Who is "energy poor" in the EU?

JRC Working Papers on Taxation and Structural Reforms No 5/2024

Maier S., Dreoni I.

2024

Contact information
Name: Ilda Dreoni
Address: Edificio EXPO, c/ Inca Garcilaso 3, 41092 Sevilla, Spain
Email: Ilda.DREONI@ec.europa.eu

EU Science Hub
https://joint-research-centre.ec.europa.eu

JRC138418

Seville: European Commission, 2024

How to cite this report: European Commission, Joint Research Centre, Maier, S. and Dreoni, I., *Who is "energy poor" in the EU*, European Commission, Sevilla, 2024, JRC138418.

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Executive summary

The Social Climate Fund regulation and the revised Energy Efficiency Directive define energy poverty as a household's lack of access to essential energy services, such as heating, hot water, cooling, lighting and energy to power appliances. The Commission Recommendation on Energy Poverty of 20 October 2023 recognises energy poverty as a multidimensional phenomenon driven by three underlying causes, namely, high energy expenditures in proportion to household budget, general low levels of income and low energy performance of buildings and appliances.

Energy poverty is a complex phenomenon that can be measured in different ways. In this paper we conduct a comprehensive analysis of the EU-wide distribution and profiles of "energy poor" using two type of indicators: "expenditure-based" indicators, which use information on energy expenditures against absolute or relative thresholds, and indicators based on a "consensual approach", which use self-reported assessments of housing conditions and ability to fulfil basic necessities[1]. Results show that between about 8% (using consensual approach indicators) and about 16% (using expenditure-based indicators) of the EU population can be classified as energy poor. About 30% of the energy poor households are also income poor[2]. Remarkably, also middle-income households experience a relative high incidence of energy poverty: up to the 6th income decile, the energy poor account for a proportion between 5% and 15% of the respective income decile, depending on the indicator chosen.

The analysis also shows that there is substantial cross-country variation in the energy poverty rate, especially in the subjective indicators, as well as in the extent to which the four indicators overlap. While in Greece and Bulgaria about 30% of the population is energy poor by at least two indicators, this share is below 5% in most Western and Northern EU countries. Moreover we examined expenditures and socio-economic profiles (assessed by means of logistic regressions, exploiting the richness of the microdata available) and found that households classified as energy poor can have rather diverse profiles. This suggests that reliance on a single indicator may overlook significant portions of the population experiencing energy-related deprivations and that further normative discussions may be needed when using one or the other, to minimize the group who may be left behind as well as the "false positives" (i.e. trying to exclude households that might not actually be struggling from energy poverty deprivations).

For example, those suffering from high expenditures on energy (expressed as share of income), are in general facing very high expenditures in other key necessity goods and services, such as food, housing and transport. The subjective poor are on average not having debts, but feature very tight budgets (with average saving rates that are practically zero). Moreover, from this analysis we also see that the main drivers of the likelihood of being energy poor are incomes, and some household composition characteristics such as number of employed among household members and quality of the house, while urban vs rural and other variables that are typically used in the policy debates around this phenomenon seem to be of much less relevance.

Our study underscores the complexity of measuring and addressing energy poverty within the EU. It highlights the need for an extremely careful use of energy poverty indicators vis- a-vis the income distribution to try to ensure no one is "left behind" in the green transition. Additionally, our findings provide valuable insights for future research and policy design aimed at tackling energy poverty and promoting a fair transition.

[1] The indicators are calculated using the EU Statistics on Income and Living Conditions (EU-SILC) and the Household Budget Survey (HBS). For the expenditure-based indicators, we refine the estimates of household disposable income using EUROMOD, the tax-benefit microsimulation model for the EU, so that our results rely on high-quality income data.

[2] Income poor are defined as those individuals with equivalised disposable income below 60% of the median income.

Who is "energy poor" in the EU?

Sofia Maier[1] and Ilda Dreoni[1,*]

[1]European Commission, Joint Research Centre, Seville, Spain
[*]Corresponding author Ilda.Dreoni@ec.europa.eu

July 12, 2024

Abstract

With the hike of global energy prices of 2022-2023 and the fairness challenges of the green transition, energy poverty is again back to the forefront of economic policy debates in Europe. However, the absence of consensus on energy poverty measurement complicates policy formulation and evaluation in this domain. This paper conducts a comprehensive analysis of the EU-wide distribution and profiles of the 'energy poor'. We use four well-known measures of energy poverty, two subjective and two based on expenditures, coming from two different household surveys, i.e., HBS and SILC, which we statistically match. With this, we fill an important gap in the literature by measuring the extent of overlap between these indicators. Our results reveal that expenditure-based indicators cover larger shares of the population, especially in middle and high-income EU countries, with very small overlap between energy poverty measures. In the EU, only 0.3% of the population qualifies as 'energy poor' when considering all four indicators, while four out of ten (40%) would enter this club by at least one of these indicators. Overall, by providing a characterization of the profiles of those who would be covered or 'left behind' by each of these indicators, as well as their relationship with incomes and expenditures, we shed new light on the heterogeneous distributional effects from policy-targeting based on these indicators.

Keywords: energy poverty, European Union, SILC, HBS.
JEL Classification: C81, D31, H20, H22

Acknowledgments

We are grateful for the insightful comments by Salvador Barrios, Olivier Bontout, Brice Ligonnet, Ragnar Horn and Alessia Fulvimari, Antonio F. Amores to early drafts of this work. We also want to thank Hannes Serruys for his work on the imputation files, and Luis Ayala and the participants of the JRC Seminar organized in Spring of 2024 on this topic for their feedback. Finally, we would also like to thank Luis Rey from his comments to the working paper version of this manuscript. The responsibility and errors remain on us.

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1 Introduction

Identifying where and who are the most vulnerable groups of the population to the EU Green Deal and its climate targets for 2030 and 2050 is essential for ensuring an inclusive transition. This is acknowledged by the European Commission's 2020-2025 authorities as a fundamental condition needed for the transition to actually succeed. In this context, the crossroad between the fairness challenges of the green transition and the recent global energy crisis (2022-23) has brought the topic of "energy poverty" to the forefront of economic policy debates. It does not seem a coincidence that the first discussions on "fuel poverty" kicked-off in the 1970s, in the context of the oil crisis (Schuessler, 2014). Since then, each crisis brings the topic back to the spotlight (Betto et al., 2020).

Despite its policy relevance and the proliferate literature on this subject (see, e.g. the good reviews of Liddell, 2012 and Drescher and Janzen, 2021) there is still a clear lack of consensus on how to measure energy poverty, both at the level of policy-making as well as in the scientific community,[1] something that does not happen when it comes to measure income poverty.[2] This is due to the multidimensional nature of the phenomenon as recently highlighted by the new Recommendation on Energy Poverty launched by the European Commission in the Autumn of 2023.[3] The multidimensional aspect of energy poverty as well as the lack of consensus on its measurement translates in the use of multiple empirical approaches and indicators to quantify the energy phenomenon for policy targeting. For example, the EU Energy Poverty Observatory recommends four main indicators classified as "expenditure-based" indicators, which use information on energy expenditures against absolute or relative thresholds, and indicators based on a "consensual approach", which use self-reported assessments of housing conditions and ability to fulfil basic necessities. These diverse empirical approaches can be attributed, at least in part, to the wide array of data sources available for studying this phenomenon and the lack of integration of these sources. However, at the same time the use of multiple indicators makes difficult to make a straightforward evaluation of incidence of the phenomenon as well as identify clearly the segment of population affected by the phenomenon and try to infer underlying causes for policy action.

There are numerous papers discussing advantages and disadvantages of different energy poverty indicators used in Europe (see, e.g., Koukoufikis and Uihlein, 2022, Rademaekers et al., 2016, Bouzarovski, 2014, Liddell, 2012, Moore, 2012, among others), but very little is known about their overlap and their inter-relationship, i.e. whether these different indicators identify clearly all forms of energy poverty and are able to identify all EU-citizens affected by some form of energy poverty. This is important because consensual-based indicators and expenditure-based indicators may identify different segment of the population as energy poor due to differences in preferences, that affect expenditure choices, differences in perceptions, that influences subjective answers, as well as differences in past experiences of different type of households. So far, the only study looking

[1] The EU institutions have launched numerous initiatives to consolidate a methodological framework for the assessment of energy poverty, mainly through the Energy Poverty Observatory -now substituted by the Energy Poverty Advisory Hub- and its methodological guideline documents (e.g., Thema and Vondung, 2020), but they do not endorse one single indicator, relying on national competencies and the subsidiarity principle (Pye et al., 2017).

[2] Beyond the proliferate literature on multidimensional poverty that tries to go beyond income (see, e.g. Bourguignon and Chakravarty, 2003,Alkire and Foster, 2011), with roots that can be traced back at least to the capability approach popularized by Amartya Sen (Sen, 1988), there is at least an implicit consensus on the use of the so-called "at-risk-of-poverty" rates (AROP), a relative uni-dimensional poverty measure that classifies as "income poor" those individuals with a an equivalised disposable income below 60% of the median.

[3] According to this new recommendation, energy poverty is a "*multidimensional phenomenon (...)*, generally driven by *three underlying root causes*, linked to high energy expenditure in proportion to the household budget, low levels of income, and low energy performance of buildings and appliances, see Recommendation C/2023/4080 on Energy Poverty, here: `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=OJ:L_202302407`; a revision of the Recommendation from 2020 (2020/1563). In the accompanying staff working document of this previous one, a set of 13 energy poverty indicators were proposed.

at this is Menyhért (2024), who exploits a unique dataset for Hungary, where SILC and HBS are administratively merged as the surveys are administered to the same population sample and the two datasets can be merged by IDs. He found that for Hungary there is very little overlap across expenditure and consensual-based indicators and that households that self-report struggle to keep the house adequately warm or to pay utility bills are often not the same as those that spend too much of their budget in energy relative to their income or too little in absolute terms. Similarly, Deller et al. (2021), who performed this type of overlap in the analysis for the UK, found that the overall prevalence of energy poverty in the UK varies considerably according to the indicator used and that the type of households identified as energy poor also varies considerably. This indicates that policies implemented to eradicate energy poverty and their effects will differ according to the indicator chosen as it will target different segment of population and different underlying causes .

In this context, our paper fills an important gap in the literature by conducting an exhaustive evaluation of the coverage, level of overlap and socio-economic profiles of the four main energy poverty indicators that have been used in the EU for cross-country comparisons, covering EU 27 countries based on harmonized microdata. Assessing the degree of overlap between these indicators as well as the different socio-economic profiles of the population covered by them is fundamental to identify who might be in or out of policy initiatives using targets based on these indicators. It is therefore a fundamental input for effective social monitoring and targeted policy action, as suggested by Menyhért (2024).

For our analysis we use two subjective indicators from the EU Statistics of Income and Living Conditions survey (SILC): the inability to keep home adequately warm, and arrears on utility bills. And two expenditure indicators based on the EU Household Budget Surveys (HBS): one that addresses affordability issues considering the impact of high energy expenditures in relation to income, and another that focuses on extremely low absolute expenditures. We use a statistically matched dataset where we impute household consumption expenditures from EU HBS to EU SILC (2015), following the semi-parametric methodology developed by Akoğuz et al. (2020). This allow us to perform an overlapping analysis for all 27 EU Member States overcoming limitations due to different data sources for the calculations of these indicators. Moreover, by combining SILC incomes with the tax-benefit microsimulation model EUROMOD[4] we further refine the estimation of household disposable (i.e. after taxes and benefits) incomes accounting for the simulation of fiscal policies included in the model and as such being able to assess the income profiles of the 'energy poor' based on high-quality income data, that ensures comparability with official statistics of income poverty and inequality for the EU countries published by Eurostat. Finally, we use a uniquely merged dataset available for Czechia, similar to the unique case of Hungary, to validate our statistical matching process as well as provide evidence of the robustness of our results at EU-wide level.[5]

From our analysis we draw four main take-aways. First, there is very little overlap between the four energy poverty indicators examined, which means that each of them classify as energy poor different groups of the population that are likely suffering from different dimensions of energy-related deprivations. This explains why at least 40% of the EU population (around 180 million citizens) would be classified as 'energy poor' if we would follow a 'union approach' (i.e. where poor is who satisfies the poverty condition in at least one of the four indicators). At the other

[4]EUROMOD is the EU tax-benefit micro-simulation model, open source, publicly available, developed and used by a wide community of researchers and national government authorities from Europe and other regions. For more information, please see: https://euromod-web.jrc.ec.europa.eu/.

[5]Although by the time this paper is written there is a new HBS wave, we prefer to report results based on 2015 because the 2020 HBS wave has big limitations due to the exceptional circumstances created by the COVID crisis.

extreme, if we would follow an 'intersection approach' (where poor is who satisfies the poverty condition of the four indicators, simultaneously) would lead to very small rates (0.3%, about 330 thousand inhabitants). Second, there is substantial cross-country variation in the energy poverty rate, especially in the subjective indicators, as well as in the extent to which the four indicators overlap. While in Greece and Bulgaria about 30% of the population is energy poor by at least two indicators, this share is below 5% in most Western and Northern EU countries. Third, we look into the distribution of energy poverty across income groups and see that, for all indicators: i) most of the energy poor are non-income poor (i.e. they have an equivalised disposable income above the AROP poverty threshold), and as such, their access to minimum income support measures and other means-tested transfers from governments is much more reduced (Almeida et al., 2022), ii) there is a non-negligible share of top income households that would be classified as 'energy poor' by each and all of these indicators. From a distributional point of view, this may suggest the need of income filtering to leave out "false positives" and for a better policy-targeting.[6] Fourth, expenditures and the socio-economic profiles (assessed by means of logistic regressions, exploiting the richness of the microdata available) are also very different across the energy poor type as classified by these four indicators, which suggest that energy poverty may interact differently with other measures of poverty that are being assessed in the policy context of the green transition (e.g. transport poverty). For example, those suffering from high income shares of expenditures on energy, are in general facing very high expenditures in other key necessity goods and services, such as food, housing and transport. The subjective poor feature very tight budgets (with average saving rates that are practically zero). From this analysis we also see that the main drivers of the likelihood of being energy poor are incomes, and some household composition characteristics such as number of employed among household members and quality of the house, while urban vs rural and other variables that are typically used in the policy debates around this phenomenon seem to be of much less relevance.

Overall, our analysis allows policy makers to get a better idea of how many, where and who could potentially be 'left behind' if green transition policies are targeted using only one of these indicators. We discuss more extensively this and other policy implications in the discussion section.

The rest of the paper is structured as follows. Section 2 provides a brief overview of the main related literature. Section 3 presents the definition of poverty rates and a description of the data and imputation method used. The main results are summarized in Section 4. Finally, in Section 5 we discuss the main results, policy implications and propose some next steps for further research while in Section 6 we provide some final concluding remarks.

2 Related literature

Energy poverty, often named also as 'fuel poverty' or energy vulnerability, is a complex phenomenon that has garnered substantial attention from scholars and policymakers alike over the years. The challenge of defining and measuring energy poverty, identifying its key determinants, and understanding its broader societal impacts have been central themes in this growing field of research. A range of studies have made substantial contributions to these topics, helping to shape our understanding and approach to addressing energy poverty (e.g., see Boardman, 1991, Liddell, 2012,

[6] We are not the first ones discussing this. At least since Hills (2011), with his proposed low-income high-cost (LIHC) indicator (used to replace Boardman's ten percent rule for the UK as official fuel poverty indicator), there is an interesting debate in the literature on how to account for this issue. Still, implementing an indicator such as the LIHC for all EU countries would be practically very difficult, especially in what concerns the after-housing cost definition of income and therefore the very different poverty lines that it involves.

Moore, 2012). The first formal discussions about fuel poverty started in the UK in the 1980s-1990s with the pioneering work of Bradshaw and Hutton (1983) and Boardman (1991). However, the adverse effects of cold weather on health had been documented for many more decades, at least since Young (1924).

The literature on energy poverty has received renewed attention over the past years in the context of the policy challenges of the just green transition (Faiella et al., 2022). Energy poverty is now included in European legislation and recognised as a form of deprivation that needs to be systematically monitored and tackled by member states. The recent revision of the EU Energy Efficiency Directive (EU/2023/1791) defines energy poverty as a phenomenon caused by a combination of factors, including affordability, insufficient disposable income (covering then, not only income-poor) as well as poor energy performance of buildings and appliances. Further, the Directive also includes in the definition of vulnerable households low-income households as well as households with lower middle income affected by energy price increases. This first definition of energy poverty at the EU level was also included in the New Energy Poverty Recommendation, launched in October of 2023. In this recommendation the European Commission acknowledges that "Enshrining a definition of energy poverty in national law is a first step to acknowledging and identifying a problem and its wider context. It will support all relevant players in designing the right responses to tackle energy poverty at local, regional, national, and Union level taking into account the combination of its main three causes, that is to say, low income, higher energy bills and low energy efficiency."[7]

The literature has systematically classified (Thomson et al., 2017) energy poverty indicators in three groups: expenditures, consensual approach and direct measurement. These measures have been compiled and evaluated in 2016-2020 by the EU Energy Poverty Observatory (Thema and Vondung, 2020). Consensual indicators are normally estimated using survey-based data and are based on subjective experience and perception of the individuals, e.g. answer to the question of the SILC questionnaire "Can your household afford to keep its home adequately warm?". Expenditure-based indicators are instead based on objective characteristics such as direct household consumption expenditures for energy products as well as the ratio of these expenditures relative to household disposable income. There are three main sub-categories of expenditure-based indicators: those that focus on the energy expenditures, the Minimum Income Standard (MIS) approach and the Low Income High Cost indicators.

An early landmark in the field of expenditure-based indicators was the seminal work of Boardman (1991) which played a pivotal role in bringing energy poverty (referred to fuel poverty in Boardman's text) to wider public and political attention as well as starting a debate regarding the choice between relative and absolute definitions of energy poverty expenditure-based indicators. Boardman proposed as first expenditure-based indicator the 10% indicator which classifies a household as energy-poor if 10% or more income is spent on energy services. The definition of the 10% threshold was originally based on a relative definition, i.e. twice the median of energy expenditures, but it then became an absolute threshold when used for monitoring by government policy. In the well-known Hills' report about the measurement of energy poverty in the UK, Hills (2011) pointed out that this absolute threshold definition is not able to capture the dynamics of fuel price rises, income levels, or energy efficiency improvements, thereby potentially failing to capture the nature of energy poverty. This critique stressed the need for more nuanced and dynamically adjusted measures of energy poverty to inform more effective policy interventions. More dynamic

[7] The new Energy Poverty Recommendation is available online at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202302407.

approaches have been proposed by other scholars such as Meyer et al. (2018), Legendre and Ricci, 2015, Romero et al., 2018. Hills (2011) developed the Low Income-High Costs (LIHC) which focuses on households with low income and high energy costs. Such approach has been subsequently developed by Meyer et al., 2018 who proposed a measured energy poverty (mEP) indicator that builds on the LIHC approach by using real energy expenditures. Various scholars (Moore (2012); Romero et al., 2018) proposed the Minimum Income Standard (MIS) based on the total income available to households to meet energy costs after considering a minimum level of expenditures for basic needs, such as food, clothes, etc.

Rademaekers et al. (2016) provided a valuable contribution by conducting an extensive analysis of the use of energy poverty indicators by governments. They conclude that energy poverty is a phenomenon that should be monitored using a set of conceptually different indicators, both expenditure-based and consensual-based ones, to be able to capture the complex and multi-dimensional nature of the energy poverty phenomenon. This has also been pointed out by Legendre and Ricci (2015) which remark that measuring fuel poverty with single indicator won't be able to capture all the households that experiences energy deprivation because the type of energy poor households differs significantly across different indicators.

Beyond the UK, as pointed out by Bouzarovski (2014), the EU energy poverty scholar debate kicked-off much later, and as such the knowledge of this complex phenomenon remains more limited. However, there seems to be agreement on the fact that energy poverty in this region is linked to high energy prices, low household incomes, inefficient buildings and appliances, and specific households energy needs. Moreover, the energy poverty phenomenon is particularly widespread in Eastern, Central, and Southern Europe, where it tends to affect groups who are already vulnerable to income poverty.

The first studies assessing the overlap between different types of energy poverty indicators refer to the UK (see, e.g., Bradshaw and Finch, 2003 and Price et al., 2012) where very little overlap is documented between expenditures and subjective measures of poverty. Similarly, Palmer et al. (2008) identifies overlap between consensual and expenditure-based indicators just among income rich households in the UK. They report, for example, that older households tend to be more prone to energy poverty (EPOV) when using expenditure-based indicators while they do not find themselves as EPOV when using consensual indicators. More recently, Deller et al. (2021) focusing on the UK shows a consistent lack of overlap across the two type of indicators (subjective/expenditures) and highlights that each indicator identifies different household types as energy poor. They explain such lack of overlap as caused by differences in preferences, affecting expenditure choices, perceptions, affecting subjective answers, as well as past experiences of different type of households.

Palmer et al. (2008), as well as Lowans et al. (2021) and Castaño-Rosa et al. (2019), argue that a possible reason for the lack of overlap across consensual and expenditure-based indicators in terms of socio-economic profiles is the difference in perceptions of what "adequate temperature" is considered by different households as well as across different countries as a result of specific cultural interpretations of thermal comfort. Furthermore, González-Eguino (2015) argues that the definition of energy poverty depends on the context. Highlighting the difference between global and EU contexts, this study emphasizes the need to consider accessibility in addition to affordability (some households can only technically access some energy carriers while others could be more affordable if they were available for them, i.e. geographically). The recent Commission Recommendation (EU) 2023/2407 on energy poverty, also outlines how energy poverty can be diagnosed at national level, but do not prescribe compulsory nor single indicators for it. The diversity of countries, which is in the motto of the EU, poses a challenge for a single suit that might fit all. On the contrary, there is a clear need of performing international comparisons, that must, undoubtedly, be based on the same indicators, but not necessarily just for a single one. Thomson et al. (2017) suggests that a combination of existing indicators could help to circumvent the limitations of single indicators. The paper that is closest to us is Menyhért (2024), who addresses the overlap between the four indicators we consider -on top of a fifth one with a fixed threshold based on expenditure shares- based on ID-merged HBS-SILC data for Hungary. We further discuss the main differences between our results and his in the Discussion section (5).

Overall, the literature on energy poverty reflects a diverse range of perspectives and findings. Together, these studies underscore the complexity and multi-dimensionality of energy poverty, highlight the limitations and potential improvements in current measurement approaches, and reveal the broader societal impacts and key determinants of energy poverty. They provide valuable insights for future research and policy-making aimed at tackling energy poverty and underscore the need for further research to refine energy poverty indicators, develop effective policy interventions, and broaden the scope of interventions to include health and societal impacts. Finally, González Garibay et al. (2023) propose the use of EUROMOD for energy poverty analysis, of which this paper is the first attempt.

3 Data and empirical strategy

In this section we first describe the data, imputation method and validation checks (section 3.1). Then, we present the energy poverty indicators analysed in our empirical work (3.2). Finally, we introduce the regression model used to explore the main socio-economic profiles of the "energy poor" (3.3).

3.1 Data

To combine EU-HBS micro data at the household level (i.e., the source dataset) with the EU-SILC data of the same year (i.e., the recipient dataset), we use a semi-parametric procedure, developed by Akoğuz et al. (2020). Such procedure combines an econometric approach similar to the estimation of Engel curves as employed in earlier studies (such as Decoster et al. (2010)) with distance matching techniques. It consists of four main steps. Firstly, a common set of relevant covariates is identified in the source and in the recipient dataset for each household. Secondly, in the source dataset, consumption expenditures are aggregated into 20 macro-categories for each household and expressed in terms of consumption shares of income. These aggregated consumption shares are regressed for each household against the set of covariates identified in the first step. Thirdly, the estimated coefficients are used to construct fitted shares of consumption in both the source and in the recipient dataset (i.e., in each of these datasets, 20 fitted consumption shares will be constructed for any household based on the regression model above). Finally, a Mahalanobis distance metric is used to find the closest match between any household in the source and in the recipient dataset using as input variables the fitted consumption shares. Once households from the recipient (SILC) and source (HBS) datasets are matched, the consumption shares of the full basket of consumption from the latter is imputed to the former. When running the analysis for policy years which are successive to the year the underlying dataset refers to, appropriate uprating factors are used to update income information. More information in Appendix A.

We used data from the 2015 wave of EU HBS and EU SILC, except for Germany and Italy for which we used 2010 due to issues in the consumption data.[8]

In order to validate our imputation we compare the SILC-HBS matched dataset with the administratively merged dataset of Czechia. This comparison as well as a more detailed explanation of the imputation method described above can be found in the Appendix A.

3.2 Energy poverty indicators

Over the past decades, several indicators of energy poverty have been proposed by the scientific community and used by policy makers. The number of available indicators for the whole of the 27 EU countries is however smaller, as this depends on the availability of harmonized microdata. The EPOV Methodology Guidebook EU Energy Poverty Observatory, published in 2020 (Thema and Vondung, 2020), presents the calculation, interpretation, and a detailed database of a group of EPOV indicators used in Europe, information that have also been used in the European Commission's EPOV recommendations. The guidebook divides the indicators in two broad categories: indicators focusing on the affordability of energy services and complementary indicators. In the first, the four indicators we use are defined there as "primary indicators".

We restrict our analysis to the indicators that satisfy four key features: i) they are available in all EU countries, ii) they are or can be harmonized across countries, iii) they can be monitored over time, iv) they have been already used for research and/or policy analysis. The first three are fundamental properties to choose energy poverty indicators that are useful to the design and evaluation of EU-level policies, such as those related to the just green transition. The fourth one is useful for external validity and communication purposes. Indicators that simultaneously satisfy these criteria are two expenditure-based indicators (based on expenditures reported by households in the EU Household Budget Surveys, HBS) and two subjective-based indicators (as self-reported by households in the Socioeconomic and Income Living Conditions, SILC). In concrete, these are: i) the low-expenditures "M2" indicator (that classifies as "energy poor" all individuals with equivalised household expenditures below half the national median); ii) the high expenditures on energy (expressed as income shares) "2M" indicator (that classifies as "energy poor" all individuals with energy expenditures expressed as income shares that are above twice the national median), iii) the adequately warm "AW" indicator (based on the SILC question on ability to keep house "adequately warm"), iv) the utility bills "UB" indicator (at least one month with arrears on utility bills, according to SILC reported answers).

Table 1 presents the four indicators used in our analysis, based on HBS- and SILC- surveys.

[8]Micro data of EU HBS 2015 for Germany is under review at Eurostat. HBS for Italy did not contain the disposable income variable needed for the matching. Notice that aggregate consumption patters seem not to change significantly across waves, as can be seen in Eurostat table [hbs_str_t211].

Table 1: EU-level standard indicators based on EU HBS and SILC

Type	Name	Acronym	Description	Source
Objective	Low absolute energy expenditure	M2	M2-poor is whose equivalised energy expenditure on residential energy is below half the national median	EU HBS
	High income share of energy expenditure	2M	2M-poor is whose income share of residential energy expenditure is above twice the national median	
Subjective	Inability to keep home adequately warm	AW	AW-poor is who answers "yes" to the question "Can your household afford to keep its home adequately warm?"	EU SILC
	Arrears on utility bills	UB	UB-poor is who answers "yes, once or twice" to the question "In the past twelve months, has the household been in arrears, i.e., has been unable to pay the utility bills (heating, electricity, gas, water, etc.) of the main dwelling on time due to financial difficulties?"	

The main four indicators that have been under discussion are two related to material deprivation, and two based on energy consumption expenditures. Two specific dimensions of the primary EU indicators of material and social deprivation (MSD) and severe material and social deprivation (SMSD) are directly relevant for the monitoring of energy poverty and are often used as proxies to monitor energy poverty in the EU: the inability to keep one's home adequately warm (AW) and arrears on utility bills (UB). Both are also part of the AROPE headline indicators that was used in the EU2020 poverty and social exclusion target and is now at the heart of three new 2030 EU poverty and social exclusion reduction target. On top of the two MSD indicators outlined above, the EPOV Observatory put forward two indicators based on energy expenditure, known as M2 and 2M indicators.

For the expenditure-based measures of energy poverty (M2 and 2M) we restrict energy expenditures to those related with housing. We use COICOP category 045 (residential energy), including electricity, town/natural gas, liquefied hydrocarbons (e.g. butane, propane, etc.), liquid fuels (e.g. fuel oil) and solid fuels (e.g. coal, biomass, etc.), other heating (e.g. district heating, hot water, etc.). And, differently from Menyhért (2024) -the only reference of overlapping analysis for these four indicators- we exclude other energy-related expenses such as vehicle fuels. We consider that those expenses relate to other types of deprivation, that are often addressed by the concept of transport poverty (see, e.g., Alonso-Epelde et al. (2023),Vandyck et al. (2023)) which is not examined in this paper.

HBS-based expenditures indicators: M2 and 2M

M2 is an indicator that tries to capture the phenomenon of hidden poverty due to under-consumption, a form of averting or defensive behaviour. According to Meyer et al. (2018), in their work for Belgium, this is "a reality that is generally not reflected in administrative and traditional energy poverty statistics. For instance, households facing difficulties in paying their energy bills can have prepayment meters installed. For these households, statistics would typically display the numbers of meters installed but would not provide any useful information as to whether these households suffer from self-rationing and consumption below basic energy needs due to their incapacity to find funds". Moreover, another limitation of this indicator is that households that produces their own electricity through solar panels, which typically are households located in the middle and upper part of the income distribution, may also be captured by this indicator as energy poor.

There are two main indicators used by the literature to capture energy deprivations related with high income shares. The oldest approach comes from the UK, which states that energy poor is who lives in a household with an income share of expenditures on energy of 10% or more (the so-called Ten Percent Rule: TPR). This indicator has received multiple criticism, among others, because of the fixed threshold. Such threshold was fixed based on the distribution of the expenditure shares of the bottom 30% income in the UK in the early 1990s, however this distribution has notably changed over time and varies substantially across countries. Alternatively, the 2M indicator sets the threshold at twice the national median. Given that of our study is cross-country, we decided to include the 2M indicator to capture the deprivations related to high-income shares of expenditures. To better understand what are the implications of one or other approach we show, in Figure 8 (Appendix B), the country-level EPOV rates according to each of these indicators. What we can see from here is that shifting from TPR to 2M brings changes in the estimated EPOV incidence: on average, 27% would be energy poor according to TPR (simple cross-country average level), whereas with the 2M indicator this average incidence is 16%. Interestingly enough, 10.5% is actually the EU-level median of income shares of consumption expenditure in energy (in 2015). This suggests that the TPR could actually be interpreted as an EU-level 2M indicator. In the Appendix we further discuss the cross-country differences from one and other approach. We would like to highlight at this point the advantages of a relative threshold in a context of heterogeneity both in economic and other contextual variables across the EU-27 countries. Given that the purposes of our analysis, it makes sense to use the 2M indicator, to be able to compare EU countries' performances in a harmonized way, as well as with respect to the remaining indicators where the implicit or explicit thresholds are also defined at the national level.

SILC-based subjective indicators: AW and UB

These two measures are classified as subjective as they depend on self-reporting in household surveys. Often also classified as "consensual approach". As for expenditure-based indicators, also subjective indicators suffer from few limitations such as the fact that they are self-reported, and as such influenced by personal and cultural perceptions, and may not be so easily comparable across countries.

In particular, the AW indicator (inability to keep house adequately warm) is based on self-reported assessments of indoor housing conditions, and the ability to attain certain basic necessities relative to the society in which a household resides. This classifies individuals as poor if the SILC variable HH050 is 1, i.e. the household is unable to keep the house adequately warm. The indicator covers the share of (sub-) population not able to keep their home adequately warm, based on the question *"Can your household afford to keep its home adequately warm?"*.

The UB indicator overs the share of (sub-) population having arrears on utility bills, based on question "*In the last twelve months, has the household been in arrears, i.e. has been unable to pay on time due to financial difficulties for utility bills (heating, electricity, gas, water, etc.) for the main dwelling?"*. It classifies an individual as energy poor if the SILC variable HS021 takes value

1 or 2, i.e. the household has had arrears at least once or more than once in the past 12 months.

3.3 Analysis: estimation strategy

First we examine the magnitude of the energy poverty headcount ratios and the degree of overlap between indicators for the whole of the EU, and then across countries. Next we examine income and expenditure profiles of the energy poor. In this section we build income deciles from equivalised household disposable income. Finally, we perform a logistic regression to explore the main socio-economic characteristics influencing the probability of being classified as 'energy poor' by each of these indicators.

The headcount income poverty ratio is calculated as follows:

$$H = \frac{1}{N}\sum_{i=1}^{N} I(y_i < z) \tag{1}$$

where:

- H_{ep} is the headcount poverty ratio.
- N_{ep} is the total population.
- y_i is the income (or consumption) of individual i.
- z is the poverty line (a threshold below which individuals are considered to be in poverty).
- $I(\cdot)$ is a function that equals 1 if the condition inside the parentheses is true, and 0 otherwise.

To estimate the energy poverty headcount ratios, we follow an identical approach. The only difference comes from the identifying condition $I(y_i < z)$. For the 2M (high income shares of expenditures) indicator, this is replaced by $I(se_i > z_{2M})$, where se_i are the income shares of expenditures of individual i (instead of incomes), and z_{2M} is the poverty threshold (i.e. twice the national median). Similarly, for the M2 (low absolute expenditures) indicator, we use $I(e_i < z_{M2})$, with e_i being (equivalised) absolute expenditures in energy and z_{M2} the poverty threshold (i.e. half the national median of e_i). For the subjective indicators, the identifying condition is directly reduced to 1 or 0 without threshold, depending on the self-reported answers to the questions in SILC, as described in detail above.

For the regression analysis, we estimate a pooled cross-section logit regression for each energy poverty indicator, exploiting the rich information embedded in SILC about household and individual characteristics, and clustering errors at the household and regional level. This follows the strategy of Thomson and Snell (2013) and Deller et al. (2021), among others.

The binary outcome variable, $y{-}_i$, takes value 1 when a person i in household j is energy poor and a value of 0 when not. For each individual, the probability p_ij of being energy poor can be expressed as: (1)

$$Y_{ij} = \begin{cases} 1, \text{with probability } p_i \\ 0, \text{with probability } (1 - p_i) \end{cases} \tag{2}$$

where the probability of being energy poor, pit, is modelled as:

$$Pr(Y_i = 1|X_i) = \frac{exp(\beta X)}{1 + exp(\beta X)} \tag{3}$$

Here p_i is the probability that individual i in household j is energy poor given the vector of potentially explanatory variables for individual i / household j ($x_i j$).

Average marginal effects are reported showing the average percentage point increase in the probability of a household being energy poor associated with a change in a particular 'explanatory' variable. Our main interest is to evaluate how socio-economic characteristics are broadly associated with each of the energy poverty measures, to identify main determinants influencing the likelihood of suffering from energy poverty.

4 Results

In this section we present and discuss the main results from our analysis. We start, in sub-section 4.1, by presenting the estimated headcount ratios of the four standard energy poverty indicators based on HBS and SILC (2M, M2, AW, UB),[9] over our matched databases. We first look at the EU-aggregate level, and discuss to what extent these energy poverty indicators overlap with others, as well as with income poverty. Then, we look into the cross-country dispersion of these indicators, as well as their incidence across the distribution of income. Then, in sub-section 4.2 we explore the expenditure profiles of the energy poor, to add some insights on who are the poor and to what extent they might also be suffering with high expenditure budgets in other necessity goods. In the third and final part, sub-section 4.3, we investigate the socio-economic profiles of the EPOV indicators, using a logistic regression analysis and estimating both a pooled model (using a cross-section of all households in the EU-27 countries) as well as country by country models.

4.1 Energy poverty: headcount ratios and overlap

We start with an overview of the energy poverty rates by indicator and the extent to which they overlap at the EU level, and then we explore the heterogeneity across countries within EU.

All EU households

Table 2 reports the main results for the pooled-EU data. The first column displays the EPOV headcounts (in millions), the second the headcount ratios (i.e. % of the population),[10] whereas the third column displays the percentage of the 'energy poor' that are simultaneously classified as 'income poor' by the standard AROP rate - with a poverty threshold defined at 60% of the national median of equivalised disposable income.

Energy poverty headcount ratios, reported in the first four rows, are very similar for the two expenditure-based indicators (M2/2M), and cover approximately 17% of the EU population each. This almost doubles the energy poverty headcount ratios of the subjective-poor (AW/UB), of about 8-9%. While these headcount ratios have been widely documented and covered by previous studies, policy and media briefs and public reports on energy poverty, what we often do not know is to what extent these indicators overlap. For example, we do not know whether those reporting that are unable to keep their houses adequately warm (AW) are also struggling with utility bills (UB)

[9] An introduction of these indicators was provided in section 3, and their precise definition in Table 1.

[10] In this study we refer to 'poverty headcount ratios", "poverty rates" and "poverty incidence" as synonymous, interchangeably.

and/or consuming very little energy (M2), etc. Based on our matched HBS-SILC files, we can estimate the coverage of these interactions, as we do in Table 2 from the fifth row onwards.

We estimate that 60% of the EU population (about 256 million - in 2015)[11] would not be classified as 'energy poor' by any of these indicators. The rest (40%, about 178 million) would be 'energy poor' by a union approach (i.e., using basic probability language, poor would be who satisfies the poverty condition in at least one of the four indicators). This union energy poverty rate more than doubles the income poverty rate (17%).

If, on the contrary, we follow an 'intersection approach' (i.e. where 'energy poor' is who lives in a household that satisfies the poverty condition in all four indicators), the energy poverty headcount ratio would be 0.1%, representing only about 330 thousand people.

Overall, the first (union) headcount seems "too much", while the second (intersection) "too little". We can also appreciate, from the third column of Table 2, that about 1/3 of the 'energy poor' by the union approach are income poor (32%), whereas for the non-energy poor this share is reduced to 7%. In contrast, all those who are poor by intersection are income poor.

Table 2: Energy poverty headcounts in the EU

	Energy poor	Energy poor	Income poor among energy poor
	(mill)	(%)	(%)
Standard rates			
M2	72.83	16.8%	27%
2M	71.74	16.5%	32%
AW	38.62	8.9%	41%
UB	36.16	8.3%	31%
Overlap			
EPOV (union)	177.97	41.0%	32%
NO EPOV (union)	255.68	59.0%	7%
EPOV (intersection)	0.33	0.1%	100%
NO EPOV (intersection)	433.32	99.9%	17%
Exclusive categories			
M2	58.66	13.5%	28%
2M	55.41	12.8%	31%
AW	14.95	3.4%	20%
UB	14.58	3.4%	17%
M22M	0.92	0.2%	100%
M2AW	4.70	1.1%	58%
M2UB	4.97	1.1%	49%
2MAW	6.88	1.6%	54%
2MUB	4.61	1.1%	54%
AWUB	5.65	1.3%	27%
M22MAW	0.30	0.1%	100%
M22MUB	0.23	0.1%	100%
M2AWUB	2.72	0.6%	73%
2MAWUB	3.06	0.7%	70%
Total	433.65	100%	17%

Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. There is no information on UB indicator for Germany. 'Exclusive categories' display the percentage of the population classified as energy poor according to that indicator while being not-poor by the rest. The interactions are signalled with the two names consecutively (e.g. "M22M") are the energy poor according to simultaneously both categories (in this case M2 and 2M indicators), and by any of the others.

The very large energy poverty rates estimated using the union approach are explained by the small degree of overlap between these indicators. Specifically, the expenditure-based indicators that produces higher headcount ratios of energy poor show much smaller overlap than the subjective-based. In fact, about 80% of the expenditure-poor (either by 2M or M2) are classified as poor just according to one expenditure-based indicator, while this happen just in 40% of the cases for the subjective poor. Moreover, the overlap between expenditure-indicators is the smallest of all: only

[11] As explained in section 3, our data refers to 2015 with the current EU composition (i.e., excluding UK and including Croatia). The total population according to our sample - EU SILC 2015 - is about 434 million, very close to official Eurostat's public estimates for that year, of about 443.4 million.

0.2% of the EU population is simultaneously poor by 2M and M2, while not being subjective poor. This proportion increases up to 0.5% if we consider those who are 2MM2 poor and also subjective poor. This small group of the population (those who are 2MM2 poor - regardless of whether they are also subjective poor by any of the other indicators) has a clear low-income profile: all of them have incomes lower than the AROP income poverty line (as the 100% in the third column shows). This is not surprising, as 2M captures individuals struggling with high energy costs (in relation to income) whereas the M2 captures deprivations associated with very low consumption. Only very low income households are likely to meet both conditions simultaneously. M2 does not only intersect little with 2M, but in general with all the others. About 80% of the M2-poor (i.e. 13.5% of the EU population) are not energy poor by any of the remaining three indicators (2M, AW, UB). While in principle one would expect little overlap between the M2 poor and the 2M and the UB (because they spend little, so in principle the income share should not be huge nor the troubles to pay the utility bills), it is quite striking to see such a small overlap with the AW indicator.

The second indicator with smallest overlap is the 2M indicator. About 77% of the 2M-poor are not identified as 'energy poor' by any of the other three indicators.

This larger coverage and smaller degree of overlap of expenditure indicators explains why such a large share -about one quarter (26.5%)- of the EU population that is poor by expenditures would not be considered if we would follow an approach based on subjective indicators. If, on the contrary, we would restrict our analysis to the use of expenditure-based poverty rates, we would be missing about 8% of the EU population (6.8% who are only poor according to either AW or UB, and 1.3% which are simultaneously AW and UB).

We have seen that only very few satisfy the poverty condition in the four indicators, and that many satisfies it in at least one. What happens in the middle, where overlap takes place in two or three dimensions? If we would classify as 'energy poor' all those who satisfy at least the poverty condition by two indicators, about 8% of the EU population would be energy poor. The largest overlap between two indicators takes place among the subjective ones: about 1.3% of the EU population are simultaneously poor by the AW and UB indicators, and not expenditure poor, a share that more than doubles up to 2.7% if we consider those who are AW-UB and also expenditure poor (by any of the two M2/2M indicators). Among the first group - those who are poor by the two subjective indicators but not expenditure poor - only 27% are income poor, whereas this share is above 70% for those who are also poor by one or the two expenditure indicators. Then we have the intersection between 2M with AW (i.e. people spending very high shares of their income in expenditures while at the same time declaring this is not enough to keep the house adequately warm): about 1.6% of the EU population. This increases to 2% if we consider those who are 2M and AW while at the same time poor in some of the other two indicators (UB/M2).

The intersection of poverty by three indicators is even smaller: only 2% of the EU population satisfies this condition. The largest triple-intersection coverage is the 2MAWUB (i.e. those who are poor by the two subjective AW/UB indicators as well as by the high expenditures indicator 2M), representing about 0.7%.

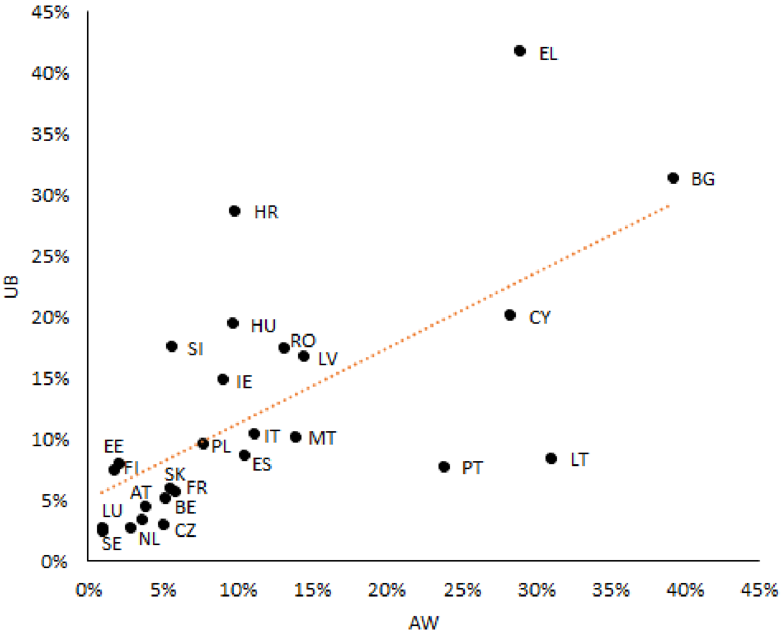
In general, we observe that the share of energy poor who are simultaneously income poor increases when we move from the non-energy-poor population to the energy-poor population, and particularly so when we move from energy poverty union approach to the groups that are poor by more than one indicator. In fact, among the very small group of the population that is poor in the four dimensions, all of them are income poor.

Cross-country dispersion

The numbers we have just presented were referring to the EU as a whole. To what extent are they representative of the 27 EU countries? In principle, we should expect large cross-country dispersion across countries and indicators. Beyond some EU-level policies (e.g. the EU Energy Taxation Directive, which sets minimum tax rates for energy consumption) most of the drivers of households' energy expenditures and energy-related deprivations are influenced by the very heterogeneous national realities, including geography, natural resources, climate, infrastructure, technology, national public policies, etc. For the subjective indicators, also cultural aspects can explain differences in self-reporting energy deprivation conditions.

Figure 1: Cross-country correlation between EPOV indicators

(a) Subjective indicators



(b) Expenditure indicators

Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. There is no information on UB indicator for Germany. Headcount ratios (%) in vertical axis.

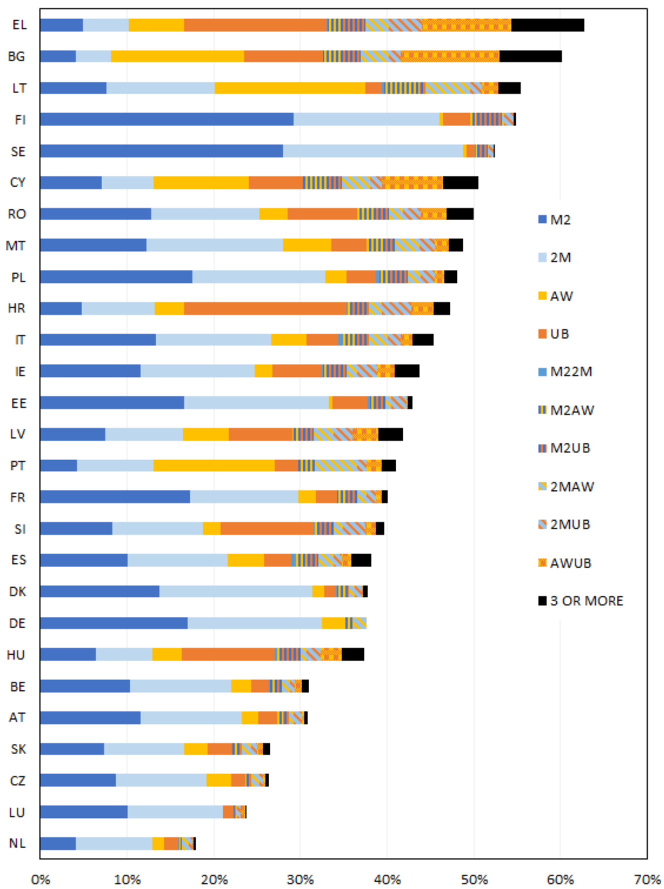
We plot the poverty rates at the country level in Figure 1 (subjective indicators in panel 1a, expenditure indicators in panel 1b). There is substantial cross-country dispersion in all indicators, and it is clearly larger in the subjective indicators. AW-poverty rates range between almost zero in Sweden (SE) and Luxembourg (LU) to about 40% in Bulgaria (BG), whereas UB-poverty rates range from zero as well (and in those same two countries) to above 40% in Greece (EL). The dispersion for the 2M poverty rates is the smallest of all. The share of 2M-poor ranges from about

10% in the Netherlands (NL) and Hungary (HU) to slightly above 20% in Sweden (SE), Malta (MT) and Latvia (LV). The M2 has a larger range, with the Netherlands against at the bottom (5%) and getting to slightly above 30% in Finland and Sweden.

There is a clear positive cross-country correlation within the subjective and the expenditure indicators, as it can be appreciated by the positive slope of the fitted line. These correlations are much weaker between these two different groups, as it can be appreciated in the scatter plots for the remaining pair-wise combinations reported in the Appendix B, Figure 9).

Our next step is to look at the level of overlap or intersection of these poverty rates across the EU countries. We summarize this in Figure 2, where the length of each of the bars represents the union EPOV rate. The bar is the result of adding exclusive categories of poverty in one, two or three or more dimensions.

Figure 2: EPOV rates and interactions across indicators, by EU countries



Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. There is no information on UB indicator for Germany. In this figure the single categories (e.g. "M2") show the percentage of the population classified as energy poor according to that indicator while being not-poor by the rest. The interactions are signalled with the two names consecutively (e.g. "M22M" are the energy poor according to both the M2 and 2M indicator, and by none of the others).

The EPOV (union) incidence ranges from slightly below 20% in the Netherlands to more than its triple in Greece, where about 2/3 of the population is classified as 'energy poor' by at least one of these four indicators.

At the top (countries with the largest shares of union-EPOV) we see a mix of Southern and Eastern countries where most of the energy poor are classified as such by the subjective indicators

(Greece, Bulgaria, Lithuania, Cyprus, Romania and Malta), together with two Nordic countries (Finland and Sweden) that have the highest expenditure-based shares of energy poor. This is an effect of the M2-indicator. If we would restrict the analysis to the more classic 2M and subjective indicators these countries would not be at the top but rather at the bottom of this cross-country ranking. In these two Scandinavian countries about 1/3 of the population live in households that restrain their energy consumption levels below half the national median (and that are not poor by any of the other three indicators). Whether this reflects energy deprivation or energy efficiency or preferences is something that needs to be addressed with more attention and falls beyond the scope of this analysis. This is a phenomenon not only associated to these two countries. In general, countries with the largest shares of exclusive M2-poor tend to be "cold" (by climate) and "rich" (by income) countries. Similar patterns are found with the 2M indicators, where colder and richer countries tend to have higher poverty rates, but with smaller exclusive rates (i.e. with higher intersection rates with other poverty indicators).[12]

Countries with the largest shares of EPOV by the union approach, except from the Scandinavian duple, are also those showing the largest overlaps. Remarkably, about 7% of the population in Greece and Bulgaria are 'energy poor' according to three or more indicators.

Among the subjective indicators, the share of individuals that are either exclusively AW- or UB-poor by one indicator are mostly in Mediterranean or Central Eastern European countries. AW-poor and non-energy-poor according to the rest is observed in Lithuania and Bulgaria (representing around 17.5% and 15.5% of the population, respectively), followed by Portugal and Cyprus (14% and 11%, respectively). Countries with the highest share of UB-exclusive poor are Croatia and Greece (19% and 16%), followed by Hungary and Slovenia (11%).

Across subjective and expenditure indicators, there is slightly more overlap between 2M with AW, while M2 goes more with UB. Still, these overlaps are in general small and largely vary across countries. In fact, the highest share of the population that is simultaneously AW- and 2M-poor is 5.2%, in Lithuania, whereas the highest share of the intersection M2-UB is 3%, in Finland.

4.2 Income and expenditure profiles of the energy poor

Income deciles

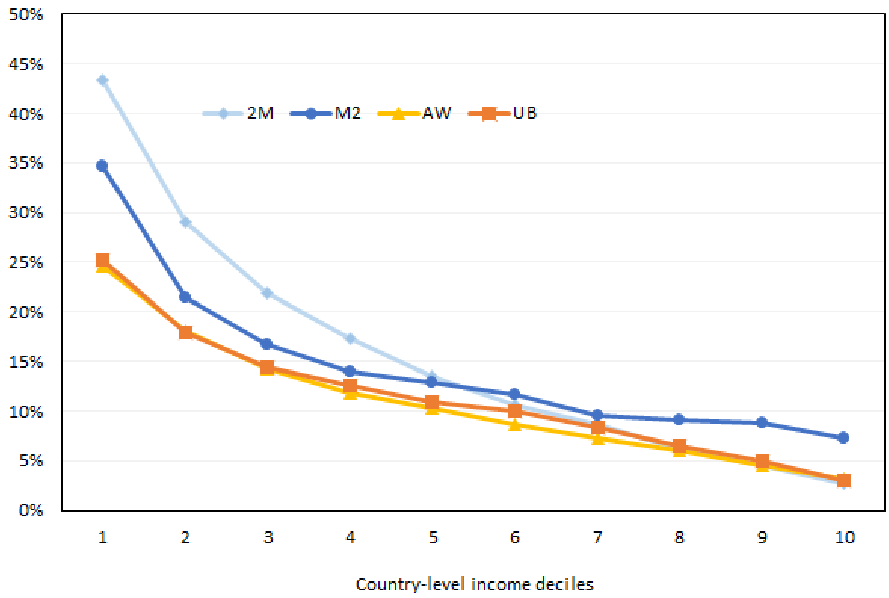
We have just seen that the majority of the 'energy poor' are not 'income poor' (i.e. the live in households with an equivalised disposable income that is above 60% the national median). The share of energy poor that are not income poor is about 60-70%, depending on the indicator. But who are these non-income poor that are energy poor? Are they bottom-middle class or do we also see top income households? In Figure 3, we plot the energy poverty headcount ratios across income deciles, defined at the level of equivalised household disposable income, at the country level (first panel, 3a), and at the pooled-EU level (second panel, 3b). The first is the average of the national-level deciles (cross-country average of the 1st decile of all 27 EU countries, and of the second decile, and so on and so forth). The value of the first decile in the first panel summarizes what happens, on average, among the lowest 10% of the population in each country. As such, the dispersion across deciles tell us about the within-country dimension of inequality. In contrast, the

[12] The relative thresholds of the expenditure indicators is what makes this EU cross-country ranking not that intuitive at first sight. As discussed in our methodological section, when addressing the differences between the 2M and the more classic ten-percent-rule (TPR) indicators to measure high income shares of energy expenditure, households in high-income countries (including the Nordics) spend much less of their incomes on energy consumption. This is why when we rank countries by the TPR (as we show in figure 8, in Appendix B), these Nordic countries are at the bottom (with the lowest EPOV rates, below 5%), whereas Bulgaria -as well as most of the low-incomes Central and Eastern European countries - are leading the ranking (with TPR-EPOV rates above 50%).

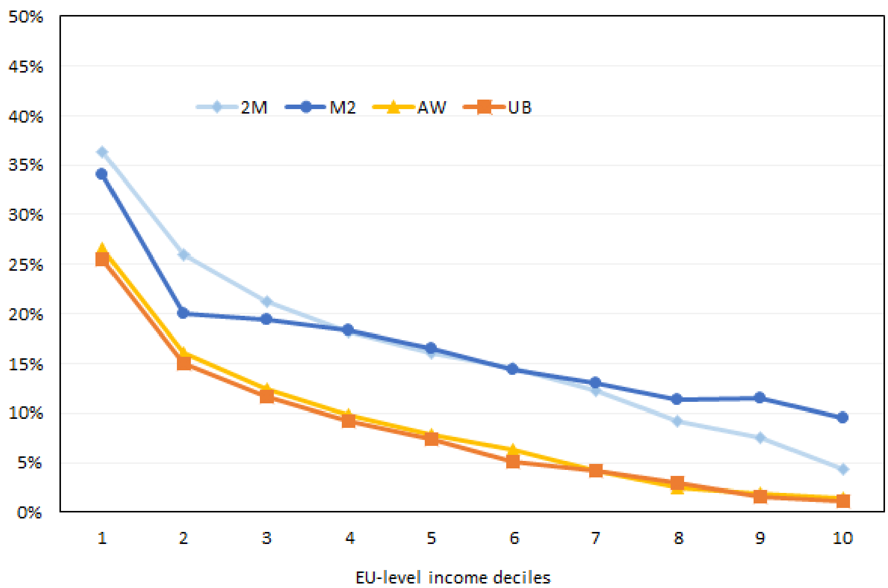
value of the first EU-level decile groups people from different countries - these are the "poorest of all" in terms of incomes - and so captures both the dispersion across households not only within countries but also between them.

Figure 3: EPOV headcount ratios across the income distribution

(a) Average country-level income deciles



(b) EU-level income deciles (pooled model)



As expected, the share of energy poor decreases along the income distribution, monotonically, regardless of the indicator used. The 2M indicator shows the steepest line. On average, about 45% of the bottom income decile (i.e. the poorest 10% of the population within EU countries) are 2M-poor, a share that decreases to about 15% in the decile 5th, and below 5% in the tenth decile. This is followed by the AW/UB indicators: about 25% of the bottom decile are energy poor according to these indicators, a rate that decreases to about 2-3% in the top decile. In fact, we can see that the energy poverty incidence between 2M, UB and AW are practically identically for middle-top income households (with energy poverty rates decreasing from about 10% in decile 6th to 3% in decile 10th). Lastly, the M2 indicator shows the 'flatter' line, and it is also the indicator with the highest share of energy poor among top-income households. In particular, the share of M2-poor is 35% on average in the first decile, while it decreases to 7% in the top decile. Although the income gradient is negative, this share is strikingly high, and suggesting that behind the M2 poor we have a very wide mix of socio-economic profiles and degrees of energy-related deprivations.

These are EU-27 simple-weighted averages per decile. In Figure 10 we plot the same lines country by country. Here we can see that the negative slopes across indicators are observed in all EU Member States, with no exception. However, we can observe some degree of cross-country dispersion. For example, in some countries, like Estonia, Latvia, Greece and the Netherlands, the expenditure-poor indicators are much steeper than average. There are also countries with very steep lines in all indicators among Western/Southern EU countries, such as Ireland, Italy and Spain. The maximum energy poverty rates in the first decile are observed in Bulgaria (80%) for the UB indicator, and Estonia (almost 80% are 2M-poor). In contrast, quite flat lines are observed for the subjective indicators in rich countries

The first approach combines in the first decile the poorest in Sweden and of Bulgaria, and the same at the top: we have an average of the richest 10% in countries from Portugal to Estonia. In order to get a better idea of the income profiles of the energy poor by these four indicators from a EU perspective, we switch to the second panel (Figure 3b). To facilitate the interpretation of these EU-level deciles, in Appendix B we show the country-composition of each of these deciles (Figure 11). There we can see that almost half of the income-poorest 10% of the EU live in Romania, Poland or Bulgaria. At the other end, about 55% of the richest 10% live in France or Germany. Towards the 'EU-middle class' we observe an important share of people in Spain and Italy.

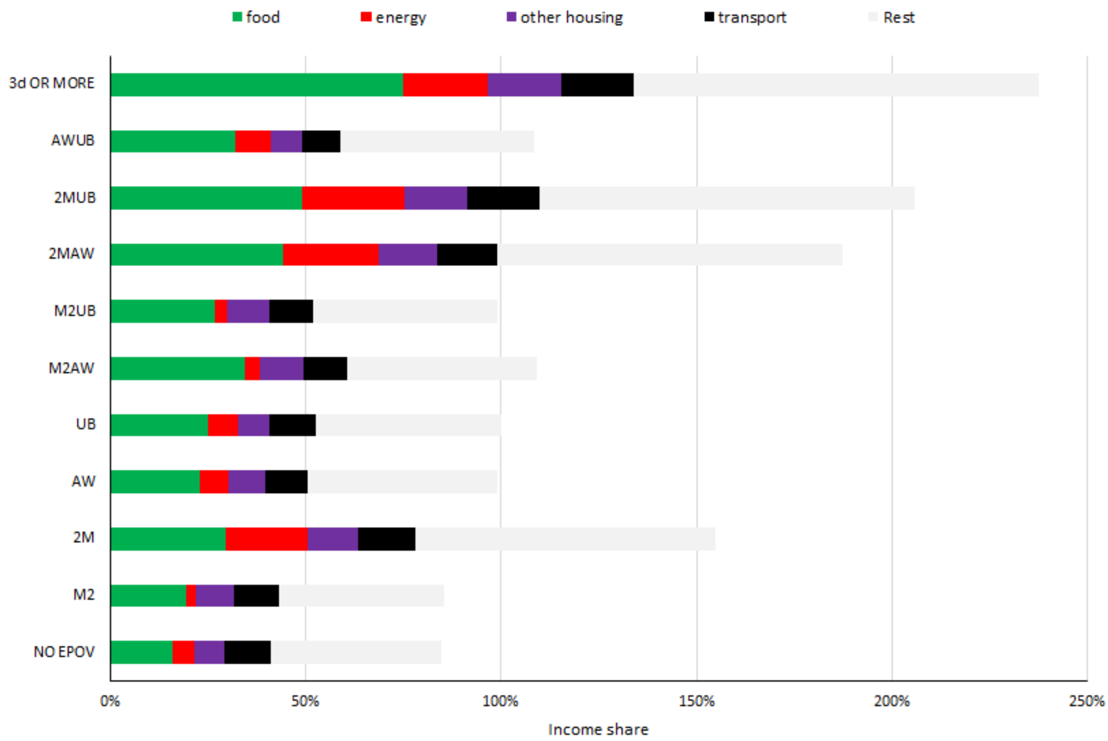
With this EU perspective we can still see the negative slopes, and that the M2 indicator has the 'flatter' line, but differently from the country-specific decile perspective, we see now that the subjective indicators show steeper lines than the 2M. This is simply the result of the within-country negative slope of both indicators combined with the larger energy poverty rates identified in lower-income countries with the subjective indicators.

The degree of overlap between these indicators varies as well from the poorest to the richest EU individuals (see Figure 11). The share of the population classified as poor by two or more indicators is about 20% in the bottom EU decile, whereas is practically zero among the top 20%. This is again the result from a within-country gradient and a cross-country effect (we saw that Central Eastern European and Mediterranean countries tend to have the largest shares of the population that are simultaneously poor by the two subjective indicators or by one subjective and one expenditure-based one).

Expenditure patterns

We have seen that the energy poor tend to have lower incomes than the non-poor, but that there are non-negligible shares of energy poor among middle and top income households. We now look into the expenditure profiles of the energy poor. Figure 4 displays the income shares of expenditures on basic need consumption categories such as (1) food, (2) energy, (3) rest of housing (i.e. rents, mortgages, maintenance and other bills, e.g. water), (3) transport, and (4) rest.

Figure 4: Expenditure profiles of the energy poor



Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. There is no information on UB indicator for Germany. In this figure the single categories (e.g. "M2") show the percentage of the population classified as energy poor according to that indicator while being not-poor by the rest. The interactions are signalled with the two names consecutively (e.g. "M22M" are the energy poor according to both the M2 and 2M indicator, and by none of the others).

Unsurprisingly, the 2M-poor are those who spend more on energy in relation to their incomes. They spend, on average, about 20%-25% of their incomes on expenditures. After food, energy is the second most important item of consumption for this group of the population (that represent almost 1 out of 5 EU citizens). This group has another particular feature: they spend more than average not only on energy, but also on other consumption categories. In fact, it is the group with the highest income shares of expenditure in total. Even tighter are budgets for those who are 2M and simultaneously poor by other indicator(s), as the length of the upper bars in Figure 4 suggests.

In sharp contrast, the M2-poor show not only much lower income shares of expenditure on energy (as expected, since the M2-poor are those who are consuming very little energy, by definition) but also in general, in the other consumption categories. On average, the M2-poor spend 2% (a share that is at least ten times lower than the 2M's) of their incomes on energy, which is one third of the average income shares of expenditures of the non energy poor. In terms of total consumption, the average income share of the M2 group is very similar to the one of the non-poor. Both tend to spend in total 85%, with an average saving rate of about 15%.

The subjective poor also have very similar expenditure profiles among them, and are somewhere in between the M2 and 2M in terms of how much of their incomes is allocated to expenditures (7-8%), as well as of the income share of total consumption expenditures (which is about 100%). This suggest that the energy poor in the EU (by subjective and 2M indicators) have very tight budgets, and would not be able -on average - to face increasing prices of energy, transport nor food without either sacrificing welfare (reducing consumed quantities) or recurring to debt.

4.3 Logistic regression results

We have seen that these four energy poverty indicators overlap very little and show very different income and expenditure profiles. We now dive deeper into the socio-economic profile of the energy poor by the estimation of a group of logistic regression models where the outcome variable is the likelihood of being classified as 'energy poor'. We start by presenting the results from the pooled model (that covers all EU households, and in which incomes are adjusted by purchasing power standards), and then we discuss the results obtained from the estimation of the country-specific analysis. The interest of the first set of regressions is that it gives as an overall idea of the main characteristics of the energy poor with an EU citizenship approach (although of course we control for country unobservables, with country fixed effects). The advantage of the second is that it sheds more light on cross-country differences in these socio-economic profiles, and also on the importance of some variables that are not present in all countries (and so were not included in the pooled model), such as region, urban/rural, quality of the house, etc.

EU-pooled model

Table 3 presents the marginal effects of the logistic regression estimated results based on the EU-pooled model (equation 3). In this case, we estimate the equation over the full sample of all households from the 27 EU countries according to each of the four selected EPOV indicators (one per column). Our estimations include a set of regional dummies that account for time invariant unobserved characteristics (across groups of households) to control for the region-specific policies, climate, infrastructure, among others drivers of both energy poverty that could also well be correlated with some or all of the other covariates.

To facilitate the interpretation of the coefficients, instead of odds we report marginal effects, in line with the standard practice in the literature (e.g. Deller et al., 2021, Llorca et al., 2020, and Price et al., 2012).

The only covariate that consistently exhibits both the same sign and significance level across the four indicators is household equivalised disposable income. As expected, the income elasticity of energy poverty is positive in all four indicators. This is, a higher (lower) income is associated with a decrease (increase) in the likelihood of being classified as 'energy poor'. Nevertheless, the magnitude changes across subjective-based and expenditure-based indicators. Unsurprisingly, the highest income elasticity of energy poverty for the 2M indicator, as this variable is by definition negatively correlated with incomes, other things equal. The income elasticity for the 2M almost doubles the subjective indicators, and for M2 it is also higher (about 50%).

For the remaining covariates, the subjective UB and AW indicators feature similar sign and significance levels, very often coinciding with those for the 2M poor too. In parallel, the M2 shows the most singular patterns.

The total number of household members with higher education as well as the number of employed household members are associated with a lower probability of being energy poor, for the two subjective and the 2M indicators. A larger number of adults employed or with higher education reduces the chances of being energy poor in about 1.5 to 3% across these three indicators. On the other end, for the indicator M2 the opposite holds: the estimated marginal probabilities associated with these two variables are positive and significant. This is in line with the idea that M2 indicator captures a different typology of energy poor. Given other characteristics, households with lower

Table 3: Logistic regression results: EU pooled model

	(1) UB	(2) AW	(3) 2M	(4) M2
Log income	-0.719***	-0.853***	-1.375***	-1.099***
	(-25.08)	(-32.09)	(-54.85)	(-45.36)
Person w/disability	0.270***	0.449***	0.0183	-0.0593
	(4.99)	(9.18)	(0.45)	(-1.29)
Non-EUc	0.943***	0.775***	-0.0763	0.115
	(11.82)	(9.85)	(-1.14)	(1.82)
Num Adults w/high-edu	-0.377***	-0.397***	-0.147***	0.0555**
	(-14.56)	(-14.53)	(-7.55)	(3.12)
Num employed	-0.189***	-0.292***	-0.175***	0.0879***
	(-8.40)	(-11.09)	(-8.96)	(4.88)
HHtype				
One adult<65 (no children)	-0.194**	0.108	0.495***	-0.0683
	(-3.12)	(1.84)	(10.34)	(-1.40)
One adult>65 (no children)	-1.092***	-0.251***	0.784***	-0.405***
	(-15.32)	(-3.77)	(14.66)	(-6.80)
One adult>65 (with children)	0.686***	-0.0590	0.0417	-0.0678
	(8.07)	(-0.67)	(0.62)	(-0.95)
Two adults (no children)	-0.0858	-0.1000	0.169***	-0.139**
	(-1.55)	(-1.86)	(3.98)	(-3.25)
Two adults (one>65) (no children)	-1.189***	-0.613***	0.563***	-0.555***
	(-20.17)	(-10.90)	(12.18)	(-10.99)
Two adults (1 child)	0.205***	-0.318***	-0.142***	-0.00226
	(4.34)	(-6.50)	(-3.41)	(-0.06)
Three+adults (with children)	0.367***	-0.00322	-0.132*	0.166***
	(6.67)	(-0.05)	(-2.49)	(3.54)
Single fem	-0.0782	0.134**	0.237***	-0.193***
	(-1.63)	(3.06)	(7.45)	(-5.09)
N	510372	537935	538238	538238

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Based on HBS-SILC matched files from 2015 energy needs (such as those working longer hours and of certain age profiles) will tend to have lower energy expenditures and could then fall below the M2 poverty threshold, even if they are not actually suffering from energy deprivations. Other socio-economic characteristics of the household member, such as being disabled or being a non-EU citizen is found to increase the probability of being energy poor for the subjective-based indicators while it is not a significant determinant for the 2M and M2 indicator.

Looking at household typology, we can evaluate the differences in probabilities of being energy poor for individuals living in different type of households compared to the reference level, i.e. individuals in a household composed by three or more adults without children. Single-adult households without children are generally less likely to be energy poor for 3 out of 4 indicators (UB, AW and M2) while they show a higher probability of being energy poor when using the 2M indicator. Single-adult households with children (as well as in general individuals living in households with children) face higher probabilities of being energy poor according to the UB indicator. Pensioners (individuals in households composed of members older than 65 without children) are also less likely to be energy poor according to the indicator AW and M2. Households composed of two members without children are also less likely to become energy poor when looking at UB, AW and M2 indicators compared to more numerous households while this is not the case when looking at the 2M indicator.

Comparing the coefficients of the two subjective-based indicators we found that the effect of household type is fairly consistent across the two indicators but more numerous households (2 or more adults with children) seem to be associated to an increased risk of being energy poor in the case of UB while the opposite is true in the case of AW. Moving on to a comparison across the two expenditure-based indicators we found instead less consistency. Specifically, for the 2M indicator single adult and senior households seem to be generally less at risk of energy poverty compared to more numerous one and the opposite is true for the M2 indicator, i.e. more numerous households are more likely to be classified as energy poor.

The variable that indicates whether the household is headed by a single female adult shows that gender may be a factor influencing the risk of energy poverty. In particular, and *ceteris paribus*, being in a household led by a women increases the chances of being energy poor according to the AW and 2M indicator, while it reduces the chances of being energy poor according to the M2 and has no significant effects on UB.

Country-specific models

We perform country-specific regression analysis with two objectives in mind. First, we would like to examine whether there are differences at country level in the socio-economic profiles of the energy poor according to these four indicators, compared to the pooled model where the coefficient represents the average effect across 27 EU countries. A further objective is to evaluate also the influence of additional variables that could not be included in the pooled model due to missing values for some of the 27 countries. We briefly comment here on the main differences found between the pooled logistic model and the country specific one, and we discuss the results obtained for the expanded set of covariates. In Tables 9-15 (Appendix B), we report the results from these country-specific regressions, where we omit (for parsimony reasons) the coefficients of the region dummies as well as the type of household categories.[13]

[13] Among significant coefficients, between the pooled model and the single-country one we observe changes in the sign for the expenditure-based indicators (2M and M2). In table 7, we show for each of the two indicators the determinants that have a reverse impact on energy poverty compared to the pooled model for the 2M and

We first focus on the income elasticity of energy poverty across countries. This is a key result from this analysis, as it is telling us to what extent sudden changes in income (e.g. through a macro or labour market shock or income-support policy measures) can, *ceteris paribus*, affect the energy poverty incidence across the 27 EU countries.

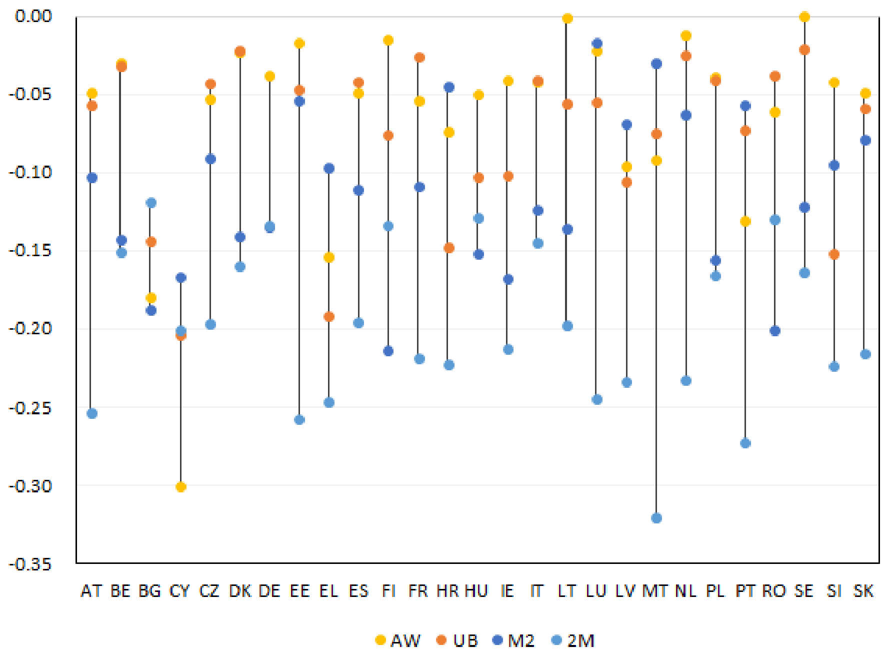
The estimated elasticity is negative and significant at the 1% level, like in the pooled-EU model, for all countries and indicators with only a few exceptions.[14] Overall, the magnitudes of these elasticities are much lower than in the pooled model. This is not a surprise, as in these country-specific model estimates we are now able to control for many more variables related to the assets and general living conditions that before were probably accounted by this income variable.

The estimated income elasticity substantially varies not only across indicators but also across countries, as it can be clearly appreciated in Figure 5. Still, we can observe some clear patterns. First, it is larger for expenditure-indicators, with respect to the subjective-indicators. Second, the highest of all is the 2M poverty income elasticity, that ranges from 0.12 to 0.32. This is followed by the M2 indicator [0.02-0.21]. Third, there is a negative cross-country correlation of these two elasticities. Countries with the highest income elasticities of the 2M-poor, such as Malta and Portugal, show very low M2-poor income elasticities, whereas at the other end we see countries with top M2-elasticities and bottom 2M-elasticities, such as Finland, Romania and Bulgaria. Fourth, in contrast to what happens between the expenditure-indicators, the elasticities for the subjective indicators are positively correlated. In this case, we observe countries with the highest income elasticities in UB showing also top elasticities in AW: Cyprus, Greece and Bulgaria, with elasticities that are above 0.15 in both indicators. At the other extreme, the smallest income elasticities in both subjective indicators are observed in high-income countries, particularly so in Sweden, Denmark, the Netherlands and Belgium.

M2 logistic regression. The first row shows the sign obtained in the pooled-EU regression, and then for each row (country) the table signals whether there was a sign reversal from one model to the other. It is important to bear in mind when interpreting these differences that we can broadly compare what are the main drivers in one model and the other but that these two models have very different degrees of freedom and slightly different specification (country-specific regressions have lower degrees of freedom because of the smaller number of observations and larger number of covariates), so these coefficients nor standard errors are not directly comparable.

[14] The AW-poor in Lithuania and Sweden (where the elasticity is negative but not significant) and the Netherlands (where it is only significant at the 10%), and the M2-poor in Malta and Luxembourg (negative but not significant).

Figure 5: Income elasticities of the energy poor



Notes: estimations from the country-specific model regressions -see equation (3)- including region-specific dummies - based on HBS-SILC matched data and simulated disposable income from EUROMOD for 2015. There is no information on UB indicator for Germany.

For the rest of the covariates included both in the pooled model as well as in the country-by-country ones, we generally see few differences. It is important to bear in mind that we are comparing models with different sample size and degrees of freedom, so we just broadly mention whether there is anything that departs from what it could be expected (i.e a change in the sign of a significant coefficient in both models or a gain of significance in the country-specific model). When looking at the likelihood of being energy poor according to the 2M indicator, we see that, differently from the EU pooled model results, single adult households without children are less likely to be classified as energy poor in Austria, Cyprus and Germany. In the case of Estonia and Greece, we also see that the number of employed adult member is associated with an increasing risk of being energy poor, whereas in Sweden, female-headed households seem to be less likely to be energy poor. For the M2-poor, we identify more differences relative to the household type across many countries. Specifically, single adult households without children seem more likely to be energy poor in Belgium, Cyprus, Czechia, Germany, Finland, Luxembourg, Slovenia and Slovakia. Similarly, also two adult households seem to be more likely to be classified as energy poor in Greece, Cyprus and Sweden. This indicates that the M2 indicator is not only the more "different" between indicators (as it tends to classify as 'energy poor' young, highly educated employed individual who consume little simply because they probably spend less time at home) but is also characterised by more heterogeneity across the household profiles across countries.

There are also a couple of variables for some indicators that were not significant in the pooled EU model and turn to be significant in the country-specific regressions. This is, for example, the case of the dummy that identifies a single female headed household. In the pooled-EU model, the associated coefficient to this variable is positive and significant for all indicators except from UB. Now it turns to be significant as well in the country-models of Austria, Denmark, Croatia, Italy, Latvia and Portugal. There are also some changes by household type. The one-adult households (without and with children) become less likely to be AW poor in many countries, whereas in the pooled model there was no significant coefficient associated with this variable for the AW-poor. For the 2M indicator, there are also a few variables that become significant, e.g., the presence of a person with disabilities in the household in countries like Finland and Poland (whereas the EU-level coefficient was not significant). The presence of a non-EU citizen in the household was also not significant in the pooled model to predict the chances of being 2M, while it becomes negative and significant in about 1/4 of the EU countries (i.e. Austria, Spain, Croatia, Luxembourg, Poland and Sweden). The opposite is identified in M2: in this case, the presence of a person with disability decreases the chances of being M2 poor in 5 MS (Estonia, Finland, Croatia, Italy, Lithuania), whereas the presence of a non-EU citizen increases the chances of being M2 poor in 6 MS (Austria, Denmark, Spain, Hungary, Luxembourg, Sweden). This makes sense, as low levels of expenditure on energy are expected among more labour-engaged groups of the population (such as it is typically the case of young adults and migrants - who are particularly over-represented in this group (see, e.g. Fiorio et al., 2023). With a similar reasoning, it is less likely to find M2-deprived individuals (i.e. consuming very little energy) in households with a member with disabilities that probably spends more time at home and demands more energy consumption, other things equal.

We have also added a new set of variables in these country-specific regressions that allow us to get a more in-depth picture of the main drivers of determinants of the likelihood of being classified as poor by these four indicators across the 27 EU countries. All coefficients, except from household types (that were presented in the pooled model, and for which differences are commented in the text) and regional dummies are not displayed in the tables with the country-specific results (Tables 9 to 15 in Appendix B).

In this setting we can better exploit the richness of our microdata, by including variables related to housing and other general living conditions,[15] such as: *house space density* (the ratio between the number of rooms and the household size), a dummy for *house bad quality* (according to self-reported problems with leaking roofs, damps walls/floors/foundation, rot in window frames or floors); geographical/location variables (a couple of dummies for *urban*, *rural* and *middle-intensity areas*); as well as a set of variables on *household assets* (phone, computer, car); as well as *house ownership* and *type of household* (detached, semi-detached or buildings).

House ownership decreases the likelihood of being UB-poor (especially in Southern European countries) and AW-poor, in about half of the 27 EU MS (mainly Western and Southern European countries). In contrast, home ownership increases the likelihood of being 2M-poor. Although perhaps counter-intuitive at first sight, house owners may have the chances to actually spend more in energy given their lower housing costs (i.e. no rent payment). For the M2, only in Finland and Greece home ownership shows a negative and significant coefficient.

House density decreases the chances of being subjectively poor (in either AW or UB) in about one third of the EU countries. It shows very mixed signs for 2M and M2 with almost no significant coefficients. An exception seems to be Germany, that displays a negative and significant coefficient in the first case (i.e. the more people per room in the house, the lower the chances of bearing high income shares of expenditure), and positive and significant in the second (the higher this density, the higher the chances of being a household with very low levels of equivalised expenditures on energy).

The group of asset variables (computer/phone/car) display in general negative coefficients (i.e. the presence of these assets decreases the likelihood of being energy poor), but these are only

[15] Not all these variables are available for all countries, but we chose those that are in principle relevant to explain energy poverty, among those for which there is at least availability for half or more of the EU 27 countries.

significant for the subjective poor measures. Among these, the computer dummy is the one that shows more significant coefficients across countries and of higher magnitude - especially in Eastern European countries. For the expenditures-based, most of these assets are not significant.

The variable that captures *bad house quality* is significant and positive for the subjective indicators for almost all countries for which this variable is reported, with marginal effects ranging 0.01 to 0.17. In this case the smallest effects are observed in Sweden, whereas the largest influence of this variable in determining the probabitlity of being energy poor is observed in Bulgaria. The *type of house* (i.e., whether the house is detached, semi-detached or in the building) does not make an important difference.

The dummies for rural/urban/middle-density (included only in about half of the EU countries, as this variable was not available for 2015 SILC in all) show mixed results. For the subjective indicator, in general individual living in urban areas have lower chances of being poor (a negative coefficient associated to the urban and middle-density dummies). This is particularly true in DK, ES and HU, but it is not significant in most countries for which this variable is available. Same for UB: urban households have lower chances of being UB poor in some countries, like in Finland and France, but in others like Bulgaria and Spain.

5 Discussion

Before concluding, we discuss the main results from our analysis, from four angles: i) their reliance on our matching method, ii) how they contribute to the existing literature, iii) their usefulness for policy-making and, iv) next steps for future research.

First, the results from the overlapping analysis of these indicators coming from two different household surveys (HBS/SILC) depend on the quality of the matching. Our semi-parametric statistical matching assigns disaggregated household consumption expenditures from HBS (donor survey) to SILC households (recipient). To validate our results, we evaluate the matching results for Czechia, country for which, exceptionally, we could access the administratively-merged datasets (with common IDs).[16] The detailed step-by-step explanation of the matching as well as the validation results for Czechia are provided in the Appendix A. Among other results, we show that the percentage of correctly matched M2- and 2M- energy poor households ranges between 95% and 99% over the three years considered, suggesting a very good overall performance of our matching method for the purposes of this study.

Second, to our knowledge, our study is the first to provide an assessment of the overlap between these indicators for the 27 EU countries. As mentioned in section 2, among the very few attempts in the literature that have looked at the overlap between indicators for some particular countries, the closest to us is Menyhért (2024). Menyhért (2024) assesses the overlap for Hungary, with administratively merged data from HBS and SILC, between five indicators (the same four we consider, plus an alternative to capture excessive energy costs based on a fixed threshold of 30% of household expenditures).[17] In contrast, we cover the 27 EU countries, using a statistically-matched

[16] We would like to thank the National Statistical Office of Czechia for sharing this database with us. The other country for which there are ID-merged HBS and SILC information is Hungary, used by Menyhért (2024) for his overlapping analysis.

[17] We are not interested in this type of indicator for the purposes of our analysis for two reasons. First, because by using expenditure shares instead of income shares, saving rates are out and this distorts the ranking and comparability (within and between countries) of any distributional assessment of energy poverty. Think, for example, about two households with shares of expenditures on energy of 30%, one with no savings (and therefore that spends 30% of their incomes on energy) and another with a saving rate of 50% (therefore, spending only 15% of their income on energy). It seems weird to compare these two as 'equals' from the viewpoint of energy affordability or

databases for 2015. Another methodological difference is that for the expenditure-based indicators (M2/2M), Menyhért (2024) includes expenditures on vehicle fuels (COICOP category 0722) and uses net incomes reported in HBS, while we focus only on expenditures on residential energy (COICOP category 045), and use SILC-based (corrected with EUROMOD simulations) incomes. Overall, despite these differences, our overlapping results for Hungary are not that different. For example, we both estimate that about 10% of the Hungarian population is energy poor by two or more indicators, simultaneously. Our results also show that energy poverty headcount ratios and overlap substantially vary across countries, and that Hungary -nor any other country- are not representative of the whole of the EU. In the particular case of Hungary, our results suggest that it does not even represent the standard pattern of the group of Central and Eastern European Countries.[18]

Third, we would like to briefly discuss how our results can be used to give advice to policy-makers. Poverty indicators are a key instrument for policy design and evaluation, as they provide a transparent tool to identify those who are "suffering the most" in a dimension of human well-being, depending on a threshold based on normative grounds. For the just green transition, and particularly so in the aftermath of the Covid-19 (2019-2020) and global energy crisis (2022-2023), monitoring and alleviating energy poverty is an explicit policy priority at the EU level. Our results show there is very limited overlap between indicators, that each indicator tends to capture different segments of the population and that using them all would lead to extremely high energy poverty rates. A question that immediately emerges here is: which one to use, and for what purpose?

Our results show that, for policy targeting, using one or the other indicator would lead to very different budgetary and distributional implications. Imagine an EU-level policy consisting on a cash transfer (lump sum, one-off) of 1000 EUR to each "energy poor" in the EU, aimed at alleviating energy-related deprivations deriving from the green transition or from a hike in prices.[19] From Table 2, we can directly calculate that this transfer, if targeted to the AW-poor, would cost the EU 39 billion EUR, whereas to cover the 2M-poor, this budget would increase to 80 billion EUR (which even surpasses the maximum budget foreseen for the EU Social Climate Fund for 2026-2032, of 65 billion).[20] The distributional consequences would also be very different: a cash transfer to the energy poor decreases income inequality (measured by changes in the Gini coefficient) using all indicators (but much strongly if targeted to 2M or AW than to M2 or UB), whereas income poverty would decrease only if 2M/AW are used, whereas for the M2- and UB-poor income poverty would even slightly increase.[21] Given the strong relationship between energy

deprivations. Second, for our EU-level analysis, absolute thresholds are of limited usefulness, as they tend to ignore the national-level particularities related to energy demand and supply as well as prices and income levels, as we discuss more in depth in Appendix A, where, with Figure 8 we compare the fixed Boardman's TPR (where poor is who lives in a household that spends more than 10% of its incomes on energy consumption) with our 2M indicator. In fact, in this comparison we can see that Hungary has one of the smallest 2M poverty rates (about 10%, very similar to Menyhért (2024)'s estimated headcount ratio) while featuring the highest poverty rate according to the TPR (close to 60%).

[18]As we have seen, expenditures on energy represent a large share of incomes in Hungary (that is why it would be the country with the highest poverty rate with a fixed 10% threshold, as we show in the Appendix), while when we use a national-level relative threshold Hungary is actually one of the countries with the lowest 2M energy poverty rates. Moreover, while it has a quite above-EU average poverty rate according to the UB indicator, more than doubling the AW-poverty rate (of about 20% and 10%, respectively). Finally, in terms of overlap, Hungary features much smaller degrees of overlap than the average EU, and also with respect to other Central and Eastern European countries, such as Bulgaria, Lithuania, Cyprus, Romania, Latvia (see Figure 2), whereas the estimated income elasticities are among the lowest in the EU, ranging from 0.05 (AW) to 0.15 (M2) - as it can be appreciated in Figure 5.

[19]Similar to the income support measures some EU Member States implemented during 2022-2023 to offset the negative welfare effects of the increase in gas/electricity/fuel bills, see, e.g. Amores et al., 2023.

[20]All our estimates refer to 2015 levels of consumption and prices.

[21]Income poverty in this hypothetical simulation exercise is measured, as standard, with the AROP rate, and a threshold defined at 60% of the median. The AROP rate would decrease, on EU-27 average, 0.7pp if the transfer is

poverty and income, income-support policies seem essential to tackle energy poverty situations, especially for households under the poverty line. However, considering that also middle-income households experience a relative high incidence of energy poverty: up to the 6th income decile, the energy poor account for a proportion between 5% and 15%, depending on the indicator chosen other type of policies may support better the energy poor within the middle-income groups. This is the case of price caps, which reduce the burden of expenditures on energy goods, or structural interventions that step up energy efficiency by reducing the need of energy consumption.

Our results could also be used to assess more critically the extent to which each of these indicators may be actually capturing energy-related deprivations, and to what extent they could be prone to 'false positives'. In this sense, our most 'puzzling' indicator seems to be the M2 (low absolute expenditures). This indicator shows the smallest overlap with other indicators: about 80% of the M2-poor in the EU are not poor by any of the other three energy poverty indicators. This means that most of the M2-poor do not declare to have arrears on utility bills, problems to keep their homes adequately warm nor suffer from very high expenditure costs in relation to their incomes. Moreover, we have seen that the M2-poor show also quite high income profiles and distinct socio-economic profiles from the regression results (e.g., differently from all the other indicators, the presence of an adult with higher education or the number of employed adults in the house increases the probability of being poor, *ceteris paribus*). From an EU perspective, the M2 indicator completely shuffles the relative performance of EU Member States and the cross-country ranking. Counter-intuitively, with the M2, the highest energy poverty rates are observed in countries with high income and generous welfare regimes, such as Finland and Sweden (countries which tend to be much closer to average or even at the bottom with the other indicators). Finally, in terms of expenditure profiles, we have also seen that the M2-poor have a saving rate similar to the non-energy-poor, and spend similar shares of income on other necessity goods/services such as food, housing and transport. Therefore, are we really capturing the "hidden poor" -i.e. those restricting consumption and suffering from cold, as those identified by Betto et al., 2020 for Italy or Meyer et al., 2018 for Belgium - or are we covering too many "false positives" (young people spending little time at home and therefore having low expenditures due to lower needs or preferences or households with lowe energy expenses due to living in efficient buildings or using self-generated energy)?[22] This and other similar normative-related questions emerge, and open the road for further research.

From our analysis and above discussions there seem to be some clear roads for future research. For example, a way to minimize the share of "false negatives" would be to explore some income-filtering, following, for example, the bi-dimensional approach of Hills (2011) for the UK with his low-income-high-cost (LIHC) measure (developed to substitute Boardman's ten percent rule). By restricting energy poverty to low- and middle-income households (leaving the rich out), we may actually be able to take on board those who are M2 or AW because they do not have other

targeted to the AW-poor and 0.4 (2M), while it would increase 0.16 with the UB (a positive rate observed in 2/3 of the EU countries) and 0.5 with the M2 (a generalized increase, across all Member States but one). The 1000 EUR lump-sum transfer would also reduce the Gini coefficient by 0.0043 with 2M-targeting, followed by 0.0029 (AW), and 0.0024 (for UB and M2). The AROP rate would be only marginally reduced by 0.1 pp (2M), 0.08 (AW) and 0.05 (M2/UB). Country-specific results available upon request.

[22] Supporting the second interpretation, from Table 2 we can see that that 89% of the M2-poor are not AW-poor (i.e., only a minority declare to be unable to keep their home adequately warm despite their very little expenditure consumption). But the "false positives" are not an exclusive M2-feature. For example, should we care about an AW-poor -i.e. someone that declares not to be able to keep her/his house adequately warm- but that perhaps is deciding not to spend enough on this? In this sense, about 50% of the AW-poor are not UB-poor (i.e. not having issues with utility bills nor) nor 2M-poor (not spending very high shares of income on energy), what make us wonder whether this does not respond to preferences (having large houses or preferring to use household budgets on other consumption items) rather than actual deprivations.

choice from those who may voluntarily decide to be in this situation (given that they have enough resources to potentially do so). This would be aligned with the new Commission's Recommendation that explicitly stresses that energy poverty is about high expenditure costs, but also low incomes and efficiency problems. In this sense, another line for future research would be to distinguish between households that have invested in energy capital (e.g. efficient appliances, insulation, etc) as this can make an important difference when assessing expenditure levels and the way they proxy deprivations.

6 Conclusions

The European Union has engaged into an ambitious 'green transition' under the roadmap of the Green Deal, with a new set of climate targets towards 2030 and 2050. President von der Leyen in her speech on the State of the Union 2024 explicitly acknowledged that this transition will be fair or it will 'not be'. In this context, identifying the 'energy poor' as well as other vulnerable groups of the population to changes in markets and institutions is a key (and challenging) input for the design of inclusive policies, as well as for transparent policy evaluation, monitoring and accountability (Kelly et al., 2020, Faiella et al., 2022, Martin and Islar, 2021, Douenne and Fabre, 2022). We know that energy is essential for the satisfaction of basic needs and energy deprivations can lead to severe and persistent welfare effects in terms of heath and well-being (Churchill and Smyth, 2021, Drescher and Janzen, 2021, Churchill et al., 2020, Liddell and Morris, 2010, Barnes et al., 2008). Therefore, early policy interventions may not only be needed to cushion the potential welfare losses from green transition policies, but also prevent in the long-term their undesired scarring effects. The recent (2022-2023) hike in energy prices has reinforced these concerns, pushing the topic of energy poverty to the forefront of scientific and economic policy debates. Still, there is a clear lack of consensus on how to properly measure this phenomenon (Thema and Vondung, 2020, Rademaekers et al., 2016, Thomson and Snell, 2013, Liddell, 2012, Moore, 2012, Bouzarovski et al., 2012).

Our study offers a comprehensive assessment of the magnitude, distribution, overlap, and socio-economic profiles of the 'energy poor' according to four energy poverty indicators based on harmonized microdata for the 27 EU countries. These are two widely-used subjective indicators based on EU-SILC, and two expenditure indicators based on EU-HBS. By matching household consumption expenditures at the very disaggregated level from EU-HBS into EU-SILC, we offer for the first time an analysis on the extent to which households in the EU are classified as energy poor by one or more indicators at the same time. Our findings reveal minimal overlap between energy poverty indicators, in line with previous country-specific studies. We show that the socio-economic profiles of the energy poor are very different across indicators, and particularly distinct features are observed for the M2 indicator based on low absolute expenditures. This suggests that reliance on a single indicator may overlook significant portions of the population experiencing energy-related deprivations and that further normative discussions may be needed when using one or the other, to minimize the group who may be left behind as well as the "false positives" (i.e. trying to exclude households that might not actually be struggling from energy poverty deprivations).

Moreover, overlapping is so small that only 20% of the 'energy poor' are classified as such simultaneously by more than one indicator. This explains why using a union approach would lead to "too many" poor: about 40% of EU citizens would be classified as 'energy poor' by at least one indicator (about 178 million people - 2015 values). In contrast, an intersection approach (i.e. if we would restrict the classification of poverty condition to all those who satisfies it in all four indicators) would lead to 'too few' poor: only 0.1% of the EU population falls in this category. Moreover, if we would restrict our analysis to the subjective indicators based on SILC (which feature on average lower poverty rates), we would be "excluding" about 26.5% of the EU population (who are energy poor according to at least one of the two expenditure indicators and not poor by the self-reported subjective ones). In contrast, if we would use expenditure-based energy poverty rates we would be missing about 8% of the EU population (who are subjective-poor but not expenditure-poor). Furthermore, we have shown that most of the energy poor by any of these indicators are not income poor, while, more strikingly, there is also a non-negligible share of energy poor among middle and top income households. This calls for a careful use of the indicators for policy targeting, and opens the road for future research. Specifically, it would be interesting to explore different ways of income filtering, as proposed by the well-known low-income- high-costs (LIHC) indicator proposed by Hills (2011) for the UK, and in line with new EU Energy Poverty Recommendation, that clearly states that low incomes are one of the three main drivers of energy poverty in the EU.

Further, we have also explored the expenditure profiles of the energy poor and identified very tight budgets (i.e. negative or none saving rates on average for the 'energy poor' expect from the M2 group) suggesting very little margin of maneuver to respond to shocks in energy prices, but also in food or transport. Therefore, further research is needed to better understand the intersection of vulnerabilities (e.g. between energy and transport affordability) in different dimensions affected by the global energy crisis and the green transition.

In conclusion, our study underscores the complexity of measuring and addressing energy poverty within the EU. It highlights the need for an extremely careful use of energy poverty indicators vis-a-vis the income distribution to try to ensure no one is (or minimize those who might be) "left behind" in the green transition. Additionally, our findings provide valuable insights for future research and policy design aimed at tackling energy poverty and promoting a fair transition.

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A Appendix A

A.1 HBS imputation into SILC

In this section, we briefly explain the main steps involved in the imputation method developed by Akoğuz et al. (2020), which we use to statistically match the SILC and HBS datasets (for 2015),[23] along with its associated strengths and limitations. Due to discrepancies in the sampled households between SILC and HBS, establishing precise correspondence between the two surveys is unfeasible for the vast majority of the EU countries. Thus, to combine information from these surveys - in our case, SILC incomes and self-reported variables related to energy deprivation and HBS expenditures- we need an imputation technique.[24]

To achieve so, we adopt the semi-parametric approach developed by Akoğuz et al. (2020). This method integrates the estimation of Engel curves, as utilized in prior studies such as Decoster et al., 2010, with matching techniques. Subsequently, we offer a comprehensive step-by-step explanation of this procedure and deliberate on its primary advantages and limitations.

For this purpose, we adopt the semi-parametric procedure developed by Akoğuz et al. (2020). This combines the estimation of Engel curve (employed in previous studies, such as Decoster et al., 2010) with matching techniques. In the following we provide a step-by-step description of this procedure and discuss its main advantages and limitations.

1. A household h's expenditure on a good i in the source dataset (the HBS, indexed by 's'), denoted by e_{shi}, is converted into a share, w_{shi}, of disposable income, y_{sh}:

$$w_{shi} = \frac{e_{shi}}{y_{sh}}, \qquad\qquad i \in N \tag{4}$$

   where N is the set of indices of goods at the most detailed level in the HBS.

2. These income shares of expenditures on detailed goods are aggregated under broader categories.[25] We index these categories by $X = A, B, ...$. Thus, the income share of expenditure category X, W_{shX}, is defined as:

$$W_{shX} \equiv \sum_{i \in N_X} w_{shi}. \tag{5}$$

3. Income shares of consumption for aggregated categories, W_{shX} are regressed against a relevant set of covariates common to both the source (ie. HBS) and the recipient dataset (ie. SILC). Though there is not a structural interpretation to the regression model, the selection of covariates is very much inspired by the specification of Engel curves.[26] Note that, aggregated categories $X = A, B, ..$ may still contain a significant number of zero observations. At this level of aggregation, these are considered to be true zeros[27]. To account for zero expenditures a two-steps regression is performed.

[23]Due to data limitations related to HBS 2015, we use 2010 HBS surveys for Austria, Italy and Germany)

[24]In the case of Italy, the complexity is exacerbated by the absence of net household income data in the 2010 HBS dataset. To address this, income data from the 2010 Survey on Household Income and Wealth (SHIW) are imputed to HBS prior to merging with SILC. For further details, refer to Akoğuz et al. (2020).

[25]These categories should be big enough to reduce the infrequent expenditure problem but small enough to allow household characteristics to explain differences in allocations of income across these goods.

[26]More specifically, a third degree polynomial in the log of incomes, and a rich set of household composition characteristics were included, containing detailed information on the number of household members in different socio–demographic groups, such as gender, labour market status, and age. A list of all potential covariates can be found in Appendix ....

[27]Which is to say not a consequence of the infrequent expenditures problem

(a) The probability that a household exhibits positive expenditures on commodity aggregate X is modelled by a probit model, using the common variables in the source and recipient dataset as explanatory variables. Formally:

$$Pr\left(W_{shX} > 0\right) = 1 - \phi\left(-\gamma_X^{'} x_{sh}\right) = \phi\left(-\gamma_X^{'} x_{sh}\right) \tag{6}$$

where $\phi(\cdot)$ denotes the standard normal distribution function, x_{sh} is the vector of explanatory variables for household h in the source dataset s, and the vector $\gamma_X^{'}$ contains parameters to be estimated.

(b) Next, an ordinary continuous regression model is formulated for assessing the relation of positive income shares of broad expenditure categories with the common variables:

$$W_{shX} = \beta_X^{'} X_{sh} + \epsilon_h X, \qquad\qquad W_{shX} > 0. \tag{7}$$

4. Using the estimated models, values are fitted for the income shares of expenditures on the broad categories $X = A, B, ...$, for all households in both the source and the recipient datasets, indexed by s,

$$W_{dhX} = \phi\left(-\widehat{\gamma}_X^{'} x_{dh}\right) \widehat{\beta}_X^{'} X_{dh}, \qquad\qquad d = s, r. \tag{8}$$

5. Denoting a vector of fitted shares retained as input for the distance by $W_{dh} \equiv (W_{dhA}, W_{dhB}, ...)$, where $d = s, r$ and using the Mahalanobis distance metric, the distance between a household h in the source data, and a household g in the recipient data is defined as:

$$dist\left(h, g\right) = dist\left(W_{rg}, W_{sh}\right) = \sqrt{\left(\widehat{W}_{rg} - \widehat{W}_{sh}\right)^{'} \Sigma^{-1} \left(\widehat{W}_{rg} - \widehat{W}_{sh}\right)} \tag{9}$$

where Σ here stands for the variance covariance matrix of the vector $\widehat{W}$, using data from both source and recipient.

6. A match for household g in the recipient dataset is defined as the household h in the source dataset that has the smallest distance to household g. Where the distance is measured in terms of equation 9.

7. For each match (h, g), income shares of expenditures at the most detailed level of good disaggregation $i \in N$ for the recipient household g, are obtained from the corresponding values of the source household h:

$$w_{rgi} = w_{shi}. \tag{10}$$

Two key advantages are worth remarking about this imputation method. Firstly, by matching observed consumption shares rather than fitting them based on a regression (as in the standard Engel Curve approach), this method can successfully impute expenditures data at the highest available level of disaggregation (which, using HBS data, is COICOP level 4 classifying consumption in about 200 good-types). This in turn underpins one of the key advantages of the new EUROMOD-ITT over its predecessor (see De Agostini et al., 2017), which only modeled household consumption at the level of 12 broad categories (i.e. COICOP level 1) and it was based on the

Engel Curve method. Indeed, thanks to this higher level of disaggregation, the new EUROMOD-ITT ensures a far more precise assessment of consumption patterns and of tax liabilities across households, resulting in a distributional analysis which is more accurate and broader in scope (e.g it allows analysing the impact of the consumption taxation over specific products such as cigars and beers). Secondly, the regression model exploits information on the relation between household characteristics (namely, the explanatory variables in the regression) and expenditures (dependent variables) in the dataset, which is neglected in other widely used imputation methods, such as the Hot Deck Matching. Effectively, this means that the distance between households in both dataset is measured based on household characteristics (e.g age, income, education etc) which are implicitly weighted in the distance function according to their ability to explain household consumption on different good categories.

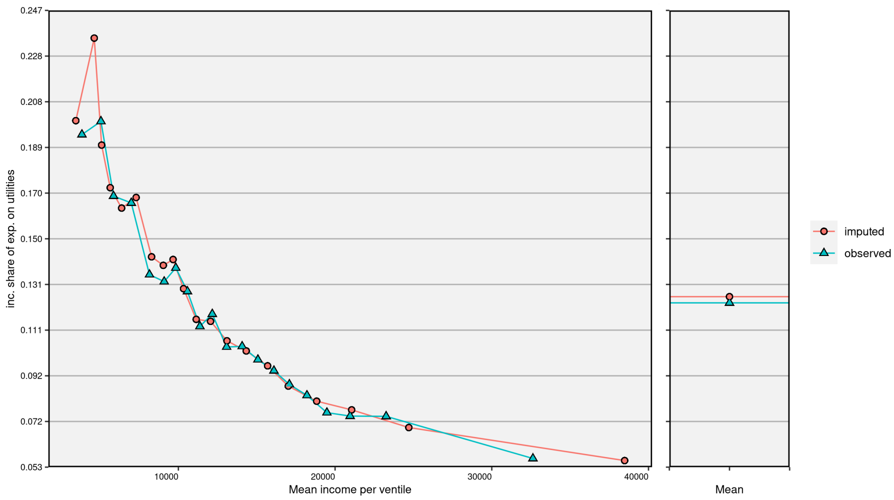
However, this imputation method also comes with some limitations. Firstly, fitted values are obtained by means of a regression model that takes the logarithm of income as input. This means this approach makes only sense for households with a sufficiently high and positive income. Expenditure behaviour of agents with negative or extremely small positive income, do not fit into this model.[28] Furthermore, it can only make reasonable predictions on expenditures on sufficiently aggregated, broad categories, so that only such aggregates enter into the distance function. Therefore, it does not guarantee that matched households will bear very similar characteristics. In fact, there might well be two households with different sets of characteristics both featuring a similar levels of expenditure on several broad categories. Therefore these two household might be matched, while we would not expect them to necessarily present similar expenditure behaviour, when it comes to allocating their budget on specific commodities within these broad category.

A.2 HBS imputation into SILC: additional validation checks based on uniquely-merged data

The microdata on household behaviour needed to calculate the four indicators of energy poverty discussed above are included both EU-SILC and HBS. EU-SILC data include detailed information on income sources as well as on household ability to pay bills and keep the house warm while HBS data include detailed information on household expenditures for energy products and services. For our analysis, we used the statistically matched dataset for 2015 that combines EU-SILC dataset with HBS dataset. Such combined dataset allows us to calculate all four different measures for the same set of households and assess jointly the relevance of these four measures and how they vary across the whole EU-SILC population. The performance of the statistical imputation process is assessed by evaluating how well the imputed expenditures reproduce the distribution of expenditure data across households' income quantiles (Figure 6). The figure shows the relationship between observed and imputed expenditures across mean income ventiles for the expense category utilities (inclusive of energy expenses, 045 COICOP, as well as other house-related services like water supply and sewage collection). The figure shows that the imputation process has been able to retrieve the same relationship between observed and imputed expenditures, i.e., the two curves mostly overlap. The figure also shows that the correspondence between observed and imputed expenses seem to be worst at the lowest extreme of the income distribution, indicating especially that income shares of expenditures for the first ventile may be overestimated.

[28] Indeed, the concept of an income share in terms of which our model is specified, makes not much sense in case of negative incomes, it is not defined in case of zero incomes, and may yield extreme values in case of incomes close to zero.

Figure 6: Utility household expenses by mean income across ventiles for observed and imputed expenditures in Czechia 2015 – dataset used as part of our EU-wide analysis



Notes: Based on statistically matched CZ data from 2015. Ventiles of equivalised household disposable income (horizontal axis), income shares of expenditures (vertical axis).

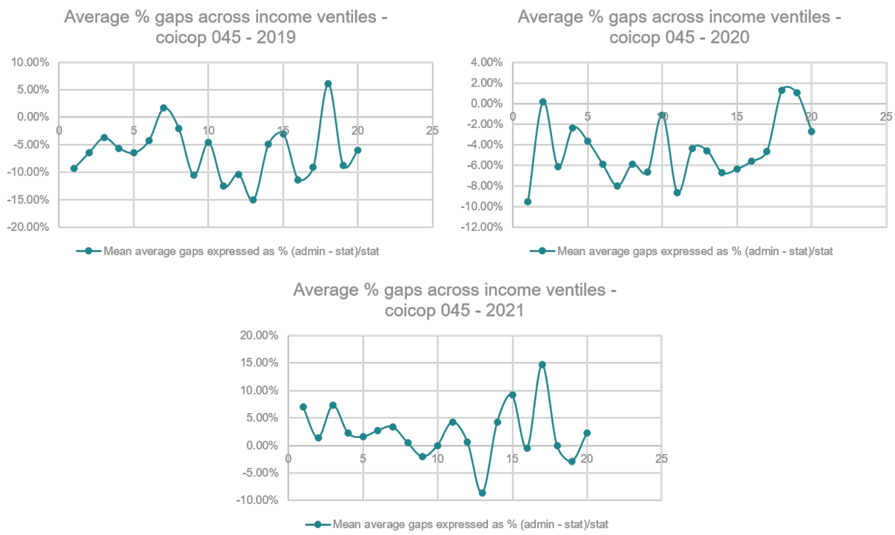
We further evaluate the relevance of distortions due to the statistical imputation procedure by performing a set of exploratory and comparative analysis using an administratively matched EU-SILC – HBS dataset for Czechia for the years 2019, 2020 and 2021. An administratively matched dataset is a joint dataset where EU-SILC household records can be matched directly with HBS household expenditure information as the sample of households interviewed is the same for both surveys and we can directly link information of the same household across the two datasets. In the following, we will first show some validation results based on comparison of administratively and statistically merged dataset. Further, we will show differences for our four EPOV indicators calculated using a statistically matched dataset for Czechia and using a directly matched dataset for Czechia. Note that SILC 2019 includes income that has been earned in 2018 while HBS expenses 2019 includes 2019 expenses, we take account of this chronological mismatch by uprating SILC incomes to 2019 using EUROMOD's uprating factors (average growth rates of wages, pensions, benefits, etc.) yearly updated. In Table 4 we show the number of exact household matched by the statistical matching procedure. By comparing the administratively merged with the statistically matched we are able to quantify how many times expenditure from a household in HBS are imputed to the same household in SILC, where the best performance would be a 100% match indicating that expenditures from recipient survey, HBS in this case, are correctly assigned to the same household in SILC. We also perform a similar check for aggregated energy expenses, coicop 045. Please note that for this analysis we used the subset of SILC data that merges with HBS data, i.e. HBS data are collected for a subsample of SILC data. In table 4 we show that the % of correctly matched household retrieved is quite high, ranging between 87% and 96%, and similarly the % of exact energy expenditures retrieved in our matched dataset is also quite high, ranging from 83% to 91%. This confirms that the distortion produced by the statistical matched procedure is relatively little and it does not prevent us from using the matched dataset for analysis based on expenditures data.

Table 4: Percentage of correctly matched households across three years

	Households - ID comparison			**Energy expenditures (c045)**		
	2019	**2020**	**2021**	**2019**	**2020**	**2021**
0 - not matching	234	77	194	304	152	248
1 - matching	1652	1692	1283	1583	1618	1229
Total sample (full HBS and SILC sub-sample)	1886	1769	1477	1887	1770	1477
% of matching	88%	96%	87%	84%	91%	83%

We further explored differences between administratively merged expenditures and statistically merged expenditures by examining the differences across income ventiles with the aim to understand whether specific distortions happen for specific ventiles.

Figure 7: Average (%) gaps across income ventiles in coicop 045 (energy)



Overall the biggest gap that we found is about 15% around ventile 13 in year 2019 but looking at across the distribution the average gap is between 3% and 7%, which indicates a fairly acceptable distortion in expenses. As can be seen by the figure for year 2019 and 2020 the poorest people seem to be characterised by rather under-estimated matched expenses but still within acceptable ranges.

Finally, we calculate the two expenditure-based indicators (M2 and 2M) across the two different datasets, i.e. statistically matched and administratively merged, to evaluate how the statistical matching distortion influences the indicator's calculation and the magnitude of differences between statistical and administrative datasets. We further checks whether the indicators M2 and 2M identify the same people as energy poor across the administratively merged vs statistically merged dataset.

Table 5: M2 and 2M headcounts in merged vs matched files

	M2			**2M**		
	2019	**2020**	**2021**	**2019**	**2020**	**2021**
0 - not matching	230	77	172	130	27	158
1 - matching	4045	3885	3140	4145	3935	3154
Total	4275	3962	3312	4275	3962	3312
% of matching energy poor households	95%	98%	95%	97%	99%	95%

In Table 5 we show that when comparing administrative merged vs statistically matched we classify as energy poor the same households across the two datasets in about 95% to 99% of the cases.

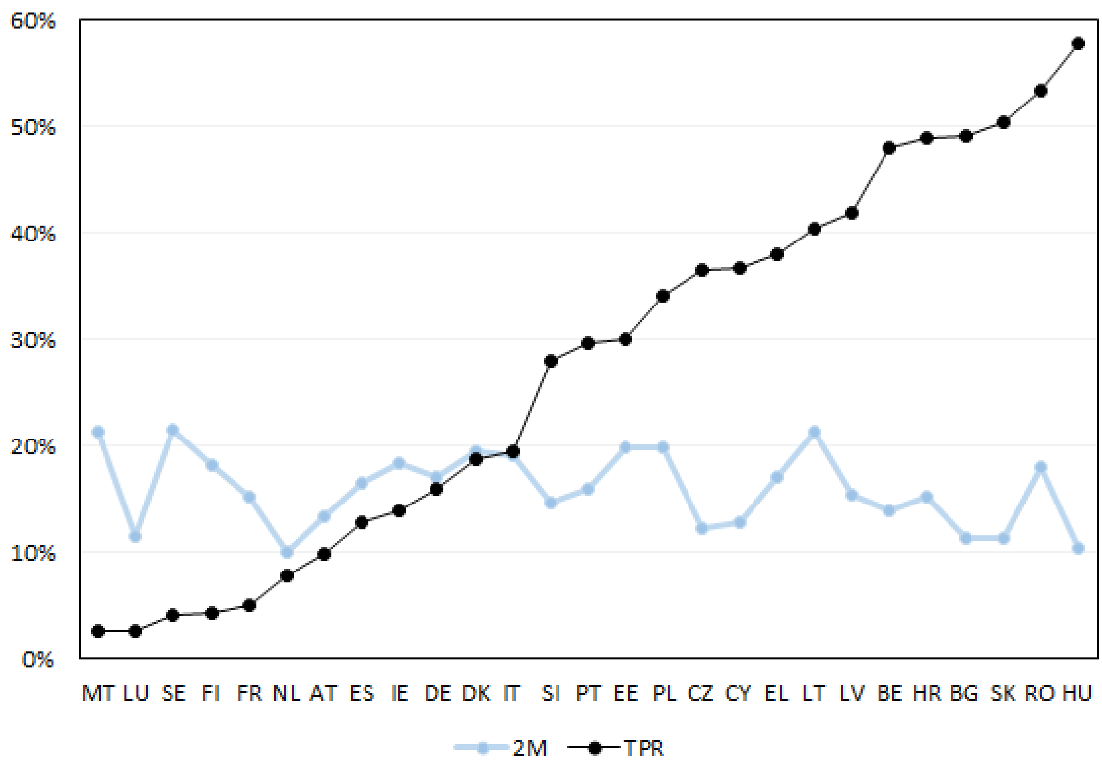
Table 6: Basic statistics: matched vs merged datasets for Czechia

	2019		**2020**		**2021**	
	Admin	**Stat**	**Admin**	**Stat**	**Admin**	**Stat**
Mean absolute HH total energy expenses	37,650.53	37,406.00	37,943.33	38,239.18	40,451.89	41,206.95
Mean absolute eq. individual energy expenses	23,346.56	23,200.24	23,624.30	23,851.17	25,168.79	25,638.08
Threshold M2 energy poverty line	9,359.77	9,378.34	9,060.21	9,162.63	9,533.10	9,836.42
Threshold 2M energy poverty line	14.11%	14.05%	12.82%	12.82%	12.90%	13.19%
% of people under M2 energy poverty line	20.11%	21.14%	18.87%	19.12%	19.79%	21.13%
% of people under 2M energy poverty line	17.99%	17.24%	18.26%	18.49%	18.00%	18.58%

B Supplementary tables and Figures

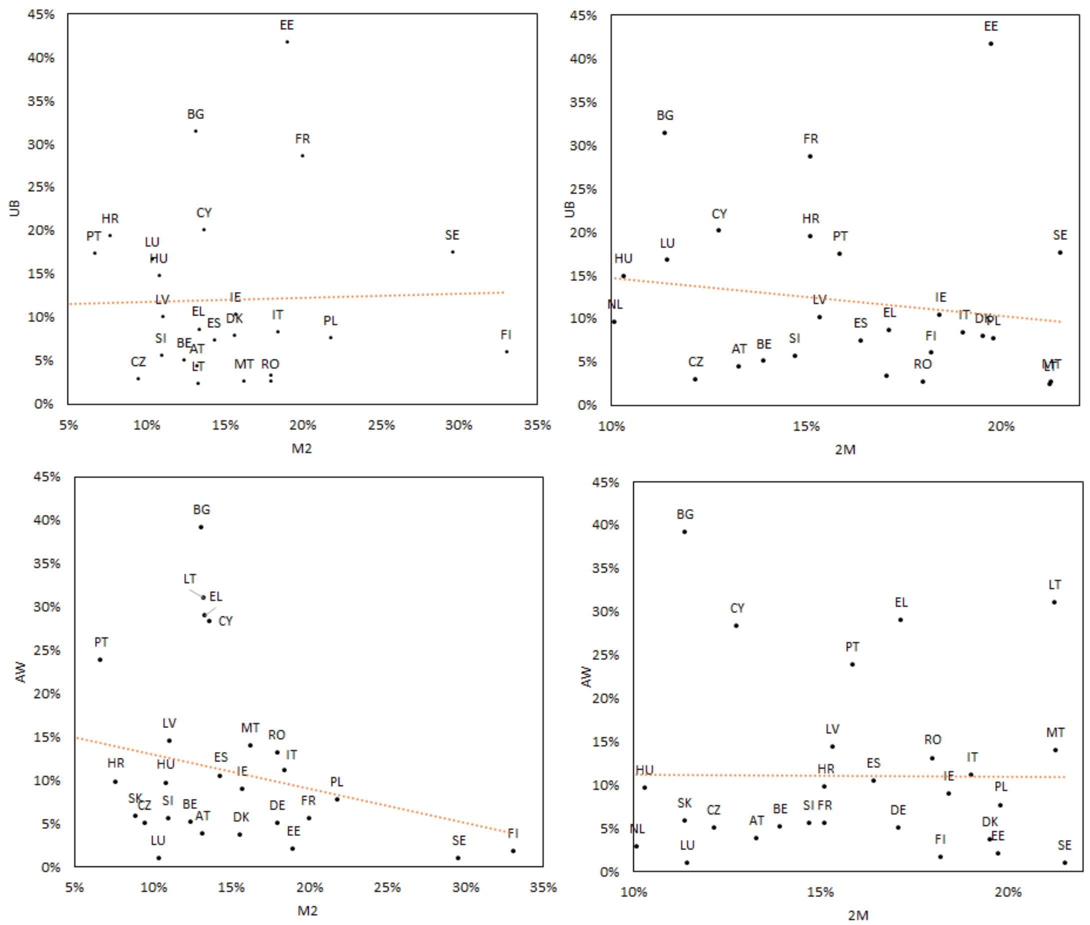
Figure 8 displays the country-level EPOV rates according to each of these indicators. What we can see from here is that shifting from TPR to 2M brings changes in the estimated EPOV incidence: on average, 27% would be energy poor according to TPR (simple cross-country average level), whereas with the 2M indicator this average incidence is 16%. Interestingly enough, 10.5% is actually the EU-level median of income shares of consumption expenditure in energy (in 2015). This suggests that the TPR could actually be interpreted as an EU-level 2M indicator. Moreover, we see that the gap is far from even across countries, and substantial changes in country-level rankings take place as well. The 2M is smaller than the TPR in the majority of EU countries but not in all. In fact, the 2M indicator leads to either larger or similar headcounts than the PTR for Western and Northern European countries (which implies that the median income shares of expenditures is lower than 5%). In contrast, in most Central Eastern European countries the opposite holds. Only in a couple of countries (Italy, Denmark and Germany) the EPOV rate would be almost identical with one or the other, which means that only these countries 10% is about twice the median of income shares in energy expenditure. In the rest, differences are of important magnitude, and particularly so and in particular in Hungary, Romania, Slovakia, Bulgaria and Croatia.

Figure 8: High income shares of energy expenditures: absolute vs relative (headcount ratios in %)



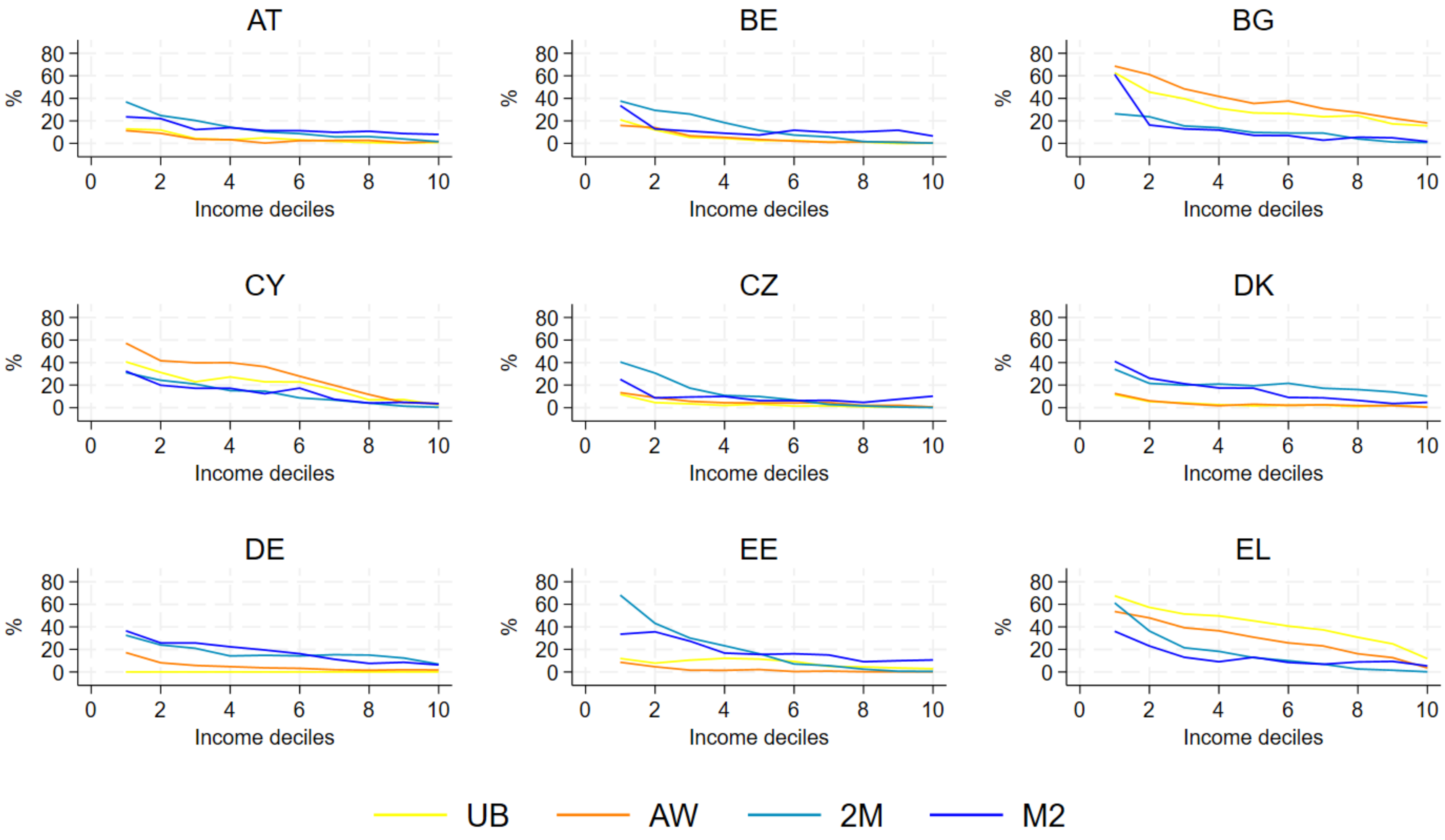
Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. TPR is the ten percent rule indicator, that defines as 'energy poor' those individuals living in a household whre the income share of expenditures on energy surpasses 10%. The 2M indicator defines this threshold as twice the national median (and therefore varies from country to country).

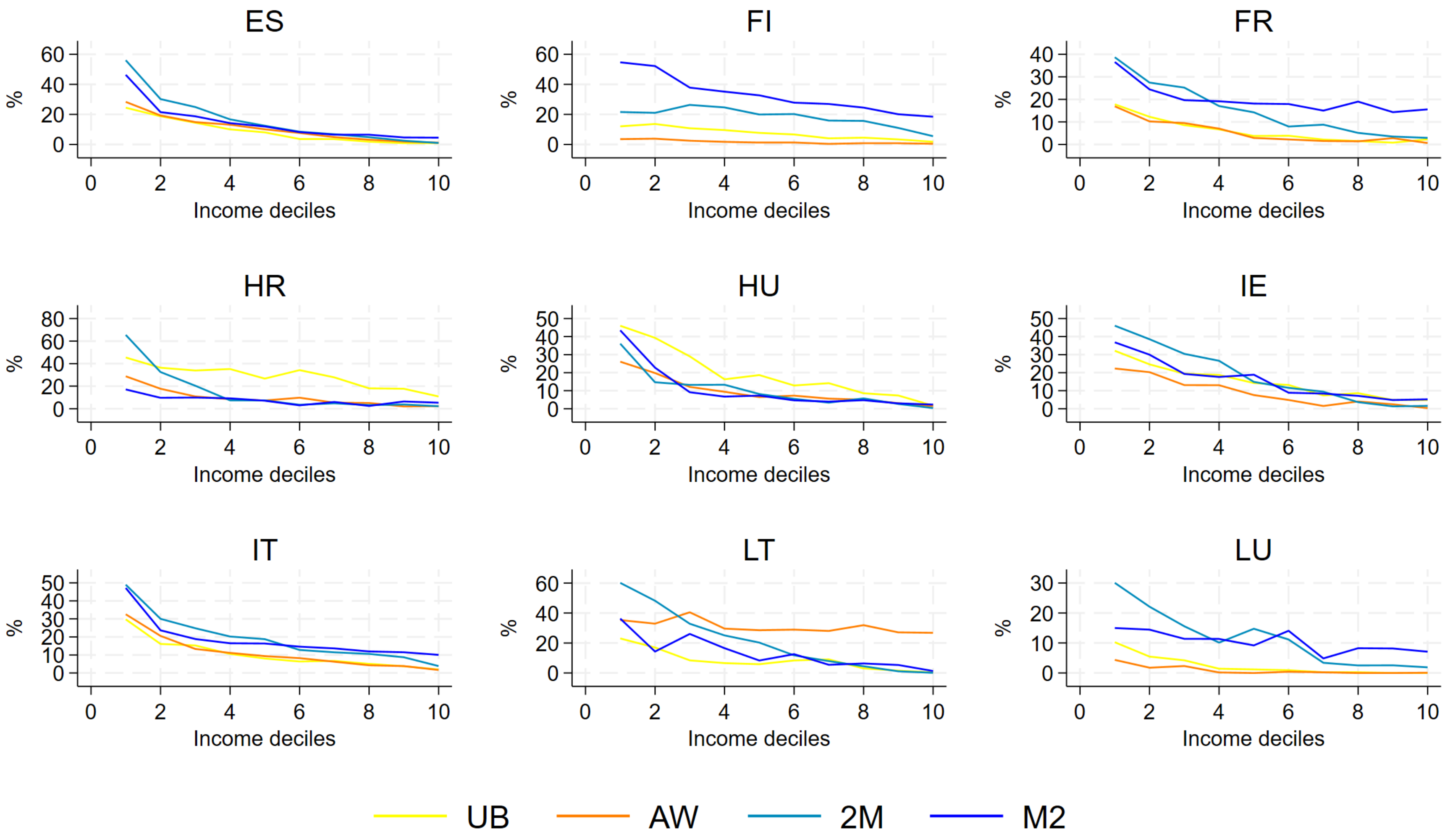
Figure 9: Cross-country correlation of energy poverty headcount rates across indicators

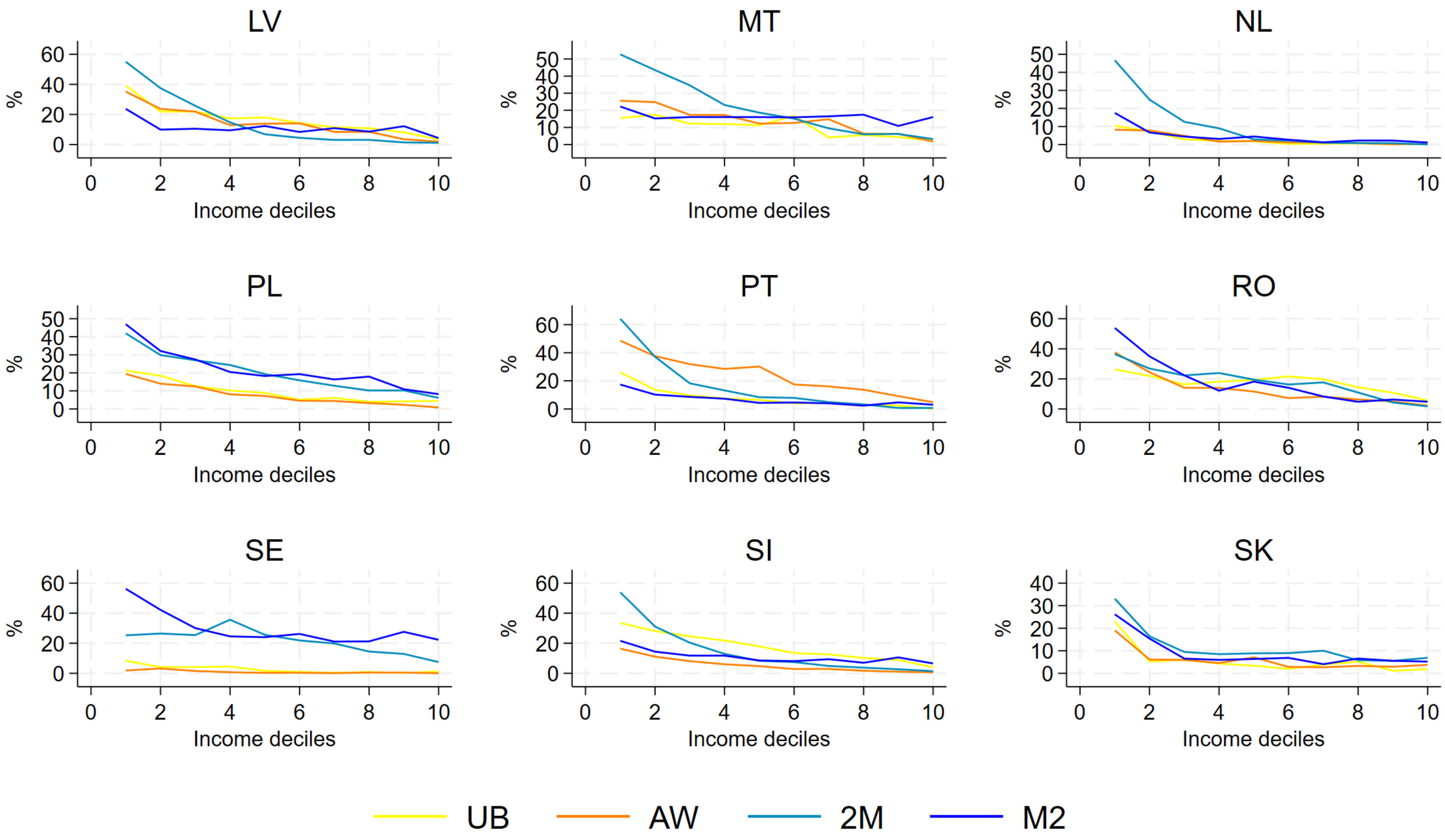


Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. There is no information on UB indicator for Germany. Dotted lines: fitted line from a linear model.

Figure 10: EPOV headcounts across country-specific income deciles



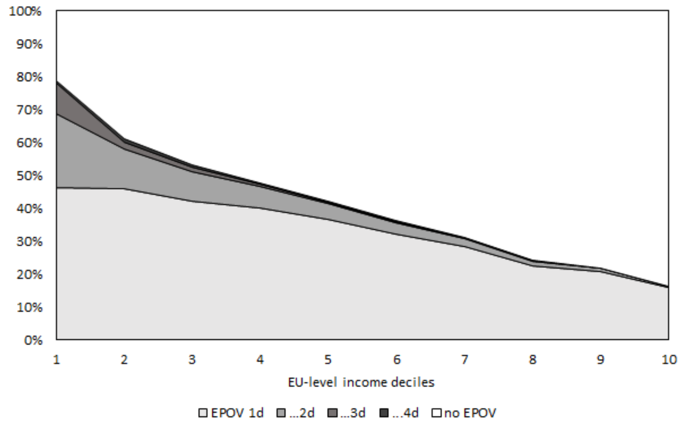

ES
FI
FR
HR
HU
IE
IT
LT
LU
%
Income deciles
UB
AW
2M
M2



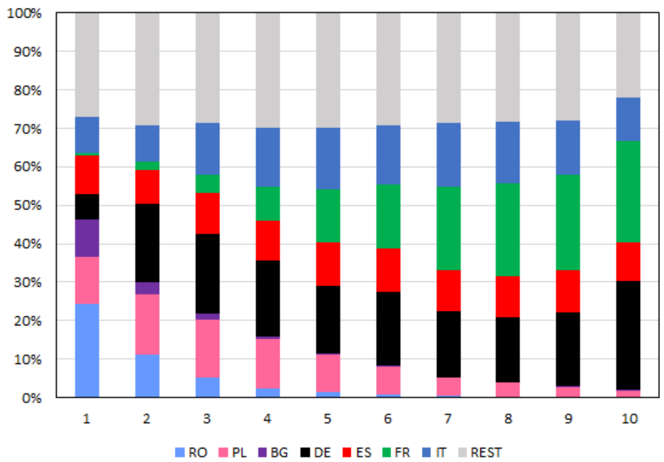
Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. Country-specific income deciles based on equivalised household disposable income. Standard modified OECD equivalence scales. See Table 1 for the definition of the EPOV indicators.

Figure 11: EU-level deciles: complementary results

(a) EPOV overlap, by EU-level income deciles



(b) Composition of EU-level deciles



Notes: estimations based on HBS-SILC matched data and EUROMOD for 2015. EU-level income deciles based on equivalised household disposable income, adjusted by purchasing power standards to account for differences in cost of living. Standard modified OECD equivalence scales. See Table 1 for the definition of the EPOV indicators.

Table 7: Change of sign among significant coefficients: pooled-EU vs country-specific models

		2M					M2				
		Single	2 Adults	Higher Education	Employed	Single headed Female	Single	2 Adults	Higher Education	Employed	Single headed Female
Pooled model	**EU**	+	+	-	-	+	-	-	+	+	-
Austria	**AT**	-									
Belgium	**BE**						+				
Bulgaria	**BG**										
Cyprus	**CY**	-					+	+			
Czechia	**CZ**						+				
Germany	**DE**	-					+				
Denmark	**DK**										
Estonia	**EE**			+	+						
Greece	**EL**				+			+			
Spain	**ES**										
Finland	**FI**										
France	**FR**										
Croatia	**HR**										
Hungary	**HU**										
Ireland	**IE**										
Italy	**IT**										
Lithuania	**LT**										
Luxembourg	**LU**						+				
Latvia	**LV**			+							
Malta	**MT**										
Netherlands	**NL**										
Poland	**PL**										
Portugal	**PT**										
Romania	**RO**										
Sweden	**SE**					-		+			
Slovenia	**SI**						+				
Slovakia	**SK**						+				
	#	3	0	2	2	1	7	3	0	0	0

Table 8: Basic descriptive statistics - pooled EU model

	UB	AW	2M	M2	Full sample
Income (equivalised - PPP) - mean	760.1051	761.4058	917.255	1056.793	1342.341
SD (σ)	575.8637	538.9052	626.5887	807.406	1156.907
Any disable person in the HH - mean (categorical var)	0.111631	0.127045	0.094257	0.081948	0.07457
SD (σ)	0.314914	0.333026	0.292188	0.274287	0.262696
Any non-EU citizen in the HH - mean (categorical var)	0.102668	0.083146	0.050067	0.065826	0.043275
SD (σ)	0.303527	0.276105	0.218084	0.24798	0.203476
Total number of adult HH member with higher education - mean	0.335901	0.295586	0.36127	0.558896	0.624367
SD (σ)	0.639833	0.609791	0.636136	0.789784	0.814038
Total number of employed HH member - mean	1.177168	0.935775	0.875433	1.360904	1.284319
SD (σ)	0.999238	0.980189	0.989136	1.074082	1.023048
One adult <65, no children - mean (categorical var)	0.064114	0.105293	0.12144	0.079976	0.082104
SD (σ)	0.244958	0.306934	0.32664	0.271258	0.274524
One adult 65, no children - mean (categorical var)	0.028759	0.076998	0.118103	0.036685	0.059121
SD (σ)	0.167131	0.266591	0.322732	0.187987	0.235851
One adult with children - mean (categorical var)	0.054227	0.044881	0.048424	0.039957	0.031233
SD (σ)	0.226467	0.207045	0.214661	0.195859	0.173946
Two adults <65, no children - mean (categorical var)	0.101896	0.111906	0.108749	0.112485	0.133716
SD (σ)	0.302514	0.315254	0.311326	0.315964	0.340347
Two adults, at least one 65, no children - mean (categorical var)	0.044755	0.08814	0.150063	0.061574	0.117312
SD (σ)	0.206766	0.2835	0.357135	0.240383	0.321792
Two adults with one or more children - mean (categorical var)	0.309169	0.22496	0.219221	0.325004	0.279428
SD (σ)	0.462155	0.417559	0.413721	0.468379	0.448719
Three or more adults, with children (categorical var)	0.180845	0.186059	0.12673	0.171287	0.175392
SD (σ)	0.384893	0.389158	0.332673	0.376762	0.380302
Three or more households without children (categorical var)	0.216234	0.161763	0.10727	0.173033	0.121694
SD (σ)	0.411679	0.368236	0.309458	0.378278	0.326933
Single female household (with or without kids) (categorical var)	0.082753	0.139777	0.184306	0.083819	0.100488
SD (σ)	0.275511	0.346758	0.387736	0.277118	0.30065

Table 9: Country-specific logistic models: AW indicator

	(1) AT	(2) BE	(3) BG	(4) CY	(5) CZ	(6) DK	(7) DE	(8) EE	(9) EL	(10) ES	(11) FI	(12) FR	(13) HR	(14) HU
Log income	-0.0498***	-0.0303***	-0.180***	-0.301***	-0.0533***	-0.0231***	-0.0388***	-0.0176***	-0.154***	-0.0490***	-0.0152**	-0.0544***	-0.0743***	-0.0509***
	(-3.80)	(-4.28)	(-10.71)	(-14.23)	(-6.27)	(-3.62)	(-8.34)	(-4.81)	(-13.91)	(-9.25)	(-2.85)	(-6.01)	(-8.78)	(-6.93)
Person w/disability	0.0198	0.00956	0.0766	0.117**	0.0198	0.00804	0.00828	-0.00304	0.00421	-0.0165	-0.00186	0.0237*	0.00133	0.00220
	(1.10)	(1.04)	(1.81)	(3.06)	(1.65)	(0.77)	(0.94)	(-0.48)	(0.13)	(-1.20)	(-0.30)	(2.25)	(0.05)	(0.18)
Non-EUc	0.0381***	0.00992	-0.0810	-0.0311	0.0296	0.0504***	0.0218*	0.0128**	0.0310	0.0599***	0.0164*	0.0236	-0.0126	0
	(3.64)	(0.86)	(-1.03)	(-1.13)	(0.92)	(4.27)	(2.18)	(2.80)	(1.26)	(3.90)	(2.42)	(1.95)	(-0.20)	(.)
Num Adults w/high-edu	-0.00342	-0.0186**	-0.0635***	-0.0582***	-0.0317***	-0.0137*	-0.0143***	-0.00425	-0.0517***	-0.0342***	-0.00265	-0.0177**	-0.00533	-0.0115
	(-0.56)	(-3.22)	(-4.14)	(-4.91)	(-3.44)	(-2.30)	(-3.76)	(-1.08)	(-6.25)	(-4.69)	(-0.80)	(-2.70)	(-0.43)	(-1.33)
Num employed	0.00665	-0.0165**	-0.0521***	0.0155	-0.00329	-0.0132	-0.0163***	-0.00632	-0.0132	-0.0191**	-0.000957	-0.0151**	-0.0127	-0.0264***
	(1.07)	(-2.64)	(-4.04)	(1.31)	(-0.52)	(-1.75)	(-3.86)	(-1.82)	(-1.44)	(-2.94)	(-0.26)	(-3.18)	(-1.87)	(-3.70)
Single fem	0.0197*	0.00702	0.00529	-0.0135	0.0133	-0.00420	0.0104*	0.00722	0.0240	0.00679	-0.00396	0.0128	0.00845	-0.0116
	(2.27)	(0.98)	(0.20)	(-0.40)	(1.89)	(-0.47)	(2.05)	(1.21)	(1.38)	(0.49)	(-0.93)	(1.96)	(0.62)	(-1.10)
Computer	-0.00660							-0.0135*	-0.0710***	-0.0401***	-0.0140**	-0.0160*	-0.0465***	-0.0576***
	(-0.79)							(-2.18)	(-5.09)	(-4.09)	(-2.70)	(-2.01)	(-4.14)	(-5.14)
Phone	-0.0146							-0.00381	-0.0904***	-0.0484***	0.0149**	0.00170	-0.0127	-0.0539***
	(-1.54)							(-0.67)	(-6.19)	(-4.85)	(2.61)	(0.25)	(-1.06)	(-5.01)
Car	-0.0467**							-0.0124	-0.0688	-0.0187	0	1.051***	-0.0514*	-0.0434**
	(-3.24)							(-1.54)	(-1.84)	(-0.77)	(.)	(13.53)	(-2.47)	(-2.88)
House owner	-0.00643						-0.0221***	0.00677	-0.0172	-0.0267**	-0.00284	-0.0206**	-0.0423**	-0.0257*
	(-0.69)						(-4.10)	(1.27)	(-1.23)	(-2.73)	(-0.59)	(-2.98)	(-2.93)	(-2.38)
House density	0.000835						0.00215	-0.000302	-0.0514***	-0.00692	0.000882	0.00906**	0.00740	0.00899
	(0.16)						(1.26)	(-0.12)	(-4.83)	(-1.12)	(0.50)	(2.97)	(1.00)	(1.31)
House bad quality	0.0392***	0.0365***	0.175***	0.128***	0.0613***	0.0364***	0.0515***	0.0166***						
	(4.75)	(5.11)	(6.92)	(7.50)	(6.95)	(5.05)	(9.62)	(3.79)						
Housetype														
semi-detached	-0.0137	0.0136	-0.0165	-0.00214	-0.00982	0.0221	-0.00295	0.00538						
	(-1.33)	(1.56)	(-0.61)	(-0.10)	(-1.02)	(1.95)	(-0.40)	(0.36)						
in building	0.00944	0.00320	-0.0333	-0.0291	0.00965	0.0269**	0.0132*	0.00411						
	(0.91)	(0.31)	(-1.27)	(-1.28)	(1.08)	(2.70)	(2.28)	(0.96)						
Urban		0.0225*	0.108***	0.0328	0.0146	-0.0249**			0.0487***	-0.0292**	-0.00429	-0.00509	-0.0232	-0.0503**
		(2.00)	(3.90)	(1.50)	(1.47)	(-2.58)			(3.39)	(-2.88)	(-0.94)	(-0.62)	(-1.74)	(-3.16)
Middle density		0.0103	0.0347	0.0234	-0.00599	-0.0125			0.0577***	-0.00172	-0.00422	0.0105	0.0334**	0.00643
		(1.00)	(1.48)	(1.00)	(-0.70)	(-1.45)			(3.77)	(-0.16)	(-0.94)	(1.35)	(3.03)	(0.59)
N	13897	14032	11944	11781	17609	13875	27419	14393	34058	32115	26368	26496	17079	18479

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Country-specific logistic models: AW indicator (cont)

	(1) IE	(2) IT	(3) LT	(4) LU	(5) LV	(6) MT	(7) NL	(8) PL	(9) PT	(10) RO	(11) SE	(12) SI	(13) SK
Log income	-0.0412***	-0.0421***	-0.00128	-0.0222**	-0.0968***	-0.0927***	-0.0126*	-0.0391***	-0.131***	-0.0614***	-0.000163	-0.0421***	-0.0490***
	(-3.52)	(-9.19)	(-0.07)	(-2.99)	(-8.14)	(-5.97)	(-2.14)	(-7.99)	(-11.80)	(-5.08)	(-0.07)	(-6.42)	(-4.36)
Person w/disability	0.0617***	0.0181*	0.0773	-0.0218*	0.0341	0.0592*	0.0256**	0.0288***	0.0226	0.00198	0.00737	0.0265***	-0.00644
	(4.22)	(2.28)	(1.49)	(-2.13)	(1.42)	(2.06)	(3.13)	(4.25)	(0.74)	(0.05)	(1.64)	(3.85)	(-0.45)
Non-EUc	0.0337	0.0441**	0.0433	0.00539	-0.00484	-0.0189	0.0130	-0.0438	-0.00886	0	0.0120*	0.0171	0
	(0.85)	(3.15)	(0.46)	(1.18)	(-0.38)	(-0.63)	(0.73)	(-0.67)	(-0.22)	(.)	(2.34)	(1.63)	(.)
Num Adults w/high-edu	-0.00480	-0.0207**	-0.0389**	0.000597	-0.0245**	-0.0418***	-0.0200**	-0.0181*	-0.0548***	-0.00866	-0.00468	-0.0131*	-0.0190*
	(-0.65)	(-2.65)	(-2.70)	(0.17)	(-2.92)	(-3.84)	(-2.72)	(-2.56)	(-4.14)	(-0.73)	(-1.65)	(-2.41)	(-2.56)
Num employed	-0.0372***	-0.0257***	-0.0177	-0.00386	-0.00221	-0.00105	-0.0157*	-0.00750	-0.00962	-0.0127	-0.00269	-0.0178***	-0.0134
	(-3.67)	(-4.96)	(-1.03)	(-1.87)	(-0.22)	(-0.09)	(-2.39)	(-1.58)	(-1.00)	(-1.65)	(-1.16)	(-4.28)	(-1.95)
Single fem	0.0151	0.00954	-0.0131	0.00252	0.0228	-0.0234	-0.00393	-0.00606	0.00140	-0.0107	-0.00149	0.00428	0.000421
	(1.23)	(1.04)	(-0.42)	(0.66)	(1.66)	(-1.13)	(-0.66)	(-0.64)	(0.08)	(-0.86)	(-0.53)	(0.38)	(0.03)
Computer	0.00336				-0.0516***	-0.0281	-0.00101	-0.0484***	-0.0941***	-0.0619***	0.000852	-0.00837	-0.0181
	(0.23)				(-3.75)	(-1.39)	(-0.13)	(-5.18)	(-5.98)	(-3.53)	(0.21)	(-1.11)	(-1.82)
Phone	-0.0522***				-0.0326*	-0.0367*	-0.0195*	-0.0138	-0.0541**	-0.0756***	-0.00281	-0.0183*	-0.00449
	(-3.57)				(-2.24)	(-2.16)	(-2.14)	(-1.63)	(-3.05)	(-4.42)	(-0.79)	(-2.28)	(-0.40)
Car	0.00430				0.0107	-0.113**		-0.00434	-0.0815**	-0.0436*	0	0.0162	-0.0553**
	(0.07)				(0.37)	(-2.90)		(-0.50)	(-2.71)	(-2.27)	(.)	(0.76)	(-2.98)
House owner	-0.0278	-0.0483***	0.0117	-0.0164*	-0.0250	-0.0497**	-0.0286***	-0.0242**	-0.0250	-0.00902	-0.00380	-0.0164*	-0.00906
	(-1.93)	(-7.00)	(0.31)	(-2.56)	(-1.93)	(-3.20)	(-3.91)	(-3.24)	(-1.84)	(-0.32)	(-0.91)	(-2.49)	(-0.77)
House density	-0.000803	-0.0180***	-0.0173	-0.00119	0.0160*	-0.0177	0.00448	-0.00356	-0.00683	-0.0388***	-0.00108	-0.00913*	-0.00472
	(-0.10)	(-4.02)	(-1.15)	(-0.94)	(2.04)	(-1.75)	(1.73)	(-0.70)	(-0.73)	(-3.41)	(-0.65)	(-2.02)	(-1.07)
Urban	0.00490												
	(0.37)												
Middle density	0.00442												
	(0.28)												
House bad quality		0.0834***	0.128***	0.00347	0.0662***	0.102***		0.0822***	0.0961***	0.115***	0.0113**	0.0456***	0.0448***
		(13.35)	(4.44)	(0.73)	(5.79)	(6.27)		(11.50)	(7.88)	(8.62)	(3.02)	(8.30)	(3.96)
Housetype													
semi-detached		-0.00871	0.142*	-0.0116	-0.0184	0.0131		-0.0116	-0.0263	0.0759	-0.00203	0.0193	0.00772
		(-0.91)	(1.98)	(-1.16)	(-0.84)	(0.40)		(-0.99)	(-1.72)	(1.74)	(-0.50)	(1.19)	(0.25)
in building		-0.00505	0.339***	-0.0179	0.0631***	0.00625		-0.0103	0.00547	0.0377*	0.00116	0.0135*	-0.00538
		(-0.68)	(16.90)	(-1.70)	(4.65)	(0.19)		(-1.37)	(0.37)	(2.32)	(0.25)	(2.14)	(-0.59)
N	13655	46179	10908	8354	13820	11220	23162	33403	21900	17330	14007	26051	16054

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Country-specific logistic models: UB indicator

	(1) AT	(2) BE	(3) BG	(4) CY	(5) CZ	(6) DK	(7) EE	(8) EL	(9) ES	(10) FI	(11) FR	(12) HR	(13) HU
Log income	-0.0573***	-0.0325***	-0.144***	-0.204***	-0.0430***	-0.0222***	-0.0478***	-0.192***	-0.0428***	-0.0761***	-0.0260**	-0.148***	-0.103***
	(-5.80)	(-4.12)	(-8.29)	(-10.44)	(-5.37)	(-3.84)	(-5.74)	(-15.62)	(-7.97)	(-6.61)	(-2.92)	(-8.71)	(-8.87)
Person w/disability	0.0252	-0.00375	0.0570	0.0433	0.00840	-0.00646	0.0150	0.108*	-0.0119	0.0355**	-0.00188	0.0995	0.0307
	(1.31)	(-0.38)	(1.77)	(1.33)	(0.98)	(-0.59)	(0.95)	(2.01)	(-0.86)	(2.88)	(-0.15)	(1.80)	(1.59)
Non-EUc	0.0232*	0.0160	-0.139	-0.0834**	0.00427	0.0312*	0.0408***	0.0253	0.0262	-0.0247	0.0435***	0.0959	0.0569
	(2.24)	(1.54)	(-1.56)	(-3.02)	(0.16)	(2.01)	(3.81)	(0.87)	(1.77)	(-1.19)	(3.55)	(1.18)	(0.33)
Num Adults w/high-edu	-0.00649	-0.0223***	-0.0620***	-0.0354**	-0.0269***	-0.00897	-0.0241**	-0.0486***	-0.0413***	-0.0207***	-0.0289***	-0.0605***	-0.0585***
	(-0.99)	(-4.22)	(-4.72)	(-3.11)	(-3.43)	(-1.48)	(-3.23)	(-5.61)	(-5.61)	(-3.53)	(-4.07)	(-3.89)	(-5.63)
Num employed	0.00167	-0.0219***	-0.0400**	-0.00365	0.00362	-0.0176*	0.0109	0.0155	-0.0106*	-0.000259	-0.0166**	0.0426***	-0.00570
	(0.29)	(-3.88)	(-3.20)	(-0.35)	(0.75)	(-2.44)	(1.40)	(1.33)	(-2.02)	(-0.04)	(-2.91)	(3.56)	(-0.62)
Single fem	-0.0170*	-0.0127	0.00314	-0.0416	-0.00485	-0.0167*	-0.0206	-0.00363	0.0114	-0.0139	-0.00688	-0.0782*	-0.0202
	(-2.23)	(-1.64)	(0.12)	(-1.21)	(-0.82)	(-2.13)	(-1.27)	(-0.16)	(0.63)	(-1.34)	(-1.02)	(-2.45)	(-1.14)
Computer	-0.0352***						-0.0116	-0.0101	-0.0417***	-0.0144	-0.0186	-0.0742***	-0.102***
	(-3.76)						(-1.04)	(-0.59)	(-4.15)	(-1.36)	(-1.68)	(-3.36)	(-7.37)
Phone	-0.00953						0.0278	-0.0204	-0.0248**	0.0403*	-0.0209*	-0.000681	-0.0321*
	(-1.01)						(1.47)	(-1.12)	(-2.59)	(2.41)	(-2.31)	(-0.03)	(-2.07)
Car	0.0198						-0.0328	-0.0725	0.0187	0.0159	-0.0214	-0.0503	-0.0866***
	(0.69)						(-0.86)	(-1.56)	(0.60)	(0.22)	(-0.47)	(-0.72)	(-3.39)
House owner	-0.00454						0.0184	-0.0493**	-0.0222*	-0.00533	-0.0387***	-0.0485	-0.000171
	(-0.41)						(1.50)	(-3.05)	(-2.22)	(-0.54)	(-4.68)	(-1.67)	(-0.01)
House density	-0.00342						0.0145	-0.0478***	-0.0209**	-0.00172	0.00199	-0.0162	-0.0127
	(-0.64)						(1.67)	(-3.71)	(-2.78)	(-0.35)	(0.45)	(-0.95)	(-0.96)
House bad quality	0.0409***	0.0259***	0.174***	0.0459**	0.0330***	0.00432	0.0475***						
	(5.23)	(3.37)	(7.54)	(2.62)	(4.46)	(0.45)	(3.95)						
Housetype													
semi-detached	-0.0102	0.0176*	-0.0210	-0.0251	-0.00248	0.0130	-0.00917						
	(-0.94)	(2.19)	(-0.77)	(-1.25)	(-0.35)	(1.33)	(-0.55)						
in building	-0.00300	0.0487***	-0.0370	0.0200	0.0150*	0.0143	0.0529***						
	(-0.27)	(3.62)	(-1.40)	(0.90)	(2.25)	(1.53)	(5.19)						
Urban		-0.00733	0.159***	0.000191	0.0118	-0.0105		-0.0163	0.0228*	-0.0273**	-0.00398	-0.0629**	0.00456
		(-0.53)	(5.96)	(0.01)	(1.40)	(-1.18)		(-0.96)	(2.18)	(-2.91)	(-0.48)	(-2.58)	(0.24)
Middle density		0.00619	0.0254	-0.00882	0.00428	-0.0110		0.0172	0.0240	-0.00526	-0.00329	-0.0567**	0.0267
		(0.51)	(1.06)	(-0.39)	(0.62)	(-1.12)		(1.00)	(1.93)	(-0.63)	(-0.35)	(-2.69)	(1.70)
N	13901	14037	11944	11781	17609	13875	14393	34058	32116	26428	26541	17079	18600

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Country-specific logistic models: UB indicator (cont)

	(1) IE	(2) IT	(3) LT	(4) LU	(5) LV	(6) MT	(7) NL	(8) PL	(9) PT	(10) RO	(11) SE	(12) SI	(13) SK
Log income	-0.102***	-0.0412***	-0.0568***	-0.0553***	-0.106***	-0.0759***	-0.0250***	-0.0418***	-0.0738***	-0.0381*	-0.0213***	-0.152***	-0.0594***
	(-5.02)	(-8.82)	(-4.79)	(-4.54)	(-8.70)	(-4.26)	(-3.95)	(-6.84)	(-9.54)	(-2.54)	(-4.91)	(-11.72)	(-4.81)
Person w/disability	0.0663*	0.0194	-0.0294	0.0113	0.0689**	0.0463	0.00806	0.00958	-0.00540	0.0627	0.0282**	0.00200	0.0239
	(2.22)	(1.92)	(-1.27)	(1.10)	(3.20)	(1.81)	(0.86)	(1.13)	(-0.33)	(1.12)	(3.08)	(0.13)	(1.29)
Non-EUc	0.00856	0.0686***	0.0216	0.00786	-0.00667	0.000518	0.0356*	0.0125	0.0572***	0	0.00535	-0.0160	0
	(0.16)	(5.38)	(0.37)	(1.01)	(-0.48)	(0.02)	(2.57)	(0.15)	(3.35)	(.)	(0.62)	(-0.75)	(.)
Num Adults w/high-edu	-0.0117	-0.0172**	0.00694	-0.00692	-0.00948	-0.0199	-0.0114*	-0.0209**	-0.0172*	-0.0135	-0.00164	-0.0353***	-0.00923
	(-1.27)	(-2.82)	(0.41)	(-1.15)	(-1.01)	(-1.36)	(-2.08)	(-3.12)	(-2.11)	(-1.06)	(-0.45)	(-4.81)	(-1.24)
Num employed	0.00792	-0.00584	-0.0267*	-0.00749	-0.0108	0.0186	-0.00530	0.00231	-0.000767	-0.0369***	-0.00683	-0.00110	0.00106
	(0.46)	(-1.16)	(-2.19)	(-1.43)	(-1.14)	(1.84)	(-0.92)	(0.57)	(-0.12)	(-4.20)	(-1.66)	(-0.16)	(0.10)
Single fem	0.0155	0.0236*	-0.0365*	0.00313	-0.0121	-0.00288	-0.0105	-0.0536***	-0.0313**	0.0155	-0.00502	-0.00655	0.00260
	(0.82)	(2.17)	(-2.10)	(0.44)	(-0.75)	(-0.14)	(-1.20)	(-3.98)	(-2.65)	(0.88)	(-0.82)	(-0.26)	(0.18)
Computer	-0.00579				-0.0654***	-0.0185	-0.0107	-0.0545***	-0.0367***	-0.0826***	-0.00191	-0.0383*	-0.0232*
	(-0.26)				(-4.57)	(-0.89)	(-1.30)	(-5.33)	(-3.47)	(-3.88)	(-0.26)	(-2.04)	(-2.34)
Phone	-0.0455				-0.00701	0.0261	-0.00646	-0.0182	-0.0209	0.0128	-0.00742	0.00937	-0.00993
	(-1.71)				(-0.41)	(1.37)	(-0.49)	(-1.59)	(-1.84)	(0.61)	(-0.67)	(0.57)	(-0.98)
Car	-0.0952*				-0.104*	-0.0580		-0.00739	-0.0160	-0.0250	0	-0.0688	-0.0319
	(-2.11)				(-2.53)	(-1.47)		(-0.69)	(-0.76)	(-0.95)	(.)	(-1.38)	(-1.27)
House owner	-0.0423*	-0.0461***	-0.0118	-0.0211*	0.0103	-0.0338*	-0.0185*	-0.0320***	-0.00915	-0.0485	-0.0124	-0.00505	-0.0111
	(-2.27)	(-6.38)	(-0.66)	(-2.30)	(0.73)	(-2.20)	(-2.21)	(-3.50)	(-1.03)	(-1.46)	(-1.69)	(-0.41)	(-0.92)
House density	-0.0117	-0.0301***	-0.0348*	0.00161	-0.0271*	-0.0489***	-0.000634	0.00209	-0.0142	-0.0300	-0.00473	-0.00233	-0.0145**
	(-0.86)	(-5.03)	(-2.19)	(0.43)	(-2.45)	(-4.06)	(-0.21)	(0.29)	(-1.79)	(-1.89)	(-1.22)	(-0.23)	(-2.69)
Urban	0.0347												
	(1.83)												
Middle density	-0.0157												
	(-0.74)												
House bad quality		0.0671***	0.0517***	0.0132	0.0533***	0.0536***		0.0965***	0.0376***	0.129***	0.0175*	0.0943***	0.0499***
		(9.94)	(3.99)	(1.86)	(4.06)	(3.41)		(10.59)	(4.79)	(6.16)	(2.47)	(10.13)	(4.74)
Housetype													
semi-detached		-0.0108	-0.0285	-0.00874	0.0550	0.0475*		0.00669	-0.00306	-0.000357	-0.0157	0.0498*	0.0224
		(-1.11)	(-1.04)	(-0.84)	(1.36)	(2.28)		(0.44)	(-0.33)	(-0.01)	(-1.57)	(1.97)	(0.75)
in building		0.0106	0.0207	-0.00651	0.0956***	0.0625**		0.0194*	0.0321**	0.143***	-0.0105	0.0412***	0.00807
		(1.29)	(0.85)	(-0.56)	(6.59)	(3.14)		(2.00)	(3.29)	(6.46)	(-1.33)	(3.61)	(0.87)
N	13678	46179	10908	8051	13820	11222	23181	33407	21900	17330	14038	26051	16054

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Country-specific logistic models: 2M indicator

	(1) AT	(2) BE	(3) BG	(4) CY	(5) CZ	(6) DK	(7) DE	(8) EE	(9) EL	(10) ES	(11) FI	(12) FR	(13) HR	(14) HU
Log income	-0.254***	-0.151***	-0.119***	-0.201***	-0.197***	-0.160***	-0.134***	-0.258***	-0.247***	-0.196***	-0.134***	-0.219***	-0.223***	-0.129***
	(-15.41)	(-8.35)	(-11.50)	(-11.01)	(-12.42)	(-7.17)	(-16.30)	(-26.86)	(-28.16)	(-25.22)	(-8.94)	(-13.55)	(-14.62)	(-12.73)
Person w/disability	-0.0486	-0.0300	0.00452	0.0250	-0.0370*	-0.0285	0.0126	-0.0340	-0.0110	-0.00719	0.0519**	0.0263	-0.0499	0.00355
	(-1.31)	(-1.68)	(0.20)	(0.86)	(-1.96)	(-1.14)	(0.75)	(-1.81)	(-0.34)	(-0.46)	(2.88)	(1.35)	(-1.48)	(0.27)
Non-EUc	-0.0843***	0.00830	0.0168	-0.00806	0.0194	-0.00909	0.00192	-0.00254	0.0176	-0.0477*	0.0118	-0.0367	-0.281**	-0.0663
	(-3.50)	(0.38)	(0.34)	(-0.36)	(0.40)	(-0.17)	(0.09)	(-0.18)	(1.03)	(-2.51)	(0.37)	(-1.46)	(-2.80)	(-0.80)
Num Adults w/high-edu	-0.0144	-0.00426	-0.0214*	0.0164	-0.0205*	0.0121	-0.0341***	0.0194*	-0.0144*	-0.0155*	-0.0203**	0.000293	-0.00842	-0.0194*
	(-1.58)	(-0.57)	(-2.40)	(1.62)	(-2.08)	(1.21)	(-5.90)	(2.32)	(-2.15)	(-2.16)	(-3.01)	(0.04)	(-0.69)	(-2.15)
Num employed	-0.0231*	-0.0694***	0.00467	-0.0352***	-0.0517***	-0.0283	-0.0442***	0.0308***	0.0213**	-0.0215**	0.0193*	-0.00772	-0.0242	-0.00590
	(-2.30)	(-6.80)	(0.56)	(-3.67)	(-5.33)	(-1.94)	(-5.66)	(3.45)	(2.63)	(-3.16)	(2.09)	(-0.95)	(-1.95)	(-0.79)
Single fem	0.0170	0.0238*	0.0202	0.0184	0.0360***	-0.000759	0.0355***	0.00390	0.0112	0.0429**	-0.0286	0.0406***	0.0340*	0.0265*
	(1.42)	(2.30)	(1.51)	(0.67)	(4.11)	(-0.05)	(3.79)	(0.21)	(0.94)	(2.71)	(-1.84)	(3.87)	(2.36)	(2.47)
Computer	-0.00898							-0.0248	-0.0127	0.000187	0.0245	-0.0199	-0.00965	-0.0251*
	(-0.69)							(-1.67)	(-1.10)	(0.02)	(1.75)	(-1.57)	(-0.82)	(-2.44)
Phone	-0.0150							0.0268	-0.00412	0.00348	-0.0184	-0.00647	-0.00878	-0.0179
	(-1.13)							(1.89)	(-0.34)	(0.35)	(-1.32)	(-0.60)	(-0.70)	(-1.76)
Car	-0.0109							0.0239	-0.00435	0.0560	0.147	0.149	0.0134	0.00490
	(-0.27)							(0.81)	(-0.16)	(1.63)	(1.25)	(1.74)	(0.57)	(0.30)
House owner	-0.00367						0.0123	-0.0161	0.0403***	0.00843	0.0382**	0.0178	-0.00910	-0.00404
	(-0.30)						(1.43)	(-1.17)	(3.50)	(0.82)	(2.84)	(1.67)	(-0.53)	(-0.36)
House density	0.00534						-0.0156***	0.000139	0.00212	0.00629	0.0136*	0.00195	0.0124	0.00104
	(0.91)						(-5.10)	(0.02)	(0.31)	(0.96)	(2.39)	(0.42)	(1.77)	(0.19)
House bad quality	0.0161	0.00909	-0.00209	-0.0197	0.00642	-0.0221	-0.0149	-0.00282						
	(1.09)	(0.78)	(-0.13)	(-1.38)	(0.42)	(-1.19)	(-1.43)	(-0.16)						
Housetype														
semi-detached	-0.0251	0.00651	0.00312	0.0205	0.00970	0.00259	-0.00167	-0.00433						
	(-1.65)	(0.58)	(0.17)	(1.22)	(0.67)	(0.14)	(-0.14)	(-0.15)						
in building	-0.0116	0.00264	0.000414	-0.0117	0.0148	0.00503	-0.00595	-0.0295*						
	(-0.82)	(0.20)	(0.03)	(-0.71)	(1.45)	(0.31)	(-0.67)	(-2.18)						
Urban		-0.0235	0.00182	-0.0284	-0.00455	0.0111			-0.00846	0.00205	-0.0157	-0.00750	0.0570**	-0.000211
		(-1.51)	(0.11)	(-1.72)	(-0.39)	(0.71)			(-0.78)	(0.22)	(-1.39)	(-0.70)	(3.07)	(-0.02)
Middle density		-0.0125	0.0151	-0.0103	-0.00334	0.0196			-0.00380	0.00926	-0.0139	-0.000374	0.00763	-0.00806
		(-0.96)	(1.05)	(-0.57)	(-0.34)	(1.20)			(-0.33)	(0.81)	(-1.29)	(-0.03)	(0.61)	(-0.77)
N	13901	14037	11944	11781	17609	13875	27436	14393	34058	32116	26428	26541	17079	18600

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Country-specific logistic models: 2M indicator (cont)

	(1) IE	(2) IT	(3) LT	(4) LU	(5) LV	(6) MT	(7) NL	(8) PL	(9) PT	(10) RO	(11) SE	(12) SI	(13) SK
Log income	-0.213***	-0.145***	-0.198***	-0.245***	-0.234***	-0.321***	-0.233***	-0.166***	-0.273***	-0.130***	-0.164***	-0.224***	-0.216***
	(-8.02)	(-20.16)	(-8.80)	(-10.05)	(-21.28)	(-13.84)	(-9.26)	(-16.66)	(-31.72)	(-9.09)	(-9.78)	(-18.78)	(-14.22)
Person w/disability	0.0205	-0.00106	-0.0289	-0.0354	-0.00964	0.00120	-0.0133	0.0141	0.00777	-0.00958	-0.0279	-0.00198	-0.0486*
	(0.95)	(-0.10)	(-1.11)	(-1.40)	(-0.58)	(0.03)	(-0.89)	(1.23)	(0.36)	(-0.15)	(-0.73)	(-0.19)	(-2.26)
Non-EUc	0.00702	0.0322	-0.0945	-0.0451	-0.00607	0.0442	-0.0198	0.0300	-0.0292	0	-0.118**	0.00619	0
	(0.12)	(1.65)	(-1.31)	(-1.89)	(-0.60)	(1.52)	(-0.77)	(0.27)	(-0.80)	(.)	(-3.19)	(0.34)	(.)
Num Adults w/high-edu	0.00288	-0.0106	-0.0282*	-0.0150	0.0300***	0.0157	-0.00553	-0.00170	-0.000513	-0.0342**	-0.0274***	-0.00586	-0.0155
	(0.29)	(-1.35)	(-2.56)	(-1.28)	(4.40)	(1.14)	(-0.72)	(-0.20)	(-0.05)	(-2.58)	(-3.43)	(-0.93)	(-1.86)
Num employed	-0.0111	-0.0168*	-0.0458***	-0.0195	-0.0150	0.0160	-0.0273**	-0.0113	-0.0118	-0.0149	-0.00922	-0.0277***	-0.0143*
	(-0.74)	(-2.38)	(-3.30)	(-1.93)	(-1.76)	(1.23)	(-2.74)	(-1.80)	(-1.45)	(-1.54)	(-0.82)	(-4.45)	(-2.02)
Single fem	0.0440**	0.0222*	0.0693**	-0.00841	0.0306*	-0.0253	0.00662	0.0312	0.0473**	0.0154	-0.0460*	-0.0188	0.0506***
	(2.76)	(2.14)	(3.15)	(-0.55)	(2.53)	(-1.08)	(0.63)	(1.85)	(2.79)	(0.98)	(-2.16)	(-1.38)	(3.70)
Computer	0.0164				-0.00504	-0.0149	0.00716	-0.00161	0.0251*	-0.0238	0.0396	0.00638	0.0156
	(0.88)				(-0.46)	(-0.70)	(0.64)	(-0.12)	(2.26)	(-1.21)	(1.93)	(0.56)	(1.31)
Phone	-0.0182				-0.000706	0.00671	-0.0150	-0.0232	0.00698	0.0409*	-0.0325	0.00537	-0.0298*
	(-1.05)				(-0.06)	(0.33)	(-1.25)	(-1.71)	(0.53)	(2.02)	(-1.43)	(0.55)	(-2.19)
Car	-0.0939				0.0231	-0.0420		-0.00949	-0.0135	-0.00763	-0.0674	-0.0218	0.0203
	(-1.81)				(0.84)	(-1.11)		(-0.66)	(-0.51)	(-0.33)	(-0.40)	(-0.60)	(0.66)
House owner	-0.0188	-0.0113	0.0322	-0.0311*	0.0228*	0.0427*	-0.00121	0.00959	0.00150	0.0237	-0.00191	0.0223*	0.0223
	(-0.96)	(-1.32)	(1.13)	(-2.01)	(2.10)	(2.46)	(-0.12)	(0.74)	(0.15)	(0.58)	(-0.11)	(2.31)	(1.47)
House density	-0.0120	-0.000825	-0.00889	0.00302	-0.00355	0.00472	0.000226	0.00976	0.00655	0.00850	0.0144	0.0000516	-0.00716
	(-1.28)	(-0.18)	(-0.92)	(0.46)	(-0.59)	(0.46)	(0.05)	(1.21)	(1.08)	(0.73)	(1.65)	(0.01)	(-1.53)
Urban	-0.0546***												
	(-3.50)												
Middle density	-0.0138												
	(-0.71)												
House bad quality		0.0165	0.0141	-0.00324	-0.00603	0.0205		-0.0125	-0.0172	0.0514*	0.0333	0.00382	-0.0379
		(1.86)	(0.77)	(-0.18)	(-0.62)	(0.94)		(-0.80)	(-1.81)	(2.33)	(1.51)	(0.49)	(-1.73)
Housetype													
semi-detached		0.0117	-0.0353	0.0259	0.0140	-0.00223		0.0130	-0.00568	-0.0419	-0.00403	0.00451	0.00904
		(1.08)	(-1.13)	(1.53)	(0.70)	(-0.06)		(0.59)	(-0.53)	(-0.83)	(-0.18)	(0.24)	(0.16)
in building		0.0134	0.0248	-0.0115	0.0326**	0.0107		0.00114	-0.00784	0.0276	-0.0276	-0.0203*	0.000840
		(1.53)	(1.44)	(-0.68)	(2.84)	(0.28)		(0.09)	(-0.72)	(1.45)	(-1.66)	(-2.50)	(0.08)
N	13678	46179	10908	8354	13820	11222	23181	33407	21900	17330	14055	26051	16054

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Country-specific logistic models: M2 indicator

	(1) AT	(2) BE	(3) BG	(4) CY	(5) CZ	(6) DK	(7) DE	(8) EE	(9) EL	(10) ES	(11) FI	(12) FR	(13) HR	(14) HU
Log income	-0.103***	-0.143***	-0.188***	-0.167***	-0.0916***	-0.141***	-0.135***	-0.0540***	-0.0978***	-0.111***	-0.214***	-0.109***	-0.0452***	-0.152***
	(-5.09)	(-10.47)	(-17.68)	(-8.29)	(-6.40)	(-8.84)	(-14.27)	(-4.62)	(-14.15)	(-15.77)	(-10.62)	(-7.99)	(-4.83)	(-13.61)
Person w/disability	0.0129	0.00480	-0.0176	0.0208	0.0342	-0.0578	-0.0269	0.0526**	-0.00223	-0.00170	-0.133***	-0.0369	0.0811**	-0.0263
	(0.30)	(0.25)	(-0.88)	(0.73)	(1.40)	(-1.89)	(-1.05)	(2.62)	(-0.09)	(-0.10)	(-4.58)	(-1.36)	(3.19)	(-1.59)
Non-EUc	0.0495*	0.000296	-0.0378	0.0416	-0.0351	0.0562*	-0.0231	0.00746	-0.0269	0.0445*	0.0224	0.0327	0.00763	0.205***
	(2.29)	(0.02)	(-0.43)	(1.86)	(-0.75)	(2.06)	(-1.07)	(0.45)	(-1.46)	(2.47)	(0.59)	(1.22)	(0.21)	(3.62)
Num Adults w/high-edu	0.00366	0.0183**	0.0208*	-0.0161	0.0255**	-0.00913	0.0244***	-0.0177	0.00988	-0.00480	-0.00452	-0.00213	-0.0105	0.0198**
	(0.40)	(2.69)	(2.25)	(-1.66)	(2.74)	(-1.10)	(4.20)	(-1.94)	(1.75)	(-0.72)	(-0.51)	(-0.24)	(-1.14)	(2.71)
Num employed	0.0163	0.0289***	0.00872	0.0378***	0.00438	-0.0169	0.0329***	-0.0307**	-0.0194**	0.00968	-0.0388***	0.0105	-0.00951	-0.000178
	(1.83)	(3.40)	(1.14)	(3.76)	(0.57)	(-1.40)	(4.76)	(-2.73)	(-2.99)	(1.53)	(-3.39)	(0.95)	(-1.23)	(-0.02)
Single fem	-0.00250	-0.00264	-0.0442	-0.0148	-0.0362***	-0.0377	-0.0483***	0.0192	0.0212	-0.0219	0.0639***	-0.00348	-0.0205	-0.0137
	(-0.16)	(-0.17)	(-1.88)	(-0.70)	(-3.34)	(-1.46)	(-4.07)	(0.88)	(1.27)	(-1.10)	(3.44)	(-0.22)	(-1.23)	(-0.92)
Computer	0.000306							-0.0148	0.0109	0.0103	-0.00951	-0.0146	0.0189	-0.0112
	(0.02)							(-0.97)	(0.97)	(0.75)	(-0.54)	(-0.81)	(1.43)	(-1.03)
Phone	0.00387							-0.0154	-0.00548	-0.00628	0.00398	-0.00722	0.00737	0.0164
	(0.24)							(-0.95)	(-0.49)	(-0.50)	(0.19)	(-0.42)	(0.44)	(1.27)
Car	0.0138							-0.0174	-0.0447	-0.0481	0.0402	-0.183**	-0.00866	-0.0129
	(0.25)							(-0.44)	(-1.16)	(-1.30)	(0.28)	(-2.70)	(-0.21)	(-0.62)
House owner	0.0135						-0.0172	-0.00131	-0.0345**	-0.0131	-0.0617***	-0.00786	-0.0262	0.00914
	(0.82)						(-1.62)	(-0.08)	(-3.13)	(-1.19)	(-4.11)	(-0.59)	(-1.58)	(0.70)
House density	-0.00774						0.0151***	-0.00193	-0.0164	-0.0122	-0.0152*	-0.00462	-0.0156	-0.0321**
	(-0.95)						(4.66)	(-0.21)	(-1.82)	(-1.51)	(-2.03)	(-0.61)	(-1.66)	(-2.84)
House bad quality	0.000913	0.0111	-0.00562	0.00532	-0.0207	0.0314*	0.00556	0.00211						
	(0.05)	(0.86)	(-0.34)	(0.34)	(-1.33)	(2.00)	(0.49)	(0.13)						
Housetype														
semi-detached	-0.00713	0.0155	0.0218	0.000691	0.0274	0.00157	0.00982	-0.0146						
	(-0.40)	(1.15)	(1.06)	(0.04)	(1.48)	(0.08)	(0.77)	(-0.49)						
in building	-0.00387	0.0201	0.00145	0.0402*	-0.0125	0.0164	-0.00508	0.0176						
	(-0.21)	(1.03)	(0.07)	(2.06)	(-1.09)	(0.85)	(-0.48)	(1.15)						
Urban		-0.0568**	-0.00435	0.00122	0.0126	-0.00808			0.0154	-0.0164	0.0381**	0.00923	-0.0249	0.00949
		(-2.67)	(-0.20)	(0.06)	(0.94)	(-0.49)			(1.32)	(-1.46)	(2.62)	(0.66)	(-1.70)	(0.68)
Middle density		-0.0359*	-0.0225	0.0189	-0.0123	-0.00919			0.0244*	-0.0114	0.0165	0.00705	0.00353	0.0153
		(-2.20)	(-1.37)	(0.92)	(-1.11)	(-0.56)			(2.03)	(-0.90)	(1.17)	(0.47)	(0.28)	(1.24)
N	13901	14037	11944	11781	17609	13875	27436	14393	34058	32116	26428	26541	17079	18600

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Country-specific logistic models: M2 indicator (cont)

	(1) IE	(2) IT	(3) LT	(4) LU	(5) LV	(6) MT	(7) NL	(8) PL	(9) PT	(10) RO	(11) SE	(12) SI	(13) SK
Log income	-0.168***	-0.124***	-0.136***	-0.0175	-0.0698***	-0.0306	-0.0636***	-0.156***	-0.0574***	-0.201***	-0.122***	-0.0951***	-0.0796***
	(-8.76)	(-19.06)	(-9.62)	(-0.69)	(-5.65)	(-1.59)	(-6.41)	(-14.87)	(-6.80)	(-13.05)	(-7.09)	(-8.88)	(-4.23)
Person w/disability	-0.0221	-0.0280*	0.0733**	0.0138	0.00103	0.00688	0.0126	-0.00444	-0.00842	0.0110	-0.0549	0.00150	0.0126
	(-1.00)	(-2.29)	(2.58)	(0.46)	(0.04)	(0.21)	(0.69)	(-0.33)	(-0.48)	(0.21)	(-1.24)	(0.10)	(0.64)
Non-EUc	-0.0109	0.00253	0.0455	0.0778***	0.00275	-0.0541	0.00751	0.133	0.000740	0	0.112***	0.0244	0
	(-0.27)	(0.13)	(0.73)	(3.39)	(0.17)	(-1.68)	(0.22)	(1.22)	(0.03)	(.)	(3.39)	(1.49)	(.)
Num Adults w/high-edu	0.00480	0.0135*	-0.0146	-0.0226*	-0.0189*	0.00406	-0.0101	-0.00542	0.00848	0.00505	0.00823	0.00811	-0.0162*
	(0.49)	(2.16)	(-1.50)	(-2.00)	(-2.19)	(0.41)	(-1.72)	(-0.56)	(1.14)	(0.37)	(0.93)	(1.40)	(-1.98)
Num employed	-0.0192	-0.00658	0.0178	0.0183	0.0141	-0.0196	-0.00696	0.0119	-0.00464	0.0256**	-0.0297*	-0.000832	0.0110
	(-1.59)	(-1.11)	(1.31)	(1.52)	(1.56)	(-1.86)	(-0.94)	(1.87)	(-0.82)	(2.82)	(-2.38)	(-0.13)	(1.24)
Single fem	-0.0502**	-0.0314*	-0.0931***	-0.0277	-0.0263	0.0442	-0.00460	-0.0397	-0.0443***	-0.0270	-0.0195	-0.00864	-0.00875
	(-3.06)	(-2.22)	(-4.11)	(-1.48)	(-1.73)	(1.61)	(-0.47)	(-1.75)	(-3.83)	(-1.57)	(-1.02)	(-0.39)	(-0.36)
Computer	-0.0282				0.0120	0.0250	-0.00165	-0.0113	-0.000898	0.00765	-0.0227	-0.0179	-0.0247
	(-1.51)				(0.87)	(1.06)	(-0.12)	(-0.70)	(-0.09)	(0.37)	(-1.16)	(-1.06)	(-1.62)
Phone	0.00571				-0.00661	-0.0175	-0.0374	0.00269	-0.0110	-0.0159	0.0475	0.0246	0.0310
	(0.32)				(-0.40)	(-0.85)	(-1.95)	(0.16)	(-1.05)	(-0.78)	(1.90)	(1.61)	(1.62)
Car	0.0925				-0.0176	0.0744		0.00821	0.0216	-0.0316	-0.0971	0.00427	-0.0529
	(1.20)				(-0.50)	(1.70)		(0.50)	(0.93)	(-1.26)	(-0.73)	(0.07)	(-1.20)
House owner	-0.0295	0.00638	-0.00869	0.0384	-0.0250	-0.0332	0.00483	0.0210	-0.0143	0.0106	-0.0318	-0.0166	-0.0187
	(-1.78)	(0.68)	(-0.32)	(1.86)	(-1.66)	(-1.84)	(0.42)	(1.40)	(-1.59)	(0.21)	(-1.87)	(-1.57)	(-1.24)
House density	0.0129	0.00437	-0.00327	0.00713	-0.00984	0.00469	-0.00496	-0.00969	0.00424	-0.00448	-0.00133	-0.00968	0.00191
	(1.20)	(0.68)	(-0.30)	(0.76)	(-0.93)	(0.39)	(-0.98)	(-0.91)	(0.72)	(-0.35)	(-0.15)	(-1.05)	(0.33)
Urban	0.0176												
	(1.02)												
Middle density	-0.00345												
	(-0.18)												
House bad quality		-0.000000446	0.0120	0.0203	-0.0128	0.00465		0.00861	-0.000334	-0.0241	-0.0263	-0.0201*	0.0109
		(-0.00)	(0.62)	(1.08)	(-0.94)	(0.21)		(0.49)	(-0.04)	(-1.01)	(-1.05)	(-2.12)	(0.49)
Housetype													
semi-detached		-0.0100	0.0715	0.00136	0.0115	0.0608*		-0.0181	-0.00354	0.0458	0.00217	-0.00275	0.0154
		(-0.90)	(1.34)	(0.08)	(0.29)	(2.26)		(-0.75)	(-0.37)	(0.56)	(0.09)	(-0.13)	(0.40)
in building		-0.00659	-0.0264	0.0344	-0.00580	0.0576*		-0.00177	0.00145	-0.00185	0.0498**	0.00301	-0.0110
		(-0.70)	(-1.49)	(1.47)	(-0.33)	(2.19)		(-0.13)	(0.16)	(-0.09)	(2.58)	(0.30)	(-0.82)
N	13678	46179	10908	8354	13820	11222	23181	33407	21900	17330	14055	26051	16054

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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