instance, data on education level were unavailable, which could be a key factor influencing both financial literacy and energy-related decision-making. Higher education levels may lead to better awareness of energy efficiency measures and improved financial management, both of which can impact energy poverty. The absence of such variables may introduce unobserved heterogeneity, potentially affecting the robustness of our findings. The inclusion of such data would enhance the accuracy of this analysis. From a policy perspective, our findings suggest that effectively addressing energy poverty among vulnerable populations requires an approach that extends beyond the energy domain, as also attested by other authors (see e.g. [61,62]). Policies focused on income support, reduction of the gender and migration pay gap, and the provision of affordable, energy-efficient housing may prove more impactful in the long run than direct energy cost compensation schemes. This is particularly relevant given the practical and legal challenges associated with accurately targeting compensation to specific income groups or housing tenure categories [59] – let alone to demographic groups defined by gender or migration background. In the short term, interventions aimed at directly supporting energy-poor households – for example, by facilitating access to low-cost energy efficiency measures or promoting energy-saving behavioral changes – should be carefully designed to reflect the structural and behavioral differences between population groups. Without such nuance, there is a risk of reinforcing inequalities or excluding those most in need. Tailoring these measures to diverse household profiles is essential to ensure that energy poverty policies are both inclusive and effective.

A limitation of our individual-level analysis is that household-level variables, such as energy poverty status, are uniformly assigned to all household members. This assumes equal access to energy services and income within the household, which may not reflect the lived experiences of all individuals. While this approach is necessary given the data structure and common in similar studies, it does not allow us to capture intra-household variations in vulnerability or resource distribution.

In conclusion, this paper highlights that while energy poverty is a deeply socio-economic issue, its apparent demographic biases can often be traced back to structural inequalities in income and housing. A just and inclusive energy transition will therefore depend not only on improving energy efficiency and affordability but also on addressing the broader socio-economic and institutional conditions that underlie energy vulnerability.

CRediT authorship contribution statement

Lisanne Visseren: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anika Batenburg:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Francesco Dalla Longa:** Writing – review & editing, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Peter Mulder:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization.

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.

Annex 1. Descriptive analysis

Table A.1
Energy poverty incidence for household categories other than gender and migration.

Category	Full sample (all households) Energy poverty Incidence (LIHELEK)				Low income sample (Households with low income) Energy poverty Incidence (HELEK)			
	Household level		Individual level		Household level		Individual level	
	#	%	#	%	#	%	#	%
All households	439,254	6.4 %	761,220	4.9 %	439,254	44.0 %	761,220	43.2 %
Income								
Income type: Social assistance	195,780	29,7 %	343,245	28.0 %	195,780	42.3 %	343,245	41.1 %
Income type: Pension	149,571	7,4 %	201,184	6.4 %	149,571	44.8 %	201,184	44.5 %
Income type: Work	93,903	2,2 %	216,791	2.0 %	93,903	46.4 %	216,791	45.6 %
Tenure								
Social rent	308,803	15.2 %	524,388	14.2 %	308,803	38.1 %	524,388	37.1 %
Commercial rent	85,166	12,0 %	135,198	10.7 %	85,166	67.2 %	135,198	66.4 %
Homeowner	45,285	1,1 %	101,634	1.0 %	45,285	73.2 %	101,634	70.3 %
Household type								
1-Person	260,776	11.3 %	260,776	11.3 %	260,776	44.3 %	260,776	44.3 %
Couples without kids	69,176	3.2 %	139,616	3.2 %	69,176	44.9 %	139,616	44.9 %
1-Parent	62,886	12.0 %	168,116	12.5 %	62,886	43.2 %	168,116	42.7 %
Couples with kids	46,416	2.4 %	192,712	2.6 %	46,416	41.5 %	192,712	41.0 %
Age group								
0–20 years	0	0,00 %	154,228	5.6 %	0	0,0 %	154,228	40.5 %
20–35 years	41,971	6.7 %	100,547	4.0 %	41,971	41.3 %	100,547	42.3 %
35–50 years	94,992	5.9 %	126,656	4.6 %	94,992	42.2 %	126,656	42.3 %
50–65 years	122,134	5.9 %	152,500	4.5 %	122,134	46.1 %	152,500	46.6 %
65–80 years	109,836	6.4 %	141,672	5.2 %	109,836	45.8 %	141,672	45.9 %
80+ years	70,321	8.5 %	85,567	7.7 %	70,321	44.1 %	85,567	43.4 %
House type								
Apartments	189,500	8.4 %	275,488	7.4 %	189,500	32.0 %	275,488	30.2 %
Terraced houses	116,423	5.4 %	224,471	4.2 %	116,423	437.3 %	224,471	42.7 %
Corner houses	83,867	9.0 %	166,200	7.2 %	83,867	79.2 %	166,200	76.8 %
(Semi-)detached houses	49,464	3.2 %	95,061	2.3 %	49,464	89.1 %	95,061	87.9 %
Construction year								
Old houses (<1950)	107,597	8.4 %	180,953	6.3 %	107,597	70.3 %	180,953	69.2 %
Intermediate houses (1950–2000)	318,073	7.1 %	558,119	5.7 %	318,073	43.2 %	558,119	42.7 %
New houses (>2000)	13,584	1.2 %	22,148	0.8 %	13,584	12.4 %	22,148	11.4 %
Urban/rural								
Urban	270,035	7.7 %	457,374	6.2 %	270,035	41.2 %	457,374	40,4 %
Rural	169,219	5.0 %	303,846	3.8 %	169,219	49.2 %	303,846	49,1 %
Urbanisation Gradient 1 (most urban)	151,838	9.0 %	249,373	7,7 %	151,838	41.4 %	249,373	39.4 %
Urbanisation Gradient 2	118,197	6.5 %	208,001	5,2 %	118,197	41.0 %	208,001	40.7 %
Urbanisation Gradient 3	66,846	5.3 %	119,802	4,0 %	66,846	43.3 %	119,802	42.9 %
Urbanisation Gradient 4	52,014	4.8 %	94,160	3,6 %	52,014	47.5 %	94,160	47.8 %
Urbanisation Gradient 5 (most rural)	50,359	5.0 %	89,884	3,6 %	50,359	63.0 %	89,884	62.8 %

Table A.2
Percentages per subgroup (intersection gender and migration generation) for different categories within each variable (low-income sample and at household level).

Individual level low-income sample		Number of observations (#)						Percentages (%)					
Variable	Category	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women
Urbanisation Gradient	Urbanisation gradient 1 (most urban)	64,940	92,281	40,714	13,457	7076	6154	28,5 %	51,3 %	44,1 %	27,0 %	52,6 %	41,9 %
Urbanisation Gradient	Urbanisation gradient 2	61,791	49,859	27,472	14,683	3841	4614	27,1 %	27,7 %	29,8 %	29,5 %	28,5 %	31,4 %
Urbanisation Gradient	Urbanisation gradient 3	38,905	20,977	12,080	9084	1498	2051	17,1 %	11,7 %	13,1 %	18,2 %	11,1 %	14,0 %
Urbanisation Gradient	Urbanisation gradient 4	31,808	11,383	7373	7155	714	1199	13,9 %	6,3 %	8,0 %	14,4 %	5,3 %	8,2 %
Urbanisation Gradient	Urbanisation gradient 5 (most rural)	30,736	5558	4649	5479	329	667	13,5 %	3,1 %	5,0 %	11,0 %	2,4 %	4,5 %
Construction Year House	Old houses (year: before 1950)	39,794	28,756	17,247	7015	1978	2414	17,4 %	16,0 %	18,7 %	14,1 %	14,7 %	16,4 %

(continued on next page)

Table A.2 (*continued*)

Individual level low-income sample		Number of observations (#)						Percentages (%)					
Variable	Category	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women
Construction Year House	Intermediate houses (year: 1950–2000)	162,053	135,496	63,914	36,701	10,144	10,393	71,0 %	75,3 %	69,3 %	73,6 %	75,4 %	70,8 %
Construction Year House	New houses (year: 2000–2020)	26,332	15,809	11,120	6143	1335	1877	11,5 %	8,8 %	12,1 %	12,3 %	9,9 %	12,8 %
Household Type	1-Person households	127,986	76,274	59,051	34,901	6846	7566	56,1 %	42,4 %	64,0 %	70,0 %	50,9 %	51,5 %
Household Type	Couples without kids	71,146	35,148	15,189	3834	1170	820	31,2 %	19,5 %	16,5 %	7,7 %	8,7 %	5,6 %
Household Type	Couples with kids	23,959	64,354	15,540	1633	1000	1017	10,5 %	35,7 %	16,8 %	3,3 %	7,4 %	6,9 %
Household Type	1-Parent households	5091	4300	2499	9488	4441	5280	2,2 %	2,4 %	2,7 %	19,0 %	33,0 %	36,0 %
Income Type	Social assistance	92,983	98,079	50,644	18,283	7388	7897	40,8 %	54,5 %	54,9 %	36,7 %	54,9 %	53,8 %
Income Type	Work	86,001	36,750	17,100	21,509	3784	3139	37,7 %	20,4 %	18,5 %	43,1 %	28,1 %	21,4 %
Income Type	Pension	49,195	45,231	24,538	10,067	2285	3647	21,6 %	25,1 %	26,6 %	20,2 %	17,0 %	24,8 %
House Type	Apartments	120,205	122,135	62,345	26,410	9093	9187	52,7 %	67,8 %	67,6 %	53,0 %	67,6 %	62,6 %
House Type	Terraced houses	53,691	40,028	18,179	13,611	3103	3589	23,5 %	22,2 %	19,7 %	27,3 %	23,1 %	24,4 %
House Type	Corner houses	27,701	14,563	7527	6008	1042	1358	12,1 %	8,1 %	8,2 %	12,1 %	7,7 %	9,3 %
House Type	(Semi-) detached houses	13,759	911	1847	1609	64	199	6,0 %	0,5 %	2,0 %	3,2 %	0,5 %	1,4 %
Age Group	20–35	21,428	15,732	17,967	4593	973	2992	9,4 %	8,7 %	19,5 %	9,2 %	7,2 %	20,4 %
Age Group	35–50	40,707	52,254	33,683	8581	3492	5129	17,8 %	29,0 %	36,5 %	17,2 %	26,0 %	34,9 %
Age Group	50–65	59,463	60,212	18,844	12,046	4213	2871	26,1 %	33,4 %	20,4 %	24,2 %	31,3 %	19,6 %
Age Group	65–80	65,830	39,289	14,008	12,220	3542	2031	28,9 %	21,8 %	15,2 %	24,5 %	26,3 %	13,8 %
Age Group	80+	40,730	12,581	7773	12,425	1236	1661	17,9 %	7,0 %	8,4 %	24,9 %	9,2 %	11,3 %
Urban	Urban	126,731	142,140	68,187	28,140	10,916	10,767	55,5 %	78,9 %	73,9 %	56,4 %	81,1 %	73,3 %
Urban	Rural	101,448	37,921	24,095	21,719	2541	3916	44,5 %	21,1 %	26,1 %	43,6 %	18,9 %	26,7 %
Ownership type	Housing Corporation	162,418	155,069	70,780	38,785	11,880	11,966	71,2 %	86,1 %	76,7 %	77,8 %	88,3 %	81,5 %
Ownership type	Homeowner	33,862	17,322	13,925	7269	1159	1928	14,8 %	9,6 %	15,1 %	14,6 %	8,6 %	13,1 %
Ownership type	Private Rent	31,899	7671	7580	3803	419	790	14,0 %	4,3 %	8,2 %	7,6 %	3,1 %	5,4 %
Country of origin	NL	228,179	0	0	49,859	0	0	100,0 %	0,0 %	0,0 %	100,0 %	0,0 %	0,0 %
Country of origin	Europe	0	23,105	32,730	0	2529	5498	0,0 %	12,8 %	35,5 %	0,0 %	18,8 %	37,4 %
Country of origin	TMS	0	63,295	31,146	0	4846	4628	0,0 %	35,2 %	33,8 %	0,0 %	36,0 %	31,5 %
Country of origin	Asia	0	55,395	2396	0	2366	330	0,0 %	30,8 %	2,6 %	0,0 %	17,6 %	2,2 %
Country of origin	Other	0	38,266	26,010	0	3715	4229	0,0 %	21,3 %	28,2 %	0,0 %	27,6 %	28,8 %

Table A.3
Percentages per subgroup (intersection gender and migration generation) for different categories within each variable (low-income sample and at individual level).

Individual level low-income sample		Number of observations (#)						Percentages (%)					
Variable	Category	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women
Urbanisation Gradient	Urbanisation gradient 1 (most urban)	104,866	106,459	49,919	15,612	7409	3339	26,6 %	47,4 %	46,9 %	24,6 %	47,5 %	45,1 %
Urbanisation Gradient	Urbanisation gradient 2	108,418	63,359	31,821	18,209	4490	2269	27,5 %	28,2 %	29,9 %	28,7 %	28,8 %	30,6 %
Urbanisation Gradient	Urbanisation gradient 3	70,056	28,906	13,691	11,842	1997	994	17,8 %	12,9 %	12,9 %	18,7 %	12,8 %	13,4 %
Urbanisation Gradient	Urbanisation gradient 4	56,913	17,173	7270	9580	1142	531	14,4 %	7,6 %	6,8 %	15,1 %	7,3 %	7,2 %
Urbanisation Gradient	Urbanisation gradient 5 (most rural)	54,466	8694	3762	8116	573	276	13,8 %	3,9 %	3,5 %	12,8 %	3,7 %	3,7 %
Construction Year House	Old houses (year: before 1950)	68,161	34,116	15,916	9250	2183	1066	17,3 %	15,2 %	15,0 %	14,6 %	14,0 %	14,4 %
Construction Year House	Intermediate houses (year: 1950–2000)	280,064	171,391	77,982	46,151	11,971	5454	71,0 %	76,3 %	73,3 %	72,8 %	76,7 %	73,6 %
Construction Year House	New houses (year: 2000–2020)	46,454	19,107	12,562	7958	1459	889	11,8 %	8,5 %	11,8 %	12,6 %	9,3 %	12,0 %
Household Type	1-Person households	143,545	66,144	17,097	28,005	4290	1168	36,4 %	29,5 %	16,1 %	44,2 %	27,5 %	15,8 %
Household Type	Couples without kids	105,142	44,740	6553	12,159	2567	393	26,6 %	19,9 %	6,2 %	19,2 %	16,4 %	5,3 %
Household Type	Couples with kids	77,120	97,925	46,938	8750	5370	2961	19,5 %	43,6 %	44,1 %	13,8 %	34,4 %	40,0 %
Household Type	1-Parent households	68,871	15,796	35,877	14,446	3385	2888	17,5 %	7,0 %	33,7 %	22,8 %	21,7 %	39,0 %
Income Type	Social assistance	160,911	123,956	61,927	22,030	8298	4181	40,8 %	55,2 %	58,2 %	34,8 %	53,2 %	56,4 %
Income Type	Work	119,035	59,766	35,941	16,917	3748	2446	30,2 %	26,6 %	33,8 %	26,7 %	24,0 %	33,0 %
Income Type	Pension	114,733	40,877	8590	24,412	3567	782	29,1 %	18,2 %	8,1 %	38,5 %	22,9 %	10,6 %
House Type	Apartments	175,198	138,577	59,660	28,074	9281	4079	44,4 %	61,7 %	56,0 %	44,3 %	59,5 %	55,1 %
House Type	Terraced houses	115,009	59,226	32,087	19,768	4399	2279	29,1 %	26,4 %	30,1 %	31,2 %	28,2 %	30,8 %
House Type	Corner houses	54,229	21,752	11,263	8839	1561	808	13,7 %	9,7 %	10,6 %	14,0 %	10,0 %	10,9 %
House Type	(Semi-) detached houses	26,526	1354	1356	3205	111	93	6,7 %	0,6 %	1,3 %	5,1 %	0,7 %	1,3 %
Age Group	0–20	80,317	28,704	57,605	8997	1491	3624	20,4 %	12,8 %	54,1 %	14,2 %	9,6 %	48,9 %
Age Group	20–35	47,243	28,030	23,027	6735	1922	1529	12,0 %	12,5 %	21,6 %	10,6 %	12,3 %	20,6 %
Age Group	35–50	53,124	53,297	12,317	8680	4162	1004	13,5 %	23,7 %	11,6 %	13,7 %	26,7 %	13,6 %
Age Group	50–65	77,318	59,833	6290	12,083	4012	522	19,6 %	26,6 %	5,9 %	19,1 %	25,7 %	7,0 %
Age Group	65–80	83,080	40,136	4576	14,408	3041	415	21,1 %	17,9 %	4,3 %	22,7 %	19,5 %	5,6 %
Age Group	80+	53,558	14,592	2637	12,456	984	317	13,6 %	6,5 %	2,5 %	19,7 %	6,3 %	4,3 %
Urban	Urban	213,285	169,819	81,740	33,821	11,899	5608	54,0 %	75,6 %	76,8 %	53,4 %	76,2 %	75,7 %
Urban	Rural	181,394	54,779	24,720	29,538	3712	1801	46,0 %	24,4 %	23,2 %	46,6 %	23,8 %	24,3 %
Ownership type	Housing Corporation	273,157	191,560	88,606	46,867	13,451	6225	69,2 %	85,3 %	83,2 %	74,0 %	86,2 %	84,0 %
Ownership type	Homeowner	65,793	10,592	8516	7895	729	539	16,7 %	4,7 %	8,0 %	12,5 %	4,7 %	7,3 %
Ownership type	Private Rent	55,689	22,449	9342	8598	1431	646	14,1 %	10,0 %	8,8 %	13,6 %	9,2 %	8,7 %
Country of origin	NL	394,679	0	0	63,359	0	0	100,0 %	0,0 %	0,0 %	100,0 %	0,0 %	0,0 %
Country of origin	Europe	0	31,424	19,960	0	2639	1615	0,0 %	14,0 %	18,7 %	0,0 %	16,9 %	21,8 %
Country of origin	TMS	0	68,570	43,940	0	5022	2945	0,0 %	30,5 %	41,3 %	0,0 %	32,2 %	39,8 %

(*continued on next page*)

Table A.3 (*continued*)

Individual level low-income sample		Number of observations (#)						Percentages (%)					
Variable	Category	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women	NL + Men	1GNL + Men	2GNL + Men	NL + Women	1GNL + Women	2GNL + Women
Country of origin	Asia	0	76,770	14,516	0	4338	906	0,0 %	34,2 %	13,6 %	0,0 %	27,8 %	12,2 %
Country of origin	Other	0	47,834	28,043	0	3613	1943	0,0 %	21,3 %	26,3 %	0,0 %	23,1 %	26,2 %

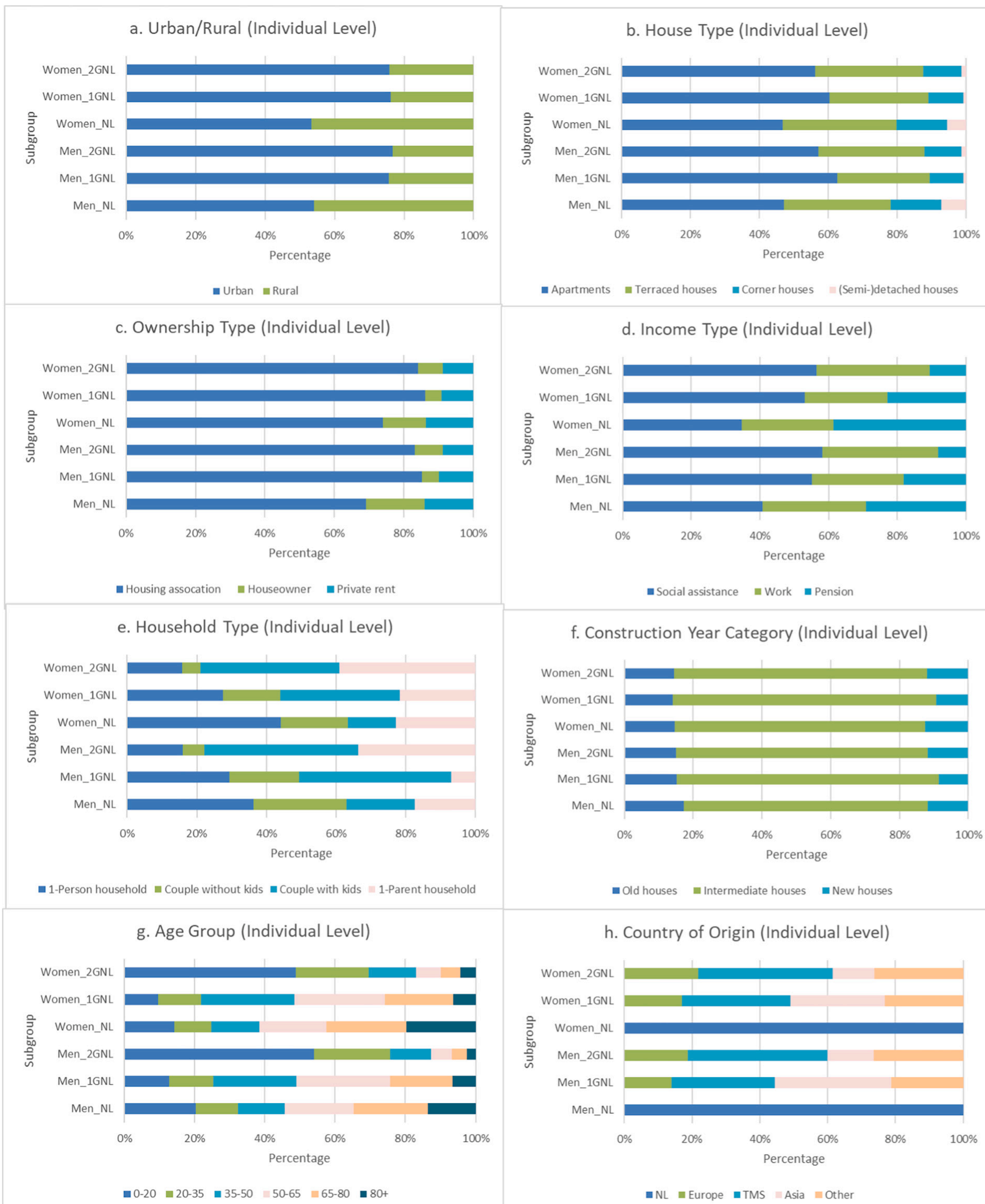

Fig. A.1. Characteristics per subgroup (intersection gender and migration generation) on individual level within the low-income sample.

Table A.4
Low income sample: median, interquartile range (IQR) and count per subgroup (intersection gender and migration generation) for the numerical features.

Subgroup	Variable	Household level			Individual Level		
		Median	IQR	Count	Median	IQR	Count
Men_NL	Standardized income (€)	16,003	14,454.0–17,284.0	288,198	15,805	14,128.0–17,088.0	394,679
Men_NL	Accommodation area (m^2)	83	64.0–104.0	288,198	89	70.0–110.0	394,679
Men_NL	Construction year	1972	1957.0–1987.0	288,198	1972	1957.0–1986.0	394,679
Men_NL	Age (years)	63	48.0–75.0	288,198	53	26.0–71.0	394,679
Men_1GNL	Standardized income (€)	15,245	13,767.0–16,449.25	180,061	15,072	13,461.0–16,353.0	224,598
Men_1GNL	Accommodation area (m^2)	78	61.0–97.0	180,061	83	65.0–101.0	224,598
Men_1GNL	Construction year	1969	1957.0–1984.0	180,061	1969	1957.0–1984.0	224,598
Men_1GNL	Age (years)	55	43.0–67.0	180,061	50	34.0–64.0	224,598
Men_2GNL	Standardized income (€)	15,691	14,149.0–16,951.0	44,090	15,141	13,388.0–16,559.0	156,716
Men_2GNL	Accommodation area (m^2)	74	57.0–95.75	44,090	87	71.0–105.0	156,716
Men_2GNL	Construction year	1971	1955.0–1985.0	44,090	1969	1957.0–1985.0	156,716
Men_2GNL	Age (years)	46	36.0–64.0	44,090	18	10.0–34.0	156,716
Women_NL	Standardized income (€)	16,424	14,896.0–18,119.0	313,284	16,233	14,640.0–17,770.0	542,022
Women_NL	Accommodation area (m^2)	84	68.0–101.0	313,284	89	72.0–108.0	542,022
Women_NL	Construction year	1974	1960.0–1989.0	313,284	1973	1959.0–1988.0	542,022
Women_NL	Age (years)	64	48.0–79.0	313,284	59	35.0–76.0	542,022
Women_1GNL	Standardized income (€)	15,868	14,599.0–17,062.0	128,800	15,426	13,766.0–16,696.0	278,659
Women_1GNL	Accommodation area (m^2)	81	67.0–97.0	128,800	86	71.0–102.0	278,659
Women_1GNL	Construction year	1971	1958.0–1986.0	128,800	1970	1958.0–1984.0	278,659
Women_1GNL	Age (years)	58	45.0–70.0	128,800	50	37.0–65.0	278,659
Women_2GNL	Standardized income (€)	16,055	14,658.0–17,452.0	44,949	15,410	13,654.0–16,806.0	166,314
Women_2GNL	Accommodation area (m^2)	81	65.0–98.0	44,949	88	72.0–105.0	166,314
Women_2GNL	Construction year	1972	1957.0–1987.0	44,949	1970	1958.0–1985.0	166,314
Women_2GNL	Age (years)	46	36.0–65.0	44,949	20	11.0–39.0	166,314

Table A.5
Distribution of HELEK Subtypes of Energy Poverty across gender, migration background, and ownership type in the Low-Income Sample (%).

Gender	Migration background	Homeownership	Subtype: HE and not LEK (%)	Subtype: Not HE and LEK (%)	Subtype: HE and LEK (%)	Subtype: Not HE and not LEK (%)
Men	*NL*	*Homeowner*	8,3 %	26,6 %	40,1 %	25,0 %
Men	*NL1G*	*Homeowner*	6,2 %	38,1 %	19,2 %	36,5 %
Men	*NL2G*	*Homeowner*	8,3 %	29,2 %	30,4 %	32,0 %
Women	*NL*	*Homeowner*	8,5 %	23,2 %	44,6 %	23,8 %
Women	*NL1G*	*Homeowner*	8,8 %	31,3 %	26,8 %	33,1 %
Women	*NL2G*	*Homeowner*	8,4 %	27,1 %	33,7 %	30,8 %
Men	*NL*	*Private rent*	5,0 %	37,8 %	30,7 %	26,6 %
Men	*NL1G*	*Private rent*	4,4 %	46,6 %	18,8 %	30,3 %
Men	*NL2G*	*Private rent*	5,3 %	40,0 %	23,5 %	31,2 %
Women	*NL*	*Private rent*	5,3 %	36,7 %	30,2 %	27,8 %
Women	*NL1G*	*Private rent*	5,8 %	42,0 %	23,8 %	28,3 %
Women	*NL2G*	*Private rent*	5,2 %	39,0 %	24,4 %	31,4 %
Men	*NL*	*Social housing*	10,6 %	19,5 %	9,1 %	60,7 %
Men	*NL1G*	*Social housing*	7,7 %	20,7 %	4,5 %	67,1 %
Men	*NL2G*	*Social housing*	11,4 %	18,0 %	7,1 %	63,4 %
Women	*NL*	*Social housing*	10,2 %	17,6 %	9,6 %	62,6 %
Women	*NL1G*	*Social housing*	12,9 %	16,5 %	7,4 %	63,2 %
Women	*NL2G*	*Social housing*	10,6 %	17,3 %	7,6 %	64,5 %

Annex 2. Regression analysis

Table A.6
Overview of the final set of selected features in regression models of Stage 1 for the compact and complex model.

Stage 1					
Compact Model			Complex Model		
Variable Name	Variable Category	Variable Type	Variable Name	Variable Category	Variable Type
LIHELEK	Energy poverty indicator	Dependent variable	*LIHELEK*	Energy poverty indicator	Dependent variable
Migration background	Sociodemographics	Independent variable	*Migration background*	Sociodemographics	Independent variable
Gender	Sociodemographics	Independent variable	*Gender*	Sociodemographics	Independent variable

(*continued on next page*)

Table A.6 (*continued*)

Stage 1					
Compact Model			Complex Model		
Variable Name	Variable Category	Variable Type	Variable Name	Variable Category	Variable Type
Primary earner status	Sociodemographics	Independent variable	*Gender * Migration background*	Sociodemographics	Independent variable
*Gender * Migration background*	Sociodemographics	Independent variable	*Accommodation area* (m^2)	Dwelling Characteristics	Independent variable
*Migration background * Primary earner status*	Sociodemographics	Independent variable	*House type*	Dwelling Characteristics	Independent variable
*Gender * Primary earner status*	Sociodemographics	Independent variable	*Ownership type*	Dwelling Characteristics	Independent variable
*Migration background * Gender * Primary earner status*	Sociodemographics	Independent variable	*Household type*	Household Demographics	Independent variable
			Income type	Socioeconomic status	Independent variable
			Construction year category	Dwelling Characteristics	Independent variable
			Urbanisation gradient	Dwelling Characteristics	Independent variable

Table A.7
Overview of the final set of selected features in regression models of Stage 2 for the compact and complex model.

Stage 2					
Compact Model			Complex Model		
Variable Name	Variable Category	Variable Type	Variable Name	Variable Category	Variable Type
HELEK	Energy poverty indicator	Dependent variable	*HELEK*	Energy poverty indicator	Dependent variable
Migration background	Sociodemographics	Independent variable	*Migration background*	Sociodemographics	Independent variable
Gender	Sociodemographics	Independent variable	*Gender*	Sociodemographics	Independent variable
Primary earner status	Sociodemographics	Independent variable	*Gender * Migration background*	Sociodemographics	Independent variable
*Gender * Migration background*	Sociodemographics	Independent variable	*Accommodation area* (m^2)	Dwelling Characteristics	Independent variable
*Migration background * Primary earner status*	Sociodemographics	Independent variable	*House type*	Dwelling Characteristics	Independent variable
*Gender * Primary earner status*	Sociodemographics	Independent variable	*Ownership type*	Dwelling Characteristics	Independent variable
*Migration background * Gender * Primary earner status*	Sociodemographics	Independent variable	*Household type*	Household Demographics	Independent variable
			Income type	Socioeconomic status	Independent variable
			Construction year category	Dwelling Characteristics	Independent variable
			Standardized income (€)	Socioeconomic status	Independent variable

Stage 1: Compact model

Table A.8
Precise ORs, 95 %-CIs and p-values of the compact models of Stage 1 (LIHELEK) – Fig. 3, panel (a).

Compact model	LIHELEK Entire data			
Variable	OR	Lower 95 %-CI	Upper 95 %-CI	p-Values
Intercept	0,58	0,58	0,58	<0,001
Migration background (*1GNL*)	4,11	4,09	4,13	<0,001
Migration background (*2GNL*)	2,83	2,82	2,85	<0,001
Gender (*Women*)	0,75	0,75	0,75	<0,001
Primary earner status (*Primary earner*)	1,18	1,17	1,18	<0,001
*Gender * Migration background* (*Women * 1GNL*)	1,05	1,04	1,05	<0,001
*Gender * Migration background* (*Women * 2GNL*)	1,06	1,05	1,07	<0,001
*Migration background * Primary earner status* (*1GNL * Primary earner*)	0,85	0,85	0,86	<0,001

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Table A.8 (*continued*)

Compact model	LIHELEK Entire data			
Variable	OR	Lower 95 %-CI	Upper 95 %-CI	p-Values
*Migration background * Primary earner status (2GNL * Primary earner)*	0,58	0,57	0,58	<0,001
*Gender * Primary earner status (Women + Primary earner)*	3,50	3,48	3,51	<0,001
*Migration background * Gender * Primary earner status (1GNL * Women * Primary earner)*	0,57	0,57	0,58	<0,001
*Migration background * Gender * Primary earner status (2GNL * Women * Primary earner)*	0,71	0,71	0,72	<0,001

Table A.9
Adjusted ORs based on the compact model of Stage 1 (LIHELEK), for subgroups compared to the reference group – Fig. 3, panel (b).

OR LIHELEK		NL	1GNL	2GNL
Primary earner	Men	1,18	4,12	1,92
	Women	3,08	6,48	3,80
Not primary earner	Men	Ref (1)	4,11	2,83
	Women	0,75	3,22	2,25

Stage 1: Complex model

Table A.10
ORs, 95 %-CIs and *p*-values for Stage 1 (LIHELEK) complex models on household and individual level.

Complex model	*LIHELEK Household Level* (Fig. 4, panel a)				*LIHELEK Individual Level* (Fig. A.2, panel a)			
Predictor	OR	Lower 95 %-CI	Upper 95 %-CI	p-Value	OR	Lower 95 %-CI	Upper 95 %-CI	p-Value
Intercept	0,04	0,04	0,05	<0,001	0,07	0,07	0,08	<0,001
1GNL	2,05	2,01	2,09	<0,001	1,95	1,92	1,99	<0,001
2GNL	1,26	1,23	1,30	<0,001	1,44	1,42	1,47	<0,001
Women	1,45	1,43	1,47	<0,001	1,06	1,05	1,08	<0,001
New houses	0,19	0,19	0,19	<0,001	0,18	0,17	0,18	<0,001
Old houses	1,67	1,64	1,69	<0,001	1,58	1,56	1,60	<0,001
1-Person household	1,49	1,46	1,52	<0,001	1,51	1,49	1,53	<0,001
1-Parent household	1,51	1,47	1,54	<0,001	1,83	1,80	1,85	<0,001
Couple with kids	0,80	0,79	0,82	<0,001	0,70	0,69	0,71	<0,001
Urbanisation gradient 1 (most urban)	1,05	1,03	1,07	<0,001	1,04	1,03	1,05	<0,001
Urbanisation gradient 3	0,97	0,96	0,99	0,00	0,98	0,97	0,99	0,002
Urbanisation gradient 4	1,01	0,99	1,03	0,17	1,02	1,01	1,04	0,006
Urbanisation gradient 5 (most rural)	1,25	1,22	1,28	<0,001	1,24	1,22	1,26	<0,001
Pension	2,65	2,62	2,69	<0,001	2,76	2,73	2,79	<0,001
Social assistance	8,21	8,08	8,35	<0,001	7,49	7,39	7,58	<0,001
Housing association	8,56	8,43	8,69	<0,001	7,83	7,75	7,92	<0,001
Private rent	11,53	11,31	11,74	<0,001	10,92	10,77	11,08	<0,001
(Semi-)detached houses	1,99	1,94	2,03	<0,001	1,79	1,76	1,82	<0,001
Corner houses	2,53	2,48	2,58	<0,001	2,40	2,36	2,43	<0,001
Terraced houses	1,35	1,33	1,37	<0,001	1,26	1,24	1,27	<0,001
*Women * 1GNL*	0,73	0,71	0,75	<0,001	0,97	0,95	0,99	0,005
*Women * 2GNL*	0,87	0,83	0,90	<0,001	0,92	0,90	0,95	<0,001
Accommodation area (m^2)	1,00	1,00	1,00	0,924	1,00	1,00	1,00	0,012

Table A.11
Adjusted ORs based on the complex model of Stage 1 (LIHELEK) at the household level (Fig. 4, panel b) and individual level (Fig. A.2, panel b), for subgroups compared to the reference group.

Complex model	Stage 1 (LIHELEK)	
	Household Level	*Individual Level*
Subgroup	OR	OR
Men_NL	Ref (1)	Ref (1)
Men _1GNL	2,05	1,95
Men_2GNL	1,26	1,44
Women_NL	1,45	1,06
Women_1GNL	2,17	2,01
Women_2GNL	1,59	1,42

Table A.12
Predictive performance metrics for complex model of Stage 1 (LIHELEK) at the individual level – Fig. A.2.

Performance Metric	Score
Accuracy	0,81
Precision	0,80
Sensitivity	0,84
Specificity	0,79
F-1 score	0,82
AUC-ROC	0,81

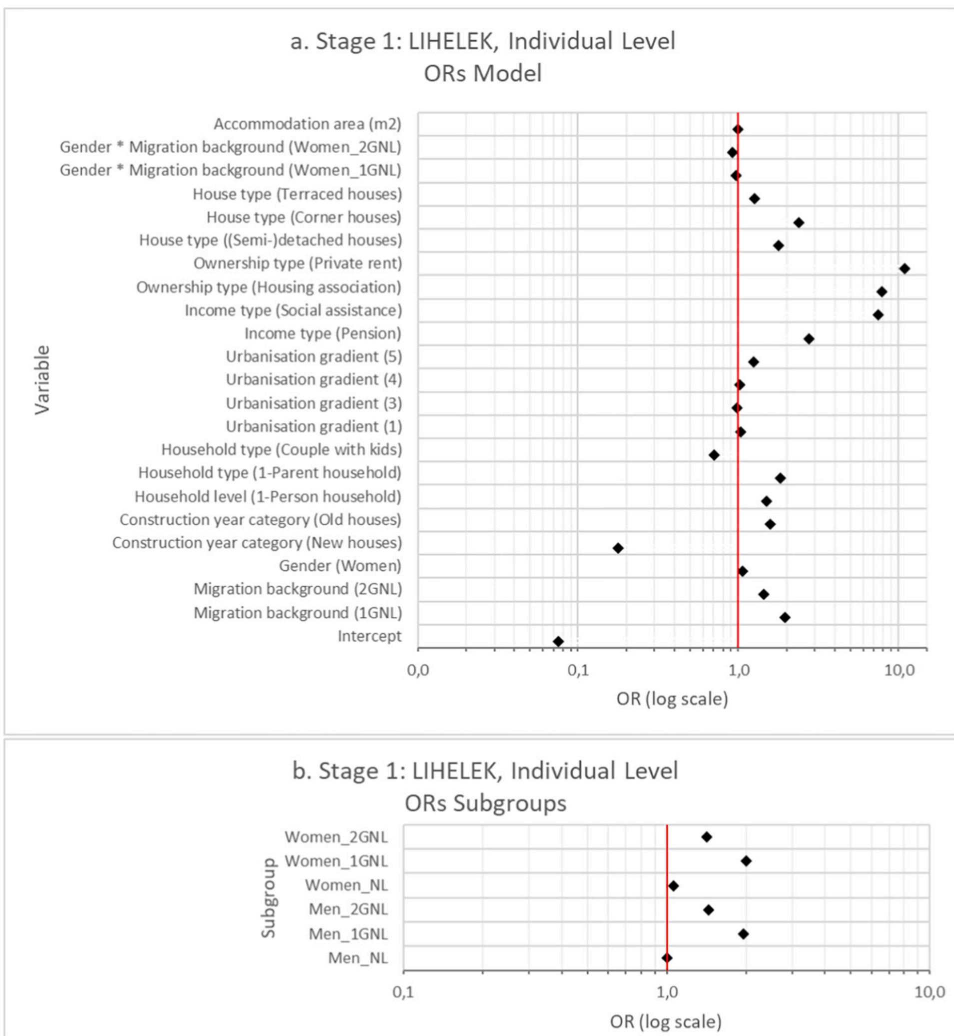

Fig. A.2. Odd ratios from the complex model in Stage 1 at the individual level, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

Stage 2: Compact model

Table A.13
Precise ORs, 95 %-CIs and *p*-values of the compact models of Stage 2 (HELEK) – Fig. 5, panel (a).

Compact model	HELEK Low-income Sample			
Variable	OR	Lower 95 %-CI	Upper 95 %-CI	p-Values
Intercept	1,32	1,31	1,33	<0,001
Migration background (1GNL)	0,63	0,62	0,64	<0,001
Migration background (2GNL)	0,55	0,54	0,56	<0,001
Gender (Women)	0,94	0,92	0,95	<0,001
Primary earner status (Primary earner)	0,96	0,95	0,97	<0,001
*Gender * Migration background (Women * 1GNL)*	1,00	0,98	1,02	0,75
*Gender * Migration background (Women * 2GNL)*	1,04	1,02	1,06	<0,001
*Migration background * Primary earner status (1GNL * Primary earner)*	0,99	0,97	1,01	0,25
*Migration background * Primary earner status (2GNL * Primary earner)*	1,47	1,43	1,50	<0,001
*Gender * Primary earner status (Women + Primary earner)*	0,92	0,90	0,93	<0,001
*Migration background * Gender * Primary earner status (1GNL * Women * Primary earner)*	1,33	1,30	1,37	<0,001
*Migration background * Gender * Primary earner status (2GNL * Women * Primary earner)*	1,02	0,98	1,05	0,37

Table A.14
Adjusted ORs based on the compact model of Stage 2 (HELEK), for subgroups compared to the reference group – Fig. 5, panel (b).

OR LIHELEK (HELEK)		NL	1GNL	2GNL
Primary earner	Men	0,96	0,60	0,77
	Women	0,82	0,68	0,70
Not primary earner	Men	Ref (1)	0,63	0,55
	Women	0,94	0,59	0,54

Stage 2: Complex model

Table A.15
ORs, 95 %-CIs and *p*-values for Stage 2 (HELEK) complex models on household and individual level.

Complex model	*HELEK Household Level* (Fig. 6, panel a)				*HELEK Individual Level* (Fig. A.3, panel a)			
Predictor	OR	Lower 95 %-CI	Upper 95 %-CI	p-Value	OR	Lower 95 %-CI	Upper 95 %-CI	p-Value
Intercept	0,80	0,78	0,83	<0,001	0,97	0,95	1,00	0,02
1GNL	0,99	0,98	1,00	0,17	0,99	0,98	1,00	0,07
2GNL	1,04	1,02	1,07	<0,001	0,98	0,96	0,99	<0,001
Women	0,88	0,87	0,89	<0,001	0,91	0,90	0,92	<0,001
New houses	0,11	0,11	0,12	<0,001	0,09	0,09	0,09	<0,001
Old houses	2,25	2,22	2,28	<0,001	2,23	2,21	2,25	<0,001
1-Person household	1,67	1,64	1,69	<0,001	1,60	1,59	1,62	<0,001
1-Parent household	1,22	1,20	1,24	<0,001	1,17	1,16	1,18	<0,001
Couple with kids	0,86	0,85	0,88	<0,001	0,86	0,85	0,87	<0,001
Pension	1,13	1,11	1,14	<0,001	1,11	1,10	1,12	<0,001
Social assistance	1,13	1,12	1,15	<0,001	1,11	1,10	1,12	<0,001
Housing association	0,34	0,33	0,34	<0,001	0,32	0,31	0,32	<0,001
Private rent	1,64	1,60	1,67	<0,001	1,66	1,63	1,68	<0,001
(Semi)-detached houses	10,35	10,06	10,64	<0,001	10,91	10,69	11,12	<0,001
Corner houses	7,03	6,92	7,15	<0,001	7,29	7,20	7,37	<0,001
Terraced houses	1,48	1,46	1,49	<0,001	1,39	1,38	1,40	<0,001
*1GNL * Women*	1,20	1,18	1,23	<0,001	1,14	1,12	1,16	<0,001
*2GNL * Women*	1,05	1,02	1,08	0,002	1,05	1,03	1,07	<0,001
Accommodation area (m^2)	1,01	1,00	1,01	<0,001	1,00	1,00	1,00	<0,001
Standardized income (€)	1,00	1,00	1,00	<0,001	1,00	1,00	1,00	<0,001

Table A.16
Adjusted ORs based on the complex model of Stage 2 (HELEK) at the household level (Fig. 6, panel b) and individual level (Fig. A.3, panel b), for subgroups compared to the reference group.

Complex model	Stage 2 (HELEK)	
	Household Level	*Individual Level*
Subgroup	OR	OR
Men_NL	Ref (1)	Ref (1)
Men_1GNL	0,99	0,99
Men_2GNL	0,98	0,98
Women_NL	0,91	0,91
Women_1GNL	1,03	1,03
Women_2GNL	0,94	0,94

Table A.17
Predictive performance measures of the compact and complex models of Stage 2 (HELEK) at the household level.

	Compact Model	Complex Model	
	Individual Level	*Household Level*	*Individual Level*
	Fig. 5	Fig. 6	Fig. A.3 (Annex 2)
Performance Metric	Score	Score	Score
Accuracy	0,55	0,71	0,73
Precision	0,54	0,77	0,78
Sensitivity	0,62	0,62	0,63
Specificity	0,48	0,81	0,82
F-1 score	0,58	0,68	0,69
AUC-ROC	0,55	0,71	0,73

Table A.18
LRT statistics for the complex model against the restricted model (including only gender, migration background and its interaction terms as predictors) at the household level and individual level.

LRT Statistics	*Household Level*	*Individual Level*
Log-likelihood Full	−636,132	−1,124,481
Log-likelihood Restricted	−636,594	−1,124,861
LRT Statistic	923,6	759,0
LRT p-value	<0,001	<0,001
df	5	5
Chi2 (0.05)	11,07	11,07
Chi2 (0.01)	15,09	15,09

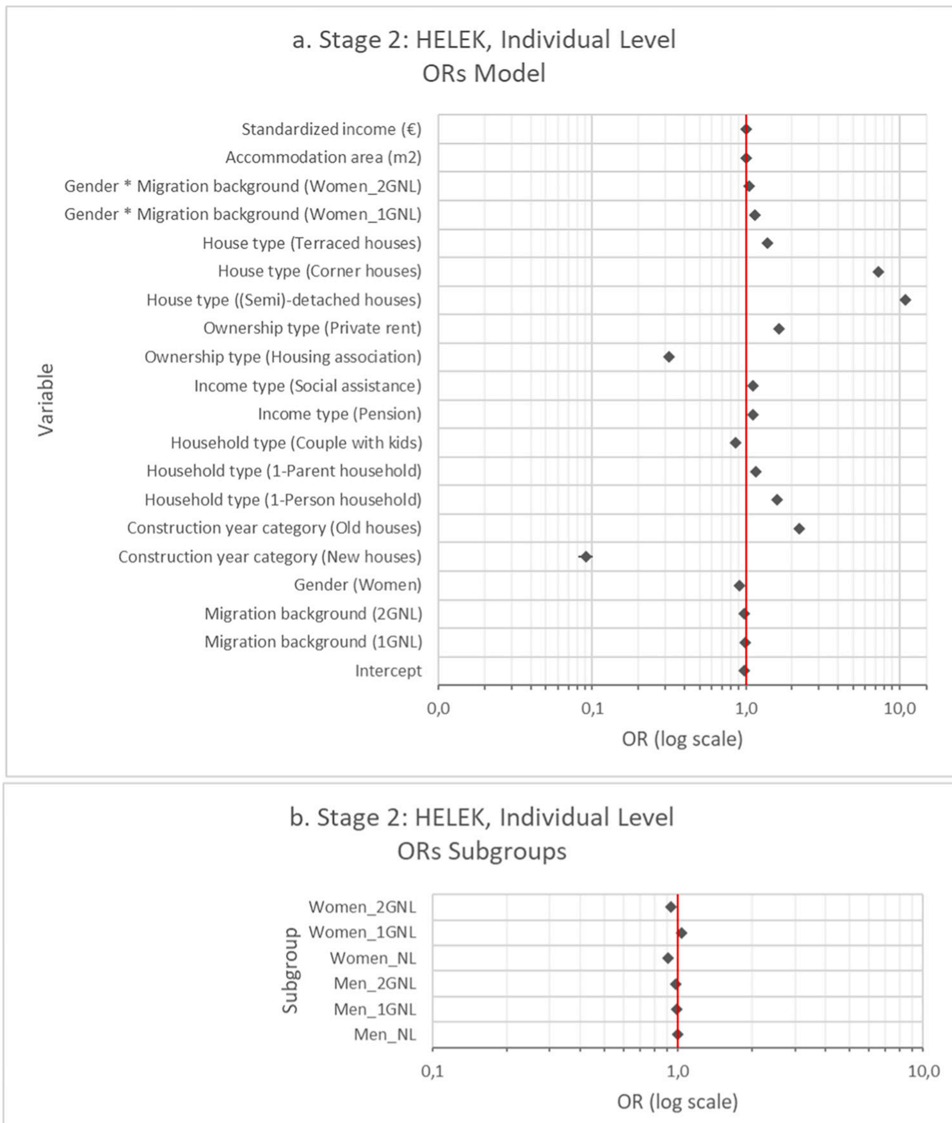

Fig. A.3. Odd ratios from the complex model in Stage 2 at the individual level, for model coefficients (panel a), and for specific subgroups compared to the reference subgroup (panel b).

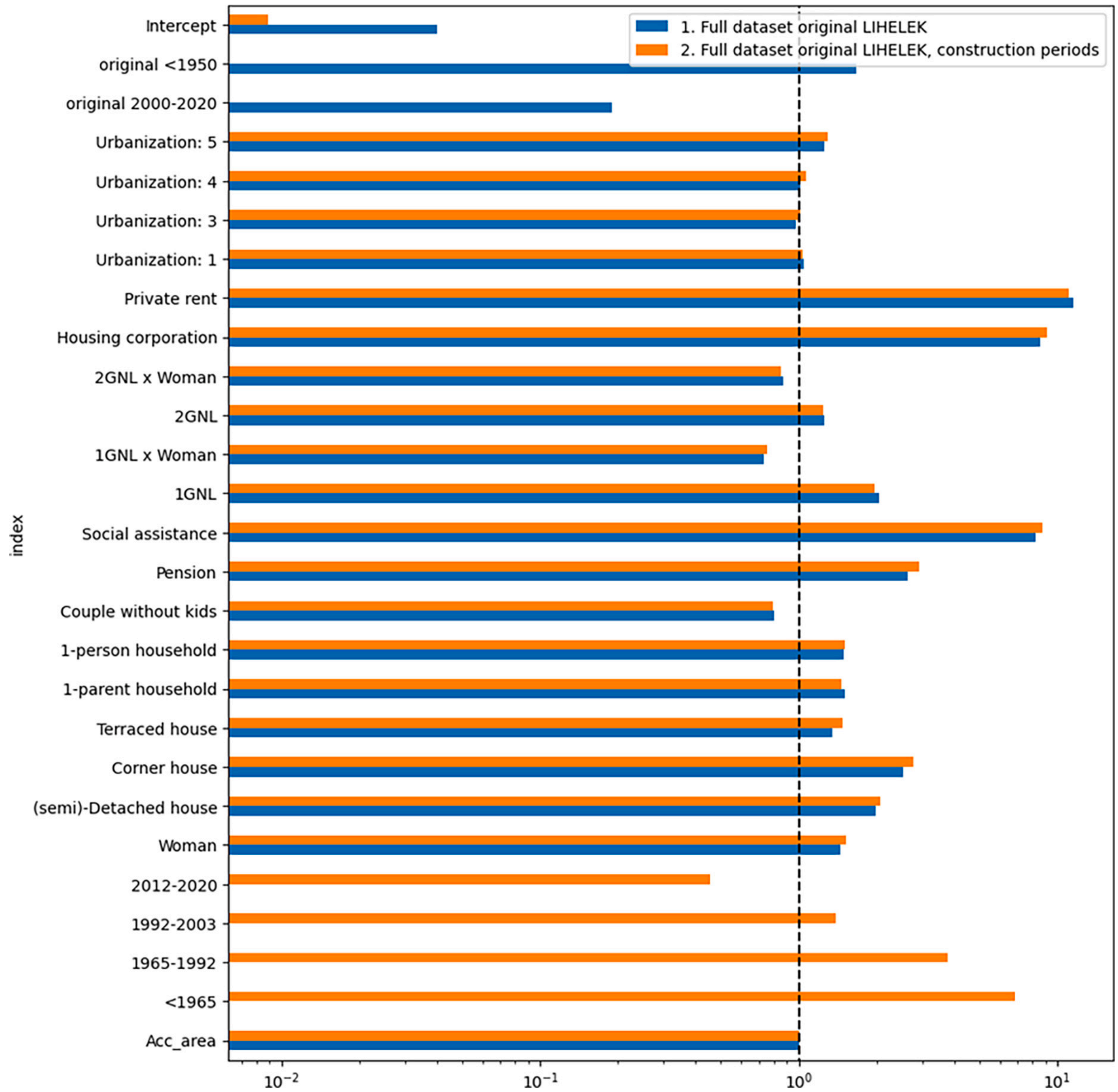

Fig. A.4. Comparison of the odds rations (OR) resulting from the logistic regression between the original model (blue bars, reference category 1950–2000) vs an alternative model that employs additional construction year categories, based on changes in building standards (in 1965, 1992, 2003 and 2012) that have brought significant improvements in house insulation. (Orange bars, reference category 2003–2012). It is apparent that introducing a finer subdivision of construction periods in the regression does not significantly alter any of the ORs. All the conclusions and considerations proffered in the manuscript still apply. This includes the main insight regarding the effect of buildings age: the older the building the higher the OR. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Data availability

The authors do not have permission to share data.

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