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Evaluating the Impact of Energy Poverty in a Multidimensional Setting

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Abstract

We study the relationship between energy poverty and subjective well-being by combining objective and subjective indicators in a multidimensional energy poverty index (MEPI). By using the Italian release of the European Survey on Income and Living Conditions, we assess the identification power of this kind of index vis-à-vis standard 'affordability' indicators and show how it can be used in econometric analysis even when the available information takes the form of an ordinal variable. We show that information on subjective well-being and multidimensional energy poverty can be framed within a simultaneous bivariate ordered probit model while accounting for endogeneity issues, especially those related to consideration of subjective indicators. Regarding the identification of the energy poor individuals, a clear additional role of the subjective indicator is detected. The degree of overlap between our multidimensional indices and affordability measures is relatively low. In parallel, econometric estimations show that, while virtually no effects are detected when only relying on affordability indicators, sizable and statistically significant reductions in the probability of being satisfied with life are found as the severity level of the MEPI rises. These effects are detected even when considering a multidimensional index restricted to the subset of objective indicators, but with a substantially smaller extent.

***JEL Classification**: C35, I31, I32*
***Keywords:** multidimensional energy poverty, subjective well-being, limited dependent variable methods, welfare analysis, fuel poverty.*

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1 Introduction

Even in wealthy countries, there may be a portion of the population that is unable to purchase a basic set of goods and services based on energy use. According to the Building Performance Institute Europe (Atanasiu, Kontonasiou, and Mariottini, 2014), in 2012, about 10.8% of the European population was unable to maintain adequate warmth in their homes or were living in energy poverty (henceforth EP). The size of the problem has been increasing over the last 15 years. People exposed to EP not only usually spend a high share of their income on electricity, oil, and gas; they also live in inefficient and unhealthy dwellings; and are exposed to severe consequences concerning health, social exclusion, and overall household welfare. When looking to EP from a macroeconomic perspective, access to modern, clean and affordable energy facilities is considered key to reduce poverty and foster economic development in lower-income countries. The correlation is less clear for countries with high levels of income (Karekezi et al., 2012). In this case, in spite of potential complete access to energy, some households could experience an unsatisfactory availability of energy for economic reasons or lack of infrastructure facilities. In fact, three main economic mechanisms display a concurrent role in shaping actual energy utilization: technical availability of modern services, their affordability in terms of price, and reliability in terms of being usable for most of the time (IEA, 2017).

In developed economies, the earliest policies to support vulnerable citizens took place in the United Kingdom in the early 1990s. In more recent times, other European countries have begun to recognize EP as a distinct phenomenon vis-à-vis income poverty and to implement specific supporting programs. Since 2006, the European Union has pushed for spreading policies supporting the energy poor across all European countries.[1] According to the latest projects (e.g. the European Energy Poverty Observatory) run by the European Commission, EP should be officially considered a distinct phenomenon from income poverty that should be separately analyzed.[2] This view embraces similar considerations made in several studies that reported EP as a complex phenomenon (where a concurrent role is played by factors such as high energy prices, the inefficiency of buildings and appliances, the low income of households and their specific

[1] See European Commission, EPEE 2006.

[2] See the European Energy Poverty Observatory and the previous EU Fuel Poverty Network. As witnessed by the name of this network, the expression "fuel poverty" is recurrently used. For the sake of simplicity, we are generally using the term "energy poverty" even when referring to studies or documents where the expression "fuel poverty" was actually used (and the focus slightly different).

energy needs and practices. Thomson, Bouzarovski, and Snell, 2017) with its peculiarities (such as the higher absolute cost for the poor to have an adequately warm dwelling, the additional detrimental effect that the lack of adequate access to energy has among income poor individual in terms of illness, mental health and social exclusion. Hills, 2012). Considering EP as a distinct phenomenon from income poverty entails that the identification and measurement of energy poor people should not be (exclusively) based on monetary indicators derived from variables such as energy prices and expenditures. In operative terms, the measurement of EP can be obtained starting from an information set that comprises a few deprivation indicators made available at the individual and/or household level in household surveys.

Most of the existing literature points to a set of objective welfare EP indicators (e.g. Boardman, 1991, Hills, 2011, Moore, 2012, Legendre and Ricci, 2015). However, the scope for including subjective measures in the economic analysis is nowadays embedded in the economic debate on welfare evaluation, where the use of subjective well-being (henceforth SWB) approaches has become common practice (e.g., see the OECD Better Life Index, 2013). SWB approaches have been applied to different fields, e.g., health care (Ferrer-i-Carbonell and Praag, 2002), social science (Frey and Stutzer, 2002), evaluation of public goods (Luechinger, 2009) and energy provision mix (Welsch and Biermann, 2014a,b). Accordingly, even in the analysis of EP, subjective indicators have been recently considered in a few studies. This is the case in the recent works by Welsch and Biermann (2017), who investigate the effects on life satisfaction of electricity, oil, and gas prices (standard objective measures) in different European countries; and by Biermann (2016), who finds that fuel poverty measures related to households' expenditure on energy are always associated with a significant negative effect on SWB that adds to that of income poverty. Other studies have adopted an SWB perspective by trying to define a subjective measure of EP (Papada and Kaliampakos (2016); Rehdanz, Welsch, Narita, and Okubo (2015); Lawson, Williams, and Wooliscroft (2015) and Waddams Price, Brazier, and Wang (2012)).

To the best of our knowledge, what is apparently missing in the extant literature is an analysis of individuals' well-being where the combined information from objective and subjective measures of EP, considered within a multidimensional approach, is exploited to econometrically assess the relationship between EP and SWB. With the aim to widening the set of the methodological tools that can be used in this field of economic analysis, we first show how to subsume a set of available indicators (pointing to both subjective and objective dimensions of households' energy deprivation), in a single multidimensional energy poverty index (henceforth MEPI) that provides information on EP even at the individual level. This is done by adapting to EP analysis (and the data at hand) the methodology that Alkire and Foster (2011) have proposed for standard multidimensional poverty measurement. Considering subjective indicators of EP makes these kinds of indices trivially endogenous in their relationship with SWB. Coupled with its ordinal nature, at least in our application, this endogeneity issue impacts on the detection of an appropriate econometric modeling strategy. We suggest estimating the individual-level relationship between SWB and the MEPI by employing a bivariate ordered probit model with exclusion restrictions. This allows us to account for the correlation between the two variables. Moreover, provided that an opportune set of instruments is available, this solution is adequate to face a general set of endogeneity problems related to unobservable factors. This approach is valid even in a cross-sectional environment and could be potentially applied when using alternative multidimensional indices partially based on subjective measures.[3]

We develop our MEPI and carry out the empirical analyses by using the Italian version of the European Union Survey on Income and Living Conditions (henceforth ITSILC). As for the information on SWB, we exploit a question about the degree of life satisfaction included in a specific module on social exclusion, which is asked to be evaluated on an 11-point scale.[4]

We first provide an exploratory analysis that shows the potential from using the MEPI to identify EP while pointing at the same time to the discrepancies between multidimensional indices and traditional monetary indicators of fuel poverty. Subsequently, we econometrically assess the relationship between SWB and the MEPI by identifying the causal relationship between EP and life satisfaction using exclusion restrictions referred to the year of construction of the dwellings. The results not only confirm theoretical predictions, by detecting a significant negative relationship between subjective well-being and energy poverty intensity, but also point to the capability of multidimensional subjective indicators in explaining the impact of EP on SWB compared with traditional expenditure-related measures.

The paper is structured as follows. In Section 2, we sketch a background of the relevant literature. Section 3 describes the construction of multidimensional poverty indices and their application

[3] A very recent example is the composite fuel poverty index proposed by Charlier and Legendre (2019).

[4] In the following, the words life satisfaction and subjective well-being will be considered interchangeable.

to the data at hand. Section 4 illustrates the conceptual model in which the empirical analysis is framed. Section 5 illustrates the results of the econometric analysis, and Section 6 contains a few concluding remarks.

2 Energy Poverty, its measurement and the Subjective Well-being approach

The two main topics in which our work is framed are the EP measurement methods and the relationship between SWB and EP.

2.1 Energy Poverty Measurement

Approaches to the analysis of EP measurement can be broadly categorized as either affordability or energy deprivation. The former is inherently unidimensional, being based on reference monetary thresholds that define the maximum level of income or expenditure share spent on energy (the term *fuel* is often used) that can be considered *affordable* by individuals or households. Boardman (1991) provides a starting point for this approach by simply stating that EP occurs when any household needs to spend more than 10% of its disposable income on total fuel use (the so-called 10%*Rule*). Variations of this elementary approach are the so-called 2M indicators, double mean, or double median, which count as energy poor those individuals whose energy expenditure share is greater than the double of the mean (or median). More recent studies, e.g., Hills (2011, 2012) propose a Low-Income High Costs composite indicator, which counts individuals as energy poor if they spend more than 60% of the median of the disposable income distribution *and* they fall below a given income poverty line. Finally, affordability has been seen within a Minimum Income Standard framework that considers as energy poor those individuals lacking a minimum income required to satisfy primary needs after paying housing costs and energy costs (Moore, 2012). Close to Moore's indicator is the Residual Income Indicator (Miniaci, Scarpa, and Valbonesi, 2014), which is aimed at understanding how many (not energy-related) goods an individual can purchase apart from energy.

By taking a different perspective, the energy deprivation approach points to the importance of considering the different dimensions of EP, thereby paralleling the debate that characterizes the comparison between multidimensional approaches to poverty measurement and unidimensional poverty measures based on income (e.g. Bourguignon and Chakravarty, 2003; Atkinson, 2003; Alkire and Foster, 2011). The focus of the analysis is on how people are affected by living in energy-inefficient houses. In this respect, both the material manifestations of EP and subjective indicators of discomfort related to living in unhealthy dwellings should be considered. Several indices and indicators have been used: Healy (2003), Healy and Clinch (2004) and Thomson and Snell (2013) carry out cross-sectional and within-country analyses by considering information often included in household surveys, such as damp walls and/or floors, heating system, window frames, self-assessed judgments such as "cannot afford to heat home adequately", "unable to pay utility bills" and "lack of adequate heating facilities". A few recent studies have compared objective and subjective measures of EP. This is particularly the case of Waddams Price, Brazier, and Wang (2012), who point to the large differences emerging in the identification of the energy poor among UK citizens when using information arising from self-assessed EP instead of the $10\% Rule$. They conclude that both sources of information should be used by policy makers to detect the actual occurrence of EP in the economy. Similar remarks have been raised by Lawson, Williams, and Wooliscroft (2015), with an application to New Zealand, and by Papada and Kaliampakos (2016) regarding Greece. Waddams Price, Brazier, and Wang (2012) also outline the need for a multidimensional objective and subjective indicator to give a more complete picture of EP incidence.

Results from the income poverty literature show that the multidimensional deprivation approaches can enable the analyst to assess even the intensity of EP problems experienced by the energy poor, thereby enriching the incidence information usually provided by affordability measures. This is the case of the work by Nussbaumer, Bazilian, and Modi (2012) who, by applying the methodology introduced in the poverty literature by Alkire and Foster (2011), were the first to develop a MEPI centered on the energy deprivations experienced by households in several African countries. Subsequent applications where a MEPI *à la* Alkire-Foster is explicitly proposed are those by Sadath and Acharya (2017), in a study on the incidence of EP among Indian households and Okushima (2017), in evaluating EP in Japan after the Fukushima accident. An alternative multidimensional index of fuel poverty, where both subjective and objective measures are considered, is proposed by Charlier and Legendre (2019).

2.2 Subjective Well-being and Energy Poverty

Individual satisfaction with living conditions is a subjective latent variable that can be reasonably assumed to range continuously between a lower bound of complete dissatisfaction and an upper bound of complete satisfaction. In practice, however, information on individual satisfaction is usually recovered from answers that use rankings, e.g., from excellent to very bad, or a numerical scale. Nonetheless, the viewpoint by the wider literature based on SWB approaches is that these kinds of self-assessed questions on satisfaction can elicit very important information on individual perceived losses caused by social exclusion, health deprivation, or more generally material deprivation, with the ultimate goal of better designing appropriate public policies for support.[5] A wide set of factors is expected to impact on individual well-being and be reflected in self-assessed indicators of SWB, e.g., income, health, leisure, job characteristics, accommodation, education, social exclusion, unemployment and status in employment, personal life shocks, and marital status (Frey and Stutzer, 2002; Blanchflower and Oswald, 2004; Ferrer-i-Carbonell, 2013 and Clark, Frijters, and Shields, 2008). Bellani and D'Ambrosio, 2011 is of particular interest for the present study because they find that the use of deprivation indicators is more relevant than the use of traditional monetary indicators to capture the effect of poverty on SWB.

Concerning energy issues, a subjective perspective was adopted by Welsch and Biermann (2014a) in an assessment of electricity supply structures in Europe; by Welsch and Biermann (2014b) and Rehdanz, Welsch, Narita, and Okubo (2015) with a focus on the impact of the Fukushima nuclear accident. The subjective view was also adopted in a study by Welsch and Biermann (2016) on the nuclear power plant externalities in Switzerland, and in an analysis by Moellendorff and Welsch (2017) on the perception of renewable power spreading in Germany. To our knowledge, the aforementioned study by Welsch and Biermann (2017) is the first where the SWB approach is applied to evaluate the welfare impact of EP.

[5]For a broader review of the SWB approach see Frey and Stutzer, 2002 and Ferrer-i-Carbonell, 2005.

3 Identifying and Measuring Energy Poverty

We use data from the IT-SILC,[6] the Italian version of EU-SILC, which is the European survey that reports the statistics on income and living conditions and is released by Eurostat. It was launched in 2003 and has been implemented since 2010 in all EU-27 countries. It is mainly designed to study social exclusion and monitor poverty in the EU. The EU-SILC questionnaire is part of more extensive national level surveys, containing a richer set of questions about energy consumption, expenditure, and dwelling inefficiency than the European survey.

The information available in IT-SILC on potential energy deprivation (henceforth *ed*) is summarized in Table 1. We can note that *ed1* and *ed5* correspond to the standard deprivation indicators usually considered in the existing literature which has already exploited the EU-SILC survey (e.g. Thomson and Snell (2013); Atanasiu et al, 2014). The *ed2* and *ed3* represent a more detailed version of a similar single question of EU-SILC; *ed4* refers to the absence of any heating expenditure.[7] *ed1*, *ed2*, and *ed3*, (directly collected by the interviewers) can be considered objective indicators referring to inefficient dwelling's condition. By contrast, *ed5* is an indicator based on the subjective perception of being able to keep home adequately warm or not.

The original survey contains information on 44,622 individuals. However, after discarding those records for which the information on the *eds* and SWB was unavailable and children aged less than 16, we end up with 23,193 observations. For these individuals, the most affecting deprivation is the presence of damp with 18%. The second more affecting deprivation is the presence of any problems with roofs and window fixtures, which regards 11% of the sample. The less recurrent deprivations are those referring to financial difficulties for utility bills and lacking heating facilities. The subjective indicator impacts 16% of the sample.

Table 1 about here.

[6] Version released in 2016 by the Italian National Institute of Statistics (ISTAT). The data refer to 2013.

[7] Unlike the national data release of the survey, EU-SILC does not provide information on the absence/presence of heating expenditure (*ed4*) and the distinction between living in a damp home (*ed2*) or a house with damages on the roof, ceilings, windows, etc (*ed3*). The remaining two indicators are common to the national and European versions of SILC.

3.1 Combining subjective and objective indicators in a Multidimensional Energy Poverty Index

To fully exploit the information provided by the previous set of *ed* indicators, we follow the approach used by Alkire and Foster (2011) to build the multidimensional poverty index (MPI). This methodology allows us to analyze both the incidence and the intensity of EP across households and is particularly suited for analyses where energy deprivations are typically categorical or ordinal variables. Its key feature is the shaping of the procedure of identification of the energy poor individuals through the use of two thresholds. This makes it possible to set the analysis at an intermediate point between the union and the intersection rules of identification that are used in the poverty measurement literature.[8] The former classifies as poor each person presenting at least one deprivation. Conversely, the intersection rule identifies as poor the individual displaying all the deprivations under scrutiny. Alkire and Foster (2011)'s identification strategy stands in-between the two, conditional on the analyst's setting of the two thresholds. In formal terms, let n be the sample size and d the number of *eds* presented in Table 1. For sake of completeness, let also introduce a vector $\mathbf{w}$ of dimension d of positive numbers summing to d, whose j-th value provides the weight associated with the j-th dimension. Given the choice of the deprivation indicators, the application of the A-F methodology formally requires the use of a first threshold, taking the form of a vector of "deprivation cut-off" ($\mathbf{z}$), which identifies how many *eds* associated with a given individual will contribute to the value of the multidimensional index. In this case, where all the *eds* are binary indicators taking value 0 or 1 (where 1 stands for "deprived"), we simply have $\mathbf{z} = [1, \dots, 1]$.

Applying the previous threshold to each observation and weighting the importance of the *eds* with the elements of $\mathbf{w}$, we obtain the weighted count of deprivations suffered by a single individual i, *i.e.*:

$$c_i^w = \sum_{j=1}^{d} (w_j \times I_j(\mathbf{z})), \tag{1}$$

where $I_j = 1$ if the person is deprived in indicator j, $I_j = 0$ otherwise.

The second threshold, which we can label by k, determines the maximum (weighted) number of the dimension for which an individual i can be deprived without being considered as energy poor: the extremes $k \leq \min w_j$ and $k = d$ will give the union and the intersection rules of

[8] See, for example, Atkinson (2003) or Bourguignon and Chakravarty (2003).

identification. On the basis the threshold k, we can compute a multidimensional index for individual i, corresponding to the weighted share of the possible deprivations identified for individual i:

$$MEPI_i^w = \frac{1}{d}\sum_{j=1}^{d}(c_i^w \times \vartheta_i(k)), \tag{2}$$

where $\vartheta_i = 1 \; iff \quad c_i^w \geq k$, $\vartheta_i = 0$ otherwise. The previous index provides information about the intensity of EP that can be usefully inserted in the regression analysis, but with the caveat that it can take a limited number of ordered values.[9]

An aggregate index of EP, for a given weighting scheme w, is obtained by taking the average of individual deprivation shares over the whole population:

$$MEPI^w = \frac{1}{n}\sum_{i=1}^{n} a_i^w, \tag{3}$$

where $a_i^w = \frac{1}{d}\sum_{j=1}^{d}(c_i^w \times \vartheta_i)$. This aggregate MEPI provides a summary evaluation of the incidence and the intensity of EP in a given economy. Alkire and Foster (2011) point out that this kind of index can be seen even as an *adjusted headcount ratio*, given by the product of two simpler statistics: the average deprivation share across the energy poor ($A = \frac{a_i^w}{pd}$); and the share of energy poor in the population, i.e. the multidimensional headcount ratio $MHR = \frac{p}{n}$, where p is the number of the energy poor and n is the population dimension. Therefore, an alternative expression for the MEPI at the aggregate level will be:

$$MEPI^w = A \times MHR. \tag{4}$$

The previous expression clarifies that the average MEPI will always range between 0 and 1. As shown by Alkire and Foster (2011), the most important property of the index is given by the dimensional monotonicity, i.e. it increases whenever the individuals' deprivation count increases (and vice versa).[10]

[9] Namely, up to $d+1$ values in the case of equal weights and the threshold k is chosen sufficiently low so as to ensure that the union identification rule applies (d values related to the counts of energy deprivation of individuals identified as poor, plus a zero value related to not being energy poor). The expected number of levels of $MEPI_i^w$ will be a weakly decreasing function of the stringency of the multidimensional poverty cut-off k. In the extreme case of totally differentiated weights, the maximum possible number of values would be $d \times d$.

[10] Specifically, the index satisfies the properties of weak monotonicity, monotonicity, and dimension monotonicity, together with decomposability (which allows subgroup analysis), replication invariance (which ensures comparisons across differently sized populations), symmetry (which ensures equal emphasis is given to any person or group), nontriviality and normalization (which ensures that the minimum (0) and the maximum (1) are different values).

The previous description points to the role of different weighting schemes and values for k that can be used for the computation of MHR and $MEPI^w$. In the case of the standard MPI used in the Human Development Reports by the United Nations Development Programme, Santos and Alkire (2011) remark that "intricate weighting systems create challenges in interpretation". One may think that all the deprivations point to the same category, and reasonably assume equal weights. Otherwise, situations where deprivation dimensions can be logically nested in separate groups naturally lead to more articulated weighting structures. The very simple rule usually adopted in this case is that of assigning the same aggregate weight to each nest and then equally sharing this aggregate weight within nests.[11] In our case - where we can distinguish between subjective and objective indicators - we will first adopt a baseline structure with equal weights; subsequently use the nested weighting structure scheme, where 50% of the overall weight is attached to the (single) subjective energy deprivation indicator and the remaining weight is equally shared among the objective eds; finally, carry out some robustness assessments.

3.2 Assessing Energy Poverty in Italy.

We appraise the potential of a multidimensional approach that aggregates the information available for the analysis of EP by computing a few simple statistics in terms of incidence (with the multidimensional headcount ratio MHR) and intensity (with the aggregate MEPI). These results are compared to the distribution and incidence of two affordability measures, namely the $10\%Rule$ and a Modified$10\%Rule$ (henceforth $10\%Rule_{modified}$).[12] The analysis is carried out both by considering equal weights for the various *eds* and the nested weighting structure defined above (where the subjective indicator takes half of the total weights).[13] As a baseline value, we set the poverty identification cutoff k equal to $d/3$, equivalent to one-third of the maximum weighted count of deprivations that an individual can achieve, which is the value typically used for the computation of the MPI.

Figure 1 is composed of two Euler diagrams providing a first insight on both the incidence

[11] In the case of the MPI, the three dimensions to which this scheme is applied are Education, Health and Living Standards. Each of them has a different number of deprivations. Likewise, Sadath and Acharya (2017) build their multidimensional energy poverty indicator by considering three equally important nests (Lighting, Cooking, Additional measures)

[12] With this label we are referring to dual-threshold indicator that has been applied to Italy by Faiella and Lavecchia (2015). More precisely, this indicator is computed as $10\%Rule_{modified} = \frac{\sum_i^N v_i}{N} \times 100$, where $v_i = 1 \quad iff$ at least one between electricity consumption $> 0.10\times$ income and fuel consumption $> 0.05\times$ income, while $10\%Rule = \frac{\sum_i^N v_i}{N} \times 100$, where $v_i = 1 \quad iff$ energy consumption $> 0.10\times$ income.

[13] Henceforth, subscripts with the expression "$_n$" will always refer to some form of nesting structure.

(represented by the area of the circles within the squares) and the overlapping degree (represented by the intersection of the circles) between the multidimensional incidence indicator and the two affordability measures considered. According to MHR and MHR_n, respectively 15.50% and 16.84% of the sample is in a EP condition. By contrast, the problem would regard 7.49% of the population when referring to 10%$Rule$, and only 3.66% according to 10%$Rule_{modified}$. As expected, the diagrams show that 10%$Rule_{modified}$ is a subsample of 10%$Rule$. It is worth pointing out that only about 1.00% of the sample is commonly detected as energy poor by the three measures in both cases. It turns out that they are capturing different potential vulnerabilities. The affordability measures are likely to capture mainly people suffering either from income poverty or high energy costs, whereas the multidimensional measure is considering all the individuals who are living in inefficient dwellings, including those who cannot even afford to reach the threshold and, therefore, cannot be considered by the affordability measure.

Figure 1 about here.

The overlapping degree between our multidimensional indices and affordability measures can be additionally assessed by means of the content of Table 2. The top panel reports the average MEPIs. The overall mean intensities are about 0.08 according to $MEPI$ and 0.10 to $MEPI_n$, whereas the average severities among the energy poor are respectively 0.49 and 0.60. The right bottom Panels display the distributions of the individual MEPIs across their different levels, then the percentage of overlapping between the two affordability measures and the different levels of the MEPIs. Looking at the $MEPI$ 0 level, 84.59% of the sample is not experiencing EP. When looking at the distribution of the 10%$Rule_{modified}$ and 10%$Rule$ energy poor, it is quite surprising to see that no energy poor people according to the indices are detected at the highest level of $MEPI$. Conversely, 77.33% of 10%$Rule$ and 72.59% of 10%$Rule_{modified}$ of energy poor would not be targeted by the MEPI. It seems quite reasonable to think of these individuals as *false positive* because they are not reporting any of the five deprivations that comprise the MEPI, including the self-assessment about whether the family can afford to keep its home warm or not, nor the indicator of having been in arrears due to financial difficulties for utility bills. The same evidence emerges when referring to $MEPI_n$ distribution.

Table 2 about here.

Figure 2 provides another view of the analysis by displaying both the incidence (MHR and $10\%Rule$) and the intensity ($MEPI$) of EP by equivalized household income quartiles, showing a decreasing relationship.[14] The richer the household, the less is affected by EP according to both measures. The decomposition is especially helpful for targeting the individuals that the affordability measure is not considering, given that only 23.25% of the first income quartile is energy poor according to the $10\%Rule$ index, whereas the MHR counts 29.56%. This confirms the apparent limitations of measures that mainly capture the income–poverty dimension.

Figure 2 about here.

An additional comparison is carried out in Table A1 in the Appendix, by reporting some additional information on the distribution of the EP measures across income poverty and different degree of urbanization. As expected, people who live in rural areas tend to be more energy vulnerable and the percentage of energy poor is higher than in urban areas. In this case, all the EP measures display the same behavior.

As a final exercise, with the Euler diagrams we assess the specific role of the subjective indicator (Figure 3) and that of the poverty identification cut-off k, which indirectly establishes a trade-off between the union and the intersection rule of identification (Figure 4). Graph (a) of Figure 3 displays the intersection between the MHR (with all the five *eds*) and MHR_{obj} (in which the *ed5* is omitted) when using equal weights. In this case, the objective measure is a subset of MHR. The comparison with MHR_n is presented in the graph (b). In this case, the intersection counts for the 5.27%, i.e. about half of the individuals detected by the "objective" multidimensional index. In both cases, the overall incidence of EP increases of about 50% when considering the subjective *ed*. These findings support the claim by Waddams Price, Brazier, and Wang (2012) when stressing the need to use subjective and objective indicators other than affordability measures when measuring EP.

Figures 3 and 4 about here.

As can be seen from Figure 4, relying on the intersection rule (MHR5) would imply a quite low incidence of EP(0.12%). Conversely, neither the strongest of the objective deprivation indicators nor the subjective one appear a reliable statistics for the identification of EP: in the latter case,

[14] The Eurostat equivalence scale has been used.

a very large share of the population would be classified as energy poor (37.3%), a value hardly compatible with a developed country such Italy. However, it may be viewed as the starting point in defining vulnerable customers. The combined use of one or two ‘objective' deprivation with the subjective indicator seems (intuitively) a viable solution (MHR2 and MHR3 have the same dimension, 10.2%),

4 Modeling the Relationship between Subjective Well-being and Multidimensional Energy Poverty

We now show how the use of the individual-level MEPI, as defined in the previous Section, may facilitate the inclusion of EP as a determinant of individual welfare in empirical analyses adopting an SWB approach.

Following Decancq, Fleurbaey, and Schokkaert (2015), we consider a "general satisfaction function" $SWB^*(l_i, R_i, s_i)$ for individual i and defined by a vector l_i of m different aspects of life that provide satisfaction, the associated R_i preference orderings on l_i and individual scaling factors s_i (related to those personal characteristics and situations that may influence the level (but not the order) of well-being evaluations). For our empirical assessment, we can summarize all the observable scaling factors and relevant aspects of life in a vector $\mathbf{x}_i$, *except* the EP aspect, which yields:

$$SWB_i^* = S(\mathbf{x}_i, EP_i^*, \mu_{iSWB}) \tag{5}$$

where μ_{iSWB} represents the unobservable individual heterogeneity that affects the perception of satisfaction.

When using data from IT-SILC, information on the latent SWB is recovered from a question (in the form of an ordered variable with eleven levels) expressing life satisfaction. Likewise, even the empirical counterpart of EP_i^* ($MEPI_i$) is an ordered variable (with five levels, including the absence of EP). For the econometric analysis, this entails the use of models for ordered variables such as the ordered probit model.

We can control for several covariates that are well discussed as determinants of SWB in the life satisfaction literature. They include social-economic conditions, demographic determinants, job conditions, household income relative position, dwelling typology and characteristics, the region of residence, and urbanization level. Nonetheless, we cannot rule out that residual unobserved subjective factors may affect both SWB_i^* and EP_i^*, the latter being based in part on subjective perceptions. This entails typical endogeneity problems, which are well known in the SWB literature (e.g. Ferrer-i-Carbonell, 2005, Blanchflower and Oswald, 2004, Frey and Stutzer, 2002). For instance, it has been pointed out that optimism affects individuals' life satisfaction as well as the perception of being energy deprived or not. The potential endogeneity of EP_i^* can be modeled using a two-equation system, which we estimate by a *bivariate* ordered probit model, given the ordered nature of the SWB indicator and of $MEPI_i$, which is our empirical measure of EP. In this model, we can achieve identification by using an instrumental variable approach, which takes the form of an exclusion restriction on the vector of explanatory variables that model SWB, while considered in the (auxiliary) equation for $MEPI_i$. Looking at the several determinants of EP detected, for example, by Legendre and Ricci (2015), it is reasonable to say that the objective and technical factors that describe dwellings directly influence the probability of being energy poor but do not directly affect the statement of SWB. As remarked, for example, by Fabbri (2015), a good predictor of the inefficiency of a dwelling is the year of construction of the building. The more recent is a dwelling, the less likely to have energy inefficiency problems. Accordingly, we set the year classes of the building construction as our instrumental variables, relevant for the $MEPI_i$ and uncorrelated to our main dependent variable SWB_i^*.

A possible objection to this identification strategy is that the choice of dwelling could be affected by self-selection. For instance, due to health status, income level (or, in general, personality traits), some people might prefer older buildings (e.g., living in historical city centers), while others may prefer newer buildings (e.g., more salubrious). As a consequence, in the absence of adequate conditioning on a wide set of controls, SWB_i^* might eventually be correlated to the oldness of the building. That is why we consider a wide set of explanatory variables: individual health status, job position, income relative position with respect to their reference group, material deprivation and value of the house. Conditional on all these controls, we claim that the SWB_i^* equation is purged from any remaining direct effect of the year of construction on life satisfaction. As a note of caution, it must be recognized that the buildings' history often includes property renovations (or lack of), this way making the age an imperfect indicator of energy inefficiency. It turns out that the strength of this set of dummy instrumental variables must be empirically tested.

4.1 A bivariate ordered probit model

Define the empirical counterpart of our latent variable equation system as:

$$\begin{aligned} SWB_i &= MEPI_i\beta_1 + \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1} + e_i \\ MEPI_i &= \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} + \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2} + u_i \end{aligned} \tag{6}$$

where SWB_i is the observed level of overall satisfaction; $MEPI_i$ is the individual EP intensity; $\mathbf{x}_{1i}$ is the vector of observable characteristics that may affect both the life satisfaction and EP, $\boldsymbol{\delta_1}$ and $\boldsymbol{\theta_1}$ are respectively the coefficient vectors associated to $\mathbf{x}_{1i}$ in each equation; $\mathbf{x}_{2i}$ refers to the set of instruments, $\boldsymbol{\theta_2}$ is the vector of coefficients associated to $\mathbf{x}_{2i}$; u_i and e_i are the unobservable components.

The two ordered dependent variables are defined as follows:

$$SWB_i = \begin{cases} 0 \quad if \quad SWB_i^* \leq t_1 \\ \vdots \\ j \quad if \quad t_j > SWB_i^* \geq t_{j-1} \\ \vdots \\ J \quad if \quad SWB_i^* > t_J \end{cases} \quad MEPI_i = \begin{cases} 0 \quad if \quad EP_i^* \leq \alpha_1 \\ \vdots \\ w_k \quad if \quad \alpha_k > EP_i^* \geq \alpha_{k-1} \\ \vdots \\ 1 \quad if \quad EP_i^* > \alpha_K \end{cases} \tag{7}$$

We also impose the standard assumption on the cutoff points that are monotonically increasing so that $t_0 = \alpha_0 = -\infty$ and $t_J = \alpha_K = +\infty$. Following Calhoun (1989), Greene and Hensher (2010), and Sajaia (2008), the conditional joint probability distribution is expressed by:

$$\begin{aligned} Pr(SWB_i = j, MEPI_i = k \mid MEPI_i, \mathbf{x}_{1i}, \mathbf{x}_{2i}) = & \\ & \Phi_2(\alpha_k - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_j - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & - \Phi_2(\alpha_{k-1} - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\theta_2, (t_j - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & - \Phi_2(\alpha_k - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_{j-1} - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & + \Phi_2(\alpha_{k-1} - \mathbf{x}_{1i}^{'}\{\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_{j-1} - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \end{aligned} \tag{8}$$

where Φ_2 is the bivariate standard normal distribution, $\xi = \frac{1}{\sqrt{(1+2\beta\rho+\beta^2)}}$ and $\tilde{\rho} = \xi(\beta + \rho)$. The error terms are normally distributed: $(e_i, u_i) \sim N(0, \Sigma)$, where $\Sigma = [\tilde{\rho}_{jk}]$ is the variance-covariance matrix. Sajaia (2008) develops this particular specification and refers to it as the simultaneous bivariate ordered probit. Applications of this model, exploiting the related *Stata* routine *Bioprobit*, can be found in health economics (Bünnings and Tauchmann, 2015); education economics (Kalb and Van Ours, 2014) and economic psychology studies (Farrell, Fry, and Risse, 2016).

5 Econometric analysis

5.1 Variables and sample definition.

We consider a broad set of potential determinants of SWB, taking advantage of the literature cited in Section 2.2. Namely, we control for individual-level characteristics (sex, age and age squared, marital status, general health conditions, education level, working conditions); dwelling typology and characteristics; region of residence and urbanization level.
The SWB variable is an individual question that ranks the degree of satisfaction within a range of 11 levels, from 0 (not at all satisfied) to 10 (completely satisfied). Figure 5 (a) displays the distribution of SWB across individuals in the sample. As expected, it follows the typical Western European trend and is left-skewed (see Layard and Sachs (2017)). Figure 5 (b) reports the distribution of SWB across the levels of the individual MEPI index. In general, the higher the index, the less satisfied the individuals on average.

Figure 5 about here.

Table 3 reports the main descriptive statistics for the control variables considered. Our final sample comprises 46% men, with an average age of about 55 years. Around 32% of the sample declared itself as an employee and 29% as retired, and the median level of education is upper-secondary was 36%, with only 13% of individuals having tertiary education. Equivalized household income is about 19450 euros. Following Clark, Frijters, and Shields (2008), we also consider the household relative position with respect to a reference group having the same class age, education level, and area of residence. An individual is defined richer than the reference group when her household equivalized income is statistically larger than the average income of the group. Around 41% of individuals are classified accordingly. Moreover, an indicator for multidimensional material deprivation (henceforth, MMDI) is built by applying the Alkire-Foster methodology to subsume in a single index a series of social-material deprivation.[15] Regarding the dwelling characteristics, around 78% of individuals are homeowners and 62% of dwellings are located in non-urban areas. Around 29% of the respondents live in semi-detached houses and 26% in buildings with more than 10 flats. Dwelling's quality is measured by the monthly paid (or imputed) rent: the average is around 550 Euros.

Table 3 about here.

The bottom part of Table 3 reports the summary information on the set of dummies indicating the dwelling's construction age, by means of which we deal with the endogeneity of the EP variable. The original variable available in ITSILC contains nine classes, where the first refers to the more recent dwelling (after 2010 up to 2013) and Class 9 to the oldest (before 1900). Figure A1 in the Appendix summarizes the distribution (left-skewed for those who experience more intense EP) across MEPI levels of this categorical variable.

5.2 Estimation Results

Table 4 reports the main results related to the estimation of equation (6). In parallel to Section 3.2, a baseline model where the components of the MEPI at the individual level are assigned equal weights is compared to a nested weighting scheme and a model based on the $10\%rule$ affordability measure. First, note that the Wald test of independent equations associated with the correlation coefficient ρ confirms the scope for considering a joint probability model. The relationship between EP and the wide set of socio-economic factors for which we are controlling for follows the economic intuition whether an equal weights or a nested weighting structure is adopted. With respect to the reference individual (employee, single, with tertiary education, in very good health and living in a detached house) the MEPI is positively associated with unemployment and material deprivation, becomes lower for richer individuals, whether in absolute terms or with respect to their reference group, augments as the level of education

[15] In details, the financial deprivation dimension is computed from the variables *hs120, hs060, hs011, hs031, pd070* ; the primary needs dimension from *hh081, hh091, pd080, pd030, frigo, hs100, hs090, hs080, hs070, hs050*; the secondary needs from *hs040, stovigli, videocam, parab* ; the cultural needs dimension from *pd060, pd050*; and finally the medical needs from *ph040, ph050.* The high number of items considered makes plausible a "cardinal" interpretation of this indicator.

and self-assessed health decreases. A decreasing relationship with age is detected for most individuals, as the estimated turning point with the coefficients of the quadratic specification is about 19 years old (value referred to Model 1).[16]. The three negative estimated coefficients of the dwelling types show that, *ceteris paribus*, living in each of the three different dwelling types reduces EP compared with living in a detached house and, as expected, a higher dwelling quality implies lower EP. Finally, our exclusion restriction based on the dummy set of dwelling's construction age (reference class is 2010–2013) has statistical support and all the coefficients are positive as expected. The older the dwelling, the higher the probability of staying in a more severe energy poverty level.[17]

In the SWB equation, given we are interested in assessing the effect of the observed EP severity, we include a full set of dummies referring to the individual MEPI levels (no EP is the reference group).[18] As expected, the estimated coefficients are negative and statistically significant and show an increasing impact, apart from the highest intensity level, which actually refers to a very limited number of individuals (28). The same nonlinear pattern is found in the case of Model 2, with the difference that the higher number of EP levels originated by the nested weighting structure detect a clearly steep gradient only for the above-median levels.[19]

To better assess the performance of the MEPIs at the individual level, we can compare the previous results with those arising from the estimation of the simultaneous system using the 10%*Rule* affordability measure. Model 3 in Table 4 shows that this indicator is not significant in the SWB equation.[20] Looking at the 10%*Rule* equation, none of the dummy instruments are statistically significant. In strictly economic terms, affordability of energy expenditures do not depend on the oldness of the building.[21]

[16]Looking at the single eds, we have noted that older people are less likely to state that they can not heat home adequately. A similar finding has been found for the UK (Deller and Waddams Price, 2018)

[17]Results, available on request, are strongly robust when considering a single dummy that takes value 1 when construction of the building was begun before 1970.

[18]For a similar specification in the case of a bivariate probit model, see Kalb and Van Ours, 2014.

[19]In this case, some of the instrument dummies for the oldest dwellings are not statistically significant, but a joint Wald test strongly supports the identification.

[20]It is worth remembering that 10%*Rule* is a binary variable (0 not energy poor, 1 when energy poor). This yields a 'semi-ordered bivariate probit model' that does not involve modifications to the formal structure described in Section 4.1 (e.g., see Greene and Hensher, 2009: 225).

[21]Other sharp differences arise. For example, the effects of the income variables, whether in absolute or relative terms, appear much stronger in their effect on 10%*Rule vis-à-vis* MEPI, as a trivial consequence of the fact that affordability indicators are based on income.

Table 4 about here.

Coming back to the SWB equation in the specifications based on the MEPI, we can appraise that the estimates related to the other covariates are mostly consistent with the economic intuition. Namely, a progressive reduction of SWB as health conditions deteriorate and material deprivation increases, a lower life satisfaction when the individual is unemployed, as compared to the baseline status of employed. The opposite applies to retired people. Related to that, the coefficients of Age and Age2 detect a positive relationship between SWB and age for over fifty-year-old people (the turning point is at about 54 years old), whereas decreasing for younger cohorts. Married people appear more satisfied with life than singles. So are individuals with children.[22] We finally highlight that the weighting structure for the MEPI indicator impacts on the statistical significance of income variables and education level dummies. Namely, a positive effect is found for both only in the case of Model (1).

We have tested the robustness of our main analysis according to several dimensions. We have first verified whether the expected negative relationship between EP and SWB could be detected by a different affordability measure ($10\%Rule_{modified}$). The related estimation results are reported in the left-hand-side of Table A2 in the Appendix: the very small estimated coefficient, considering it actually different from zero by considering a level of statistical significance at 10%, would point to a counter-intuitive positive effect on SWB. A second possible challenge to robustness of the results in Table 4 could be related to the presence of historical buildings (quite common in Italy) characterized by important restoration works, for which the positive relationship between ancientness and energy inefficiency could not hold. Because of that, we have considered a restricted sample that excludes the dwellings built before 1900. The results reported in the middle part of Table A2 not only confirm that the effect of the MEPI levels is stable in magnitude, but also that the results for the other covariates are in line with the main estimation results. The same applies (right-hand-side of the table) to the lack of explanatory power of $10\%Rule$.[23]

[22]Without specific identification strategies designed for these socio-demographic characteristics, we do not assign any causal relationship to these findings. For example, several studies report empirical evidence of a negative or non-significant effect of children on SWB. For a discussion of the effects of divorce, widowhood, first child, and marriage see Clark, Frijters, and Shields (2008).

[23]For the sake of brevity, we omit to report additional robustness checks carried out by using other specifications of the MEPI - obtained by excluding some *eds*, or adding the 10% Rule indicator as sixth *ed*, which all confirm the negative and significant estimates for MEPI levels.

Given the bivariate ordered probit estimation, the magnitude of the coefficients is not informative about the size of the effects. To assess the impact of the MEPI on different levels of SWB, we have computed (by means of the finite difference method) the average partial effects (APEs) of increases of EP intensity on the predicted probability of being in a given level of SWB. We have subsumed this exercise with the plots inserted in 6 and 7. The Y-axis represents the average predicted probabilities of different levels of life satisfaction, while the X-axis refers to all the possible levels of the MEPI. The vertical distance between two dots provides the APE between two related MEPI levels. As a consequence, the difference with respect to the Level 1 dot represents the APE when starting from a condition of no EP. The left Panels of 6 illustrate how a higher EP intensity increases the probability of being completely dissatisfied (SWB= 0) up to the penultimate MEPI level, where the predicted probability is nearly 4 times as much that of the "no EP" level whether the estimates from the equal weights (Model 1) or nested weights case (Model 2) are used. Even at the lowest MEPI level identifying a condition of EP (level 2), the class probability would be 65% higher (0.028 *vs.* 0.017 in the case of equal weights). Similar values at the highest EP level reflect the lack of statistical significance of the related coefficient. The central and the right panels report respectively the probabilities of being satisfied at the median (SWB = 7) and the highest levels (SWB = 10). In the latter case, symmetrically to the lowest life satisfaction level, very strong reductions in the predicted probability can be possible. At the median SWB level, the APEs are smaller - for example, a change from level 5 to level 6 in MEPI_i implies a reduction of about 12% (from 0.22 to 0.199) - because the predicted class probability arises from the combination of "exits" to lower life satisfaction levels with "entries" from higher levels.

Figure 6 about here.

Figure 7 presents the same type of exercise, but carried out by considering different reference individuals, namely being richer than the reference group, unmarried, having very bad health, and being retired. Only the predicted probabilities from Model (1) are shown. As can be easily seen from the values reported within the plots, retired people broadly follow the sample averages of 6. Individuals richer than their reference group are less sensitive at the lowest level of SWB, but strongly affected at the highest level of SWB. The opposite applies to unmarried people. A clear exception is represented by the worst health condition. Starting from a very high incidence of the SWB = 0 condition even in the absence of EP (about 14%), the estimated variations are smaller is percentage values but dramatic in absolute terms (nearly 32% when the highest level of MEPI with a significant coefficient is considered). By contrast, this switch towards the left tail of the distribution of SWB yields very high percentage variations even at the median level of life satisfaction.

Figure 7 about here.

We additionally exploit the graphical representation of the APEs to illustrate - Figure A2 in the Appendix - an additional category of robustness checks, related to the effects of the omission of the subjective *ed* from the analysis and considering a lower number of *eds*. Four additional specifications of the MEPI have been used. For the comparison with the results arising from Model (1) included in the top panel of Figure 6, we first consider an EP index with four equally weighted *eds* obtained by excluding the subjective deprivation *ed5* ($MEPI_{obj}$, reported in the top panel of Figure A2). As it can be seen, the variations in the predicted probabilities are clearly smaller (e.g. the maximum variation at SWB = 0 moves from 0.047 to 0.034, i.e. 38% lower; at the median level, the same difference reaches 52%; 17% at SWB = 10). This difference cannot be ascribed to having 4 *eds* instead of 5. In fact, higher APEs are found (and very similar to those arising from the baseline MEPI with five *eds*), when considering a four *eds* structure of the MEPI ($MEPI4$) that excludes another objective indicator ($ed4$). The same applies to the predicted probabilities related to the third and fourth index considered, labeled by $MEPI4_{ned5}$ and $MEPI4_{ned2}$, which exclude *ed4* and assign, respectively, 50% of the weight to *ed5* and *ed2*. This confirms the importance of the subjective *ed* and the fact that the size of the estimated effects obtained in the main models are not driven by the adoption of alternative nested structures.

As a final input, especially to have a "touchstone" for the discussion of the policy implications of our analysis, in Table 5 we have reported the APEs (in absolute terms and as percentage variations) arising from the two baseline specifications of the individual MEPI and those related to a few covariates that are commonly expected to affect life satisfaction. For sake of simplicity, a change from no EP to an intermediate intensity level is considered. In addition to the usual big percentage variations at the extremes of the SWB distribution, we can appraise that the impact of EP is broadly comparable to that of being unemployed can be seen and much stronger than that associated with the condition of being richer than the reference group. As expected, the partial effects of having very bad health are the strongest.

Overall, our results are in line with previous work on EP and SWB (e.g., Welsch and Biermann (2017)). Nonetheless, exploiting a multidimensional measure of EP instead of energy prices to proxy energy affordability seems to provide a complementary framework for investigating the effect and the size of EP intensity on SWB.

Table 5 about here.

6 Concluding remarks

This work has shown that multidimensional EP indices can be fruitfully used to subsume objective and subjective energy deprivation indicators used previously in economic analyses. Measuring the extent to which EP impacts households or individuals may help policymakers identifying the energy poor and developing strategies to improve social welfare.

When assessing the EP in a multidimensional deprivation framework, its incidence on the population is usually higher than when evaluated in a mere affordability framework. Moreover, the degree of overlapping with affordability indicators is generally low. Including in the analysis a "subjective" indicator such as "cannot afford to keep home adequately warm" may increase the number of people classified as energy poor by nearly 50%. As a "rule-of-thumb", a threshold for EP identification set at an intermediate level between the intersection and union rules seems to represent a satisfactory indicator for the identification of most of people suffering energy deprivation.

Our MEPI has been subsequently exploited to model the welfare losses due to EP in an SWB framework. The analysis detected relevant negative effects of EP on life satisfaction that appear robust to changes in the sample considered and the way single deprivations are included in the MEPI. Even an intermediate intensity of EP is found to cause changes in the probability of being in a given level of stated life satisfaction comparable to those associated with the unemployment status. Not accounting for the subjective dimension substantially reduces the estimated impact of EP on life satisfaction.

Concerning the implementation of policies supporting energy poor people, the aforementioned findings first point to the importance of the method adopted to identify energy poor households to avoid the exclusion of an important share of vulnerable individuals not detected by affordability measures. Considering indicators pointing to the energy efficiency is a first necessary step. Then, disclosure of information on perceived thermal discomfort would be important, especially when dealing with developed countries, in which the basic material needs are usually ensured. It is an open question whether collecting information on buildings' energy efficiency and individuals' subjective evaluation would represent a manageable task for public bodies (compared to the collection of information on energy bills) in terms of monetary costs and privacy issues.

While recognizing that the use of an SWB approach may represent an important tool for detecting social and economic hardship and avoiding the exclusion of frail individuals, some caveats might be cast on a plain reliance on mere subjective welfare indicators. The fact that inclusion in the MEPI of subjective energy deprivation largely increases the incidence of EP and its estimated impact on SWB also means that "objective" deprivation indicators are generally detecting some aspects that the individuals may not perceive as a real problem but that, nonetheless, could legitimate public policies promoting responsible behavior both in terms of energy consumption and care of dwellings.

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Tables

Table 1: *Energy Deprivation Questions and their Incidence*

Variable acronym	Question	Mean
ed1	Has the household been in arrears due to financial difficulties for utility bills for the main dwelling?	0.09
ed2	Has the dwelling any problems with the damp on walls, floors, ceilings or foundations?	0.18
ed3	Has the dwelling any problem with damaged roof, ceilings, doors, windows or floors?	0.11
ed4	Absence of any heating expenditure.	0.05
ed5	Can your household afford to keep its home adequately warm?	0.16

The variables can be found in the dataset as hs021, umid, tetti, hh050, except for the ed4, which is recovered from the energy-specific expenditure analysis. The 'Mean' column refers to the incidence of each deprivation in the sample. ITSILC data referring to 2013. Sample size: 23,193.

Table 2: *Multidimensional Energy Poverty: Summary Statistics and Overlapping Degree between Affordability Measures*

		Average Intensity			
		Equal weights		Nested Weights	
		Overall MEPI	0.0754	Overall MEPI_n	0.1013
		MEPI among poor	0.4867	MEPI_n among poor	0.6020
Overlapping of affordability measures across MEPI levels (%)					
Scenario		Energy Poor		Non-Energy Poor	
$MEPI$		$10\%Rule$	$10\%Rule_{modified}$	$10\%Rule$	$10\%Rule_{modified}$
Level 0	84.50	77.33	72.59	85.09	84.96
Level 1	10.23	13.58	14.82	9.96	10.05
Level 2	3.94	7.25	9.76	3.67	3.72
Level 3	1.21	1.84	2.82	1.16	1.15
Level 4	0.12	0	0	0.13	0.13
$MEPI_n$					
Level 0	83.16	74.05	66.00	83.90	83.82
Level 1	1.01	1.55	2.00	0.97	0.98
Level 2	6.69	9.78	12.24	6.44	6.48
Level 3	4.92	7.08	9.18	4.74	4.75
Level 4	2.93	5.70	7.76	2.70	2.74
Level 5	1.17	1.84	2.82	1.11	1.11
Level 6	0.12	0	0	0.13	0.13

The 10% rule considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. The $10\%Rule_{modified}$ is a dual threshold affordability measure, which considers an individual as energy poor if at least one condition holds between the electricity consumption equal or greater than the 10% of household disposable income and the fuel consumption equal or greater than the 5% of household disposable income. $MEPI$ refers to the intensity measure of EP with equal weights. $MEPI_n$ refers to the intensity measure of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. ITSILC data referring to 2013; Sample size:23,193.

Table 3: *Respondents Related Characteristics: Summary Statistics*

Variable	Label	Mean	Std. Dev.
Equivalised Income	equivalised household income	19,444	14,701
Richer than reference group	1 if richer than reference group	0.41	
MMDI	multidimensional index of material deprivation	0.14	
Male	1 if male	0.46	
Age	age at the date of the interview	54.73	16.49
Employee	1 if employed	0.32	
Unemployed	1 if unemployed	0.07	
Self-employed	1 if self-employed - full and part time	0.11	
Retired	1 if retired	0.29	
Pre-Primary	1 if ISCED level = 0	0.03	
Primary	1 if ISCED level = 1	0.19	
Low-secondary	1 if ISCED level = 2	0.26	
Upper-secondary	1 if ISCED level = 3	0.36	
Post-secondary	1 if ISCED level = 4	0.03	
First-tertiary	1 if ISCED level = 5	0.13	
Married	1 if married	0.61	
Separated	1 if separated	0.04	
Divorced	1 if divorced	0.03	
Never married	1 if never married	0.20	
Widowed	1 if widowed	0.12	
Children	1 if they have children	0.23	
Self-assessed health1	very good health	0.10	
Self-assessed health2	good	0.53	
Self-assessed health3	fair	0.25	
Self-assessed health4	poor	0.10	
Self-assessed health5	very bad health	0.02	
Owner	1 if dwelling owner	0.78	
Detached	1 if living in detached house	0.22	
Semi-detached	1 if living in a semi detached house	0.29	
Flat-less10	1 if living in a building with less than 10 flat	0.23	
Flat-more10	1 if living in a building with more than 10 flat	0.26	
N. of rooms	number of rooms available to the household	3.41	1.10
No-urban area	1 if living in a no urban area	0.62	
Proxy for dwelling quality	paid or imputed rent (in Euros)	551	286
Dwelling's construction 2013-2010	1 if constructed between 2013 and 2010	0.00	
Dwelling's construction 2000-2009	1 if constructed between 2000 and 2009	0.09	
Dwelling's construction 1990-1999	1 if constructed between 1990 and 1999	0.10	
Dwelling's construction 1980-1989	1 if constructed between 1980 and 1989	0.14	
Dwelling's construction 1970-1979	1 if constructed between 1970 and1979	0.19	
Dwelling's construction 1960-1969	1 if constructed between 1960 and 1969	0.18	
Dwelling's construction 1950-1959	1 if constructed between 1950 and 1959	0.11	
Dwelling's construction 1900-1949	1 if constructed between 1900 and 1949	0.12	
Dwelling's construction before 1900	1 if constructed between before 1900	0.07	

ITSILC data referring to 2013; Sample size: 23,193.

Table 4: *Main Estimation Results*

	(1)		(2)		(3)	
	$MEPI$ equation	SWB equation	$MEPI_n$ equation	SWB equation	$10\%Rule$ equation	SWB equation
	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
MEPI Level2		-0.240 (0.039)***		-0.288 (0.079)***		
MEPI Level3		-0.391 (0.055)***		-0.236 (0.039)***		
MEPI Level4		-0.668 (0.081)***		-0.294 (0.047)***		
MEPI Level5		-0.214 (0.215)		-0.371 (0.058)***		
MEPI Level6				-0.611 (0.083)***		
MEPI Level7				-0.181 (0.203)		
10% Rule						0.056 (0.049)
Log Equivalized Income	-0.057 (0.008)***	0.045 (0.009)***	-0.070 (0.008)***	0.020 (0.012)	-0.517 (0.056)***	-0.449 (0.112)***
Richer than reference group	-0.217 (0.024)***	0.058 (0.019)***	-0.272 (0.024)***	-0.027 (0.035)	-0.763 (0.059)***	-0.669 (0.146)***
MMDI	1.874 (0.110)***	-0.907 (0.112)***	1.337 (0.103)***	-0.578 (0.195)***	0.493 (0.148)***	-0.090 (0.478)
Male	0.008 (0.023)	-0.046 (0.014)***	-0.003 (0.022)	-0.047 (0.016)***	-0.123 (0.033)***	-0.137 (0.031)***
Age	0.008 (0.005)*	-0.027 (0.003)***	0.008 (0.004)*	-0.023 (0.004)***	0.007 (0.007)	-0.007 (0.012)
Age2	-0.021 (0.004)***	0.025 (0.003)***	-0.019 (0.004)***	0.019 (0.004)***	0.001 (0.006)	0.014 (0.011)
Unemployed	0.181 (0.037)***	-0.377 (0.032)***	0.241 (0.036)***	-0.279 (0.050)***	0.228 (0.062)***	0.021 (0.180)
Self-employed	-0.068 (0.037)*	-0.079 (0.023)***	-0.107 (0.039)***	-0.109 (0.026)***	0.305 (0.049)***	0.251 (0.081)***
Retired	-0.026 (0.033)	0.014 (0.022)	-0.033 (0.032)	0.001 (0.024)	0.078 (0.042)*	0.081 (0.040)**
Pre-Primary	0.509 (0.074)***	-0.177 (0.060)***	0.682 (0.073)***	0.046 (0.096)	0.330 (0.114)***	0.192 (0.169)
Primary	0.449 (0.050)***	-0.125 (0.037)***	0.643 (0.052)***	0.084 (0.079)	0.343 (0.074)***	0.231 (0.130)*
Low-Secondary	0.349 (0.043)***	-0.135 (0.028)***	0.511 (0.045)***	0.033 (0.063)	0.183 (0.067)***	0.087 (0.105)
Upper-Secondary	0.140 (0.041)***	-0.082 (0.021)***	0.271 (0.044)***	0.012 (0.038)	0.143 (0.062)**	0.089 (0.077)
Post-Secondary	0.154 (0.072)**	0.032 (0.040)	0.179 (0.078)	0.082 (0.049)*	0.253 (0.099)**	0.243 (0.099)**
Married	-0.055 (0.033)*	0.191 (0.022)***	-0.070 (0.033)**	0.156 (0.029)***	-0.277 (0.050)***	-0.166 (0.119)
Separeted	0.025 (0.057)	-0.153 (0.040)***	0.097 (0.055)*	-0.108 (0.045)**	0.103 (0.088)	0.024 (0.107)
Divorced	0.068 (0.064)	-0.084 (0.043)**	0.182 (0.061)***	-0.015 (0.048)	0.166 (0.081)**	0.108 (0.093)
Widowed	0.054 (0.047)	-0.055 (0.032)*	0.051 (0.046)	-0.039 (0.034)	0.184 (0.061)***	0.140 (0.074)*
Children	0.012 (0.030)	0.149 (0.019)***	-0.089 (0.030)	0.099 (0.026)***	-0.134 (0.046)***	-0.057 (0.082)
Good Health	0.113 (0.039)***	-0.216 (0.026)***	0.185 (0.040)***	-0.141 (0.039)***	-0.072 (0.063)	-0.174 (0.092)*
Fair Health	0.432 (0.044)***	-0.483 (0.037)***	0.470 (0.044)***	-0.321 (0.076)***	-0.093 (0.068)	-0.339 (0.186)*
Poor	0.646 (0.051)***	-0.808 (0.051)***	0.633 (0.051)***	-0.592 (0.107)***	0.016 (0.075)	-0.406 (0.319)
Very Bad Health	0.889 (0.071)***	-1.102 (0.078)***	0.870 (0.070)***	-0.809 (0.149)***	-0.068 (0.109)	-0.642 (0.425)
Dwelling Quality	-0.031 (0.006)***	0.018 (0.003)***	-0.044 (0.007)***	0.004 (0.007)	0.025 (0.007)***	0.033 (0.008)***
Owner	-0.323 (0.025)***	0.066 (0.025)***	-0.332 (0.025)***	-0.031 (0.044)	-0.067 (0.039)*	-0.006 (0.064)
No urban area	0.035 (0.027)	0.082 (0.017)***	0.050 (0.026)*	0.091 (0.018)***	0.239 (0.039)***	0.254 (0.037)***
N. Rooms	-0.004 (0.011)	0.029 (0.007)***	0.026 (0.011)***	0.040 (0.008)***	0.034 (0.016)**	0.046 (0.016)***
Semi-detached	-0.132 (0.029)***	0.033 (0.020)	-0.121 (0.028)***	-0.000 (0.025)	-0.107 (0.038)***	-0.074 (0.048)
Flat-less10	-0.155 (0.031)***	-0.003 (0.023)	-0.128 (0.030)***	-0.033 (0.027)	-0.299 (0.045)***	-0.266 (0.069)***
Flat-more10	-0.142 (0.035)***	-0.038 (0.024)	-0.143 (0.034)***	-0.074 (0.029)***	-0.559 (0.052)	-0.523 (0.094)***
2010-2013	-0.938 (0.234)***		-0.491 (0.181)***		-0.074 (0.087)	
2000-2009	-0.577 (0.056)***		-0.206 (0.067)***		-0.021 (0.038)	
1990-1999	-0.549 (0.057)***		-0.190 (0.071)***		-0.000 (0.018)	
1980-1989	-0.464 (0.051)***		-0.131 (0.063)**		0.010 (0.015)	
1970-1979	-0.360 (0.047)***		-0.053 (0.053)		0.020 (0.017)	
1960-1969	-0.326 (0.045)***		-0.110 (0.054)**		-0.001 (0.019)	
1950-1959	-0.158 (0.051)***		0.074 (0.052)		0.055 (0.039)	
1900-1949	-0.085 (0.048)*		0.034 (0.055)		0.049 (0.032)	
ρ	0.114***		0.356***		0.891*	
Regional residence	Yes		Yes		Yes	
AIC	110345.147		115349.368		96471.849	
BIC	111118.101		116154.529		97196.494	
Log-Likelihood	-55076.573		-57574.684		-48145.924	
Observation	23193		23193		23193	

*Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the significance level of ρ is referred to a Wald test of independent equations. The 10%rule considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. $MEPI$ refers to the intensity measure of EP with equal weights. $MEPI_n$ refers to the intensity measure of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. MMDI is the multidimensional material deprivation index*

ITSILC data referring to 2013; Sample size: 23,193.

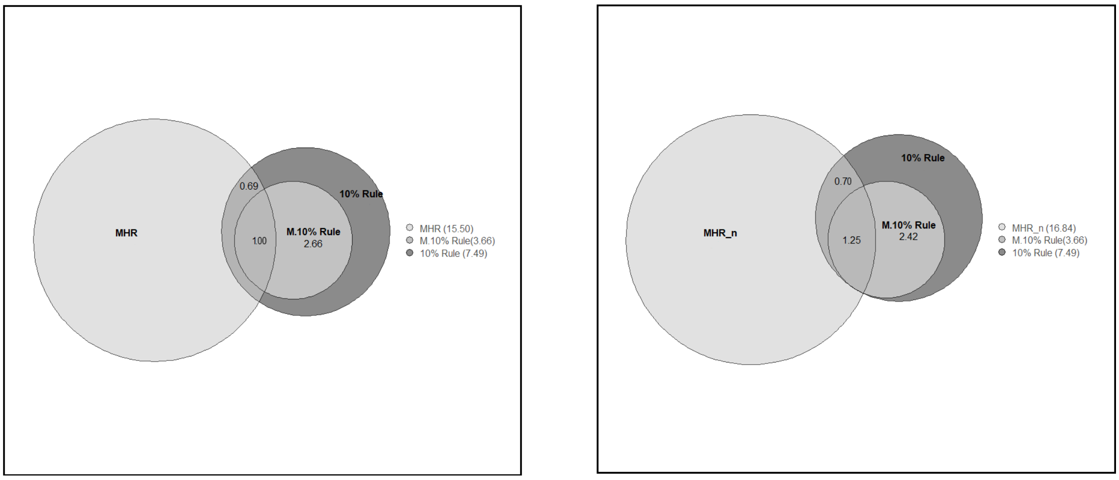
Table 5: *Average Partial Effects of a few SWB determinants: absolute and percentage variations*

	APE			Average Variation in Predicted Probabilities (%)		
	p0	p7	p10	p0	p7	p10
Median Level $MEPI$	0.021	-0.015	-0.039	126.2	-6.4	-52.8
Median Level $MEPI_n$	0.016	-0.010	-0.033	94.7	-4.1	-44.6
Richer	-0.003	0.001	0.010	-15.2	0.2	15.2
Unemployed	0.023	-0.016	-0.038	119.8	-6.8	-53.1
Very bad health	0.134	-0.106	-0.070	703.1	-45.3	-93.0

APE yields the change in the probability that SWB equals 0, 7, and 10 when a covariate changes ceteris paribus. APEs are calculated using the finite difference method. Median Level MEPI reflects a change from the pre-median to the median level of MEPI. Median Level $MEPI_n$ reflects a change from the pre-median to the median level of $MEPI_n$. For the other covariates the switch is from 0 to 1. Richer indicates being richer than reference group; very bad health indicates the lowest level of Self-Assess Health; unemployed indicates the current job situation when in unemployment. The average variation in predicted probabilities reflects the percentage variation in the total probability of belonging to the level 0, 7, and 10 of SWB, with respect to the baseline (before the variable change).
ITSILC data referring to 2013; Sample size: 23,193.

Figures

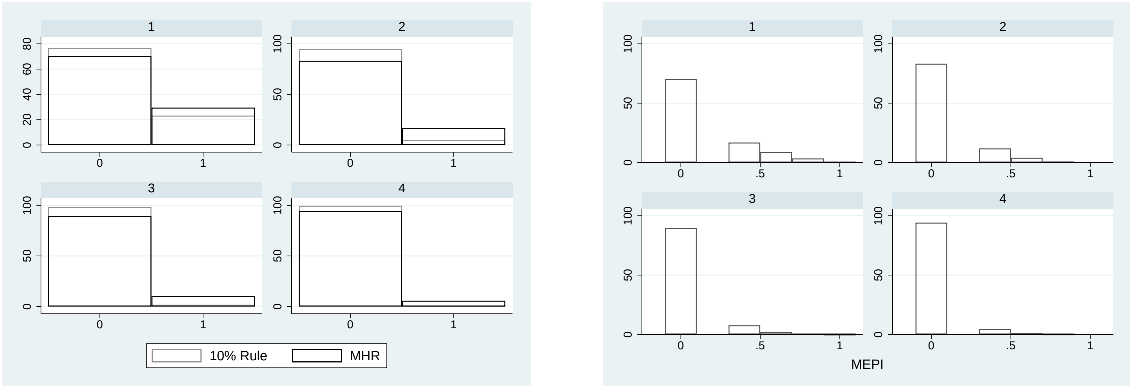
Figure 1: *Overlapping degree between Multidimensional Headcount Ratios and Affordability Measures*



(a) (b)

Graph (a) presents the Euler diagram of MHR, $10\%Rule$ and $M.10\%Rule$, which corresponds to the $10\%Rule_{modified}$. Graph (b) presents the Euler diagram of MHR_n, $10\%Rule$ and $10\%Rule_{modified}$. Figures report the percentages of overlapping areas between the different sets. MHR refers to the multidimensional headcount ratio with equal weights. The $10\%Rule$ considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. The $10\%Rule_{modified}$ is a dual-threshold affordability measure, which considers an individual as poor if at least one condition holds between electricity consumption equal or greater than 10% of household disposable income and the fuel consumption equal or greater than 5% of household disposable income. MHR_n refers to the multidimensional headcount ratio with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations.
ITSILC data referring to 2013; Sample size: 23,193.

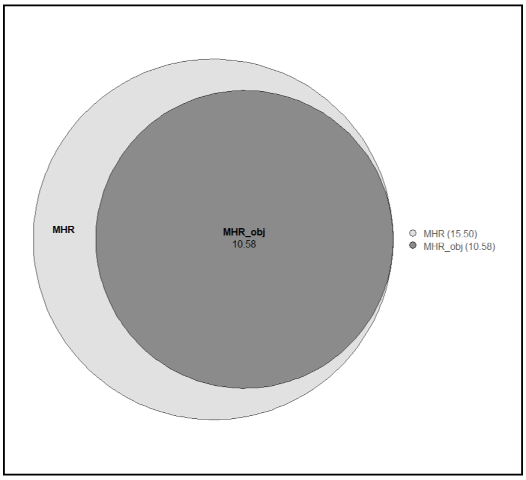
Figure 2: *Percentage distribution of* $10\%Rule$*,* MHR*, and* $MEPI$ *by equivalized income quartiles*



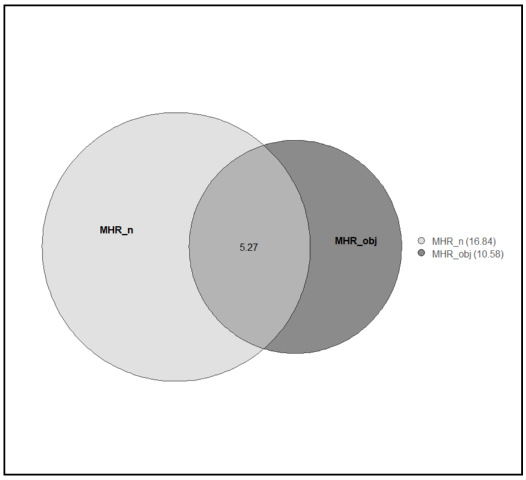
(a) (b)

MHR refers to the multidimensional headcount ratio with equal weights. The $10\%Rule$ considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. $MEPI$ refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations.
ITSILC data referring to 2013; Sample size: 23,193.

Figure 3: *Overlapping degree between Multidimensional Headcount Ratios*



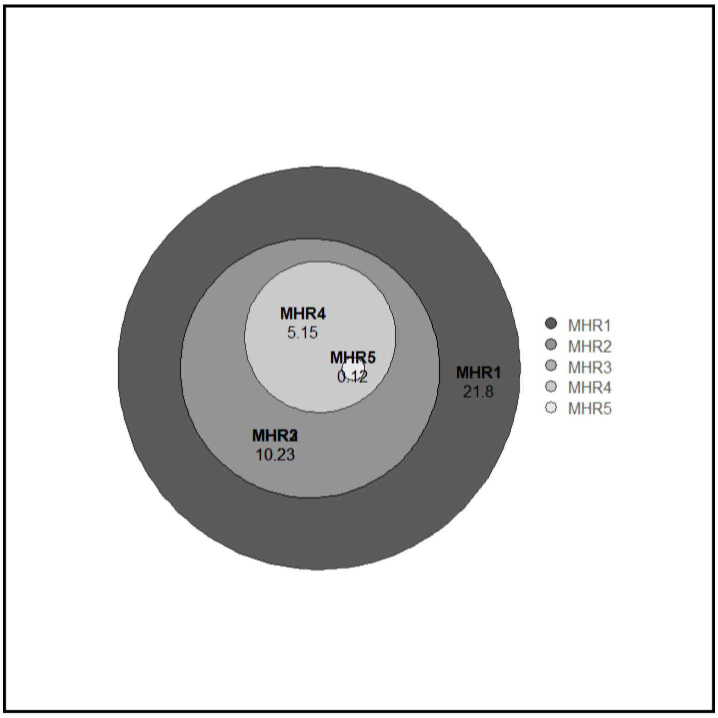
(a)



(b)

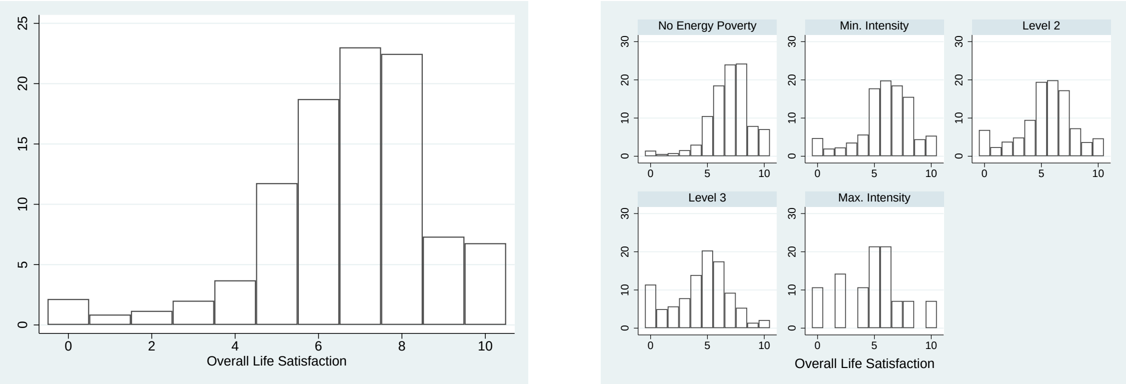
Graph (a) presents the Euler diagram of MHR and MHR_{obj}. Graph (b) presents the Euler diagram of MHR_n and MHR_{obj}. Figures report the percentages of overlapping areas between the different sets. MHR refers to multidimensional headcount ratio of EP with equal weights. MHR_{obj} refers to the multidimensional headcount ratio of EP that excludes the subjective ed, with equal weights. MHR_n refers to the multidimensional headcount ratio of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations.
ITSILC data referring to 2013; Sample size: 23,193.

Figure 4: *Multidimensional Headcount Ratios: different poverty cut-off scenarios*



All MHRs are computed by applying an equal weights scheme. For $MHR1$ the energy poverty cut-off is set to d/d (union rule); for $MHR2$ the energy poverty cut-off is set to d/4; for $MHR3$ the energy poverty cut-off is set to d/3;For $MHR4$ the energy poverty cut-off is set to d/2;For $MHR1$ the energy poverty cut-off is set to d/1 (intersection rule).
ITSILC data referring to 2013; Sample size: 23,193.

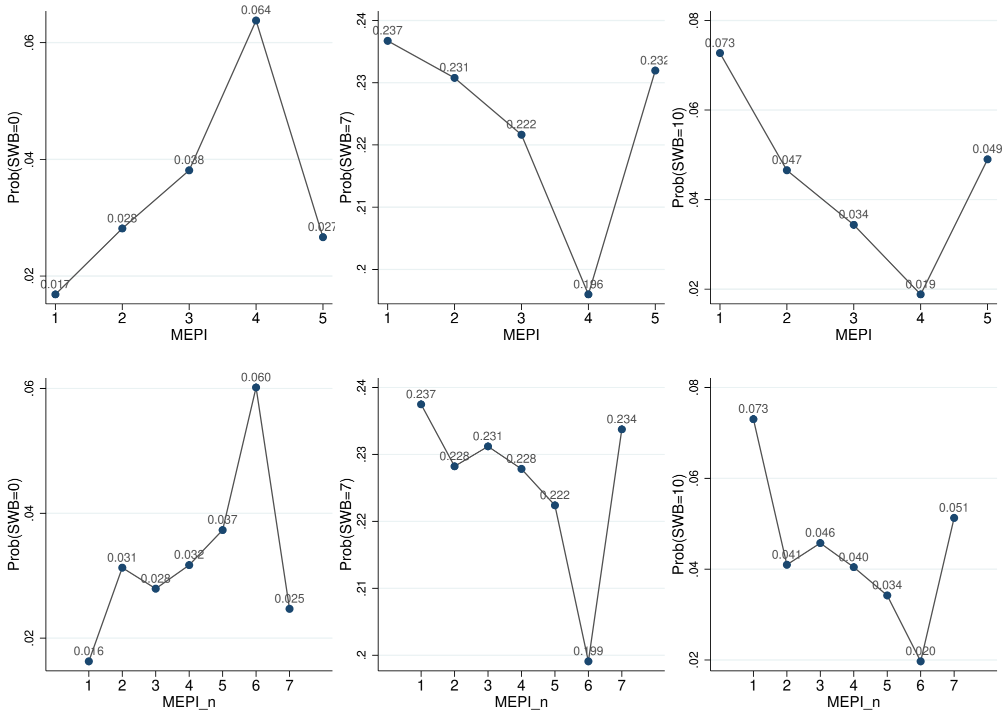
Figure 5: *Percentage distribution of overall life satisfaction.*



(a) (b)

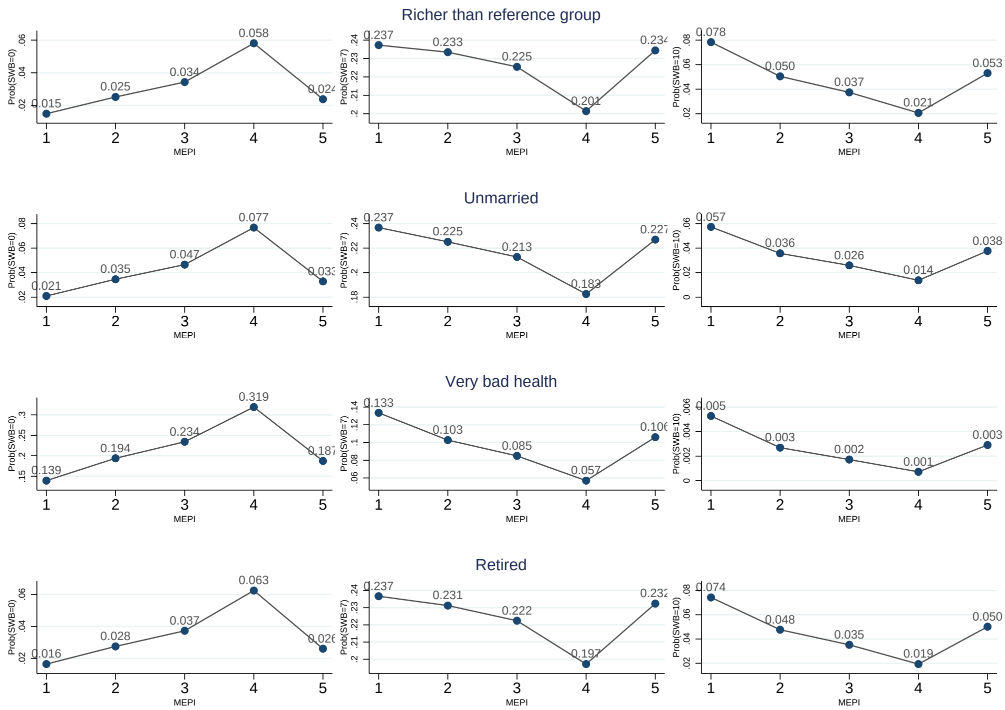
Graph (a) shows the distribution of the overall satisfaction across the whole sample. Graph (b) reports the distribution of the overall individual satisfaction for the different MEPI levels. $MEPI$ refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations.
ITSILC data referring to 2013; Sample size: 23,193.

Figure 6: *Predicted Probabilities of Being Satified 0, 7, and 10 for any level of MEPI and $MEPI_n$*



$MEPI$ refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations. SWB=0 refers to stay at the lowest level of satisfaction; SWB=7 refers to stay at the level of satisfaction of the median individual; SWB=10 refers to stay at the maximum level of satisfaction.
ITSILC data referring to 2013; Sample size: 23,193.

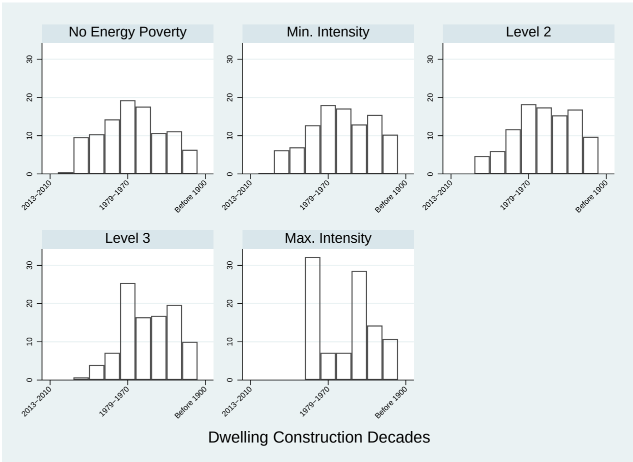
Figure 7: *Predicted Probabilities of Being Satified 0, 7, and 10 for any level of MEPI, at some specific characteristics*



$MEPI$ refers to the intensity measure of EP with equal weights. $MEPI_n$ refers to the intensity measure of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. For each row, the first plot refers to being at lowest level of satisfaction; the second refers to the level of satisfaction of the median individual; the third refers to the maximum level of satisfaction.
ITSILC data referring to 2013; Sample size: 23,193.

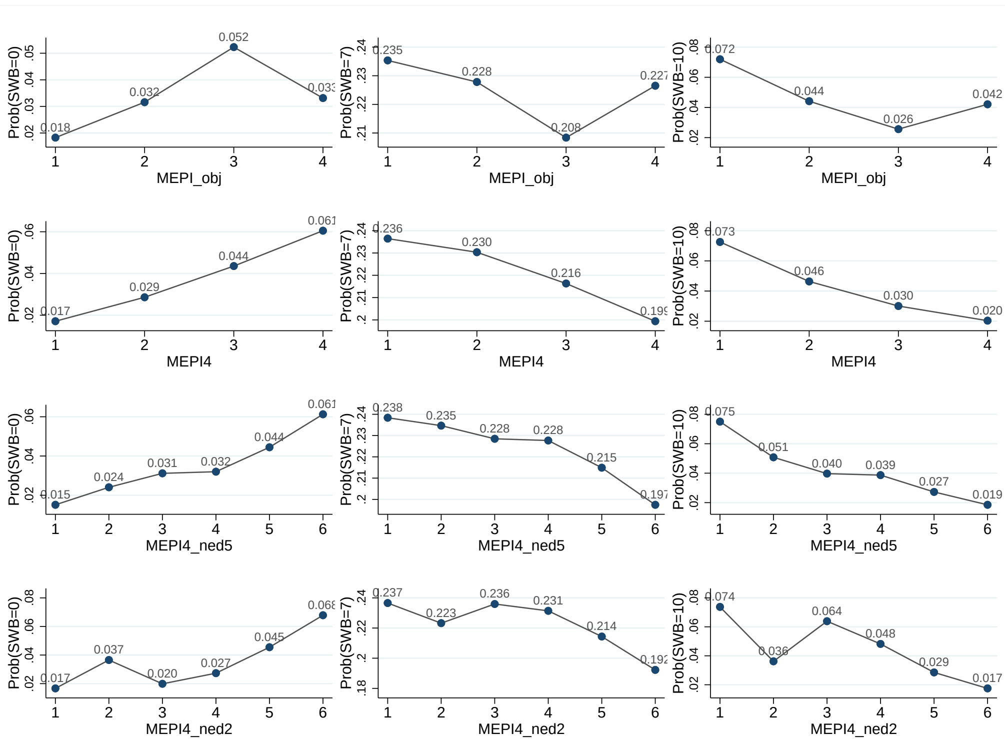
A Appendix

Figure A1: *Percentage distribution of dwelling construction decades among MEPI levels (2013–before 1900)*



ITSILC data referring to 2013; Sample size: 23,193.

Figure A2: *Predicted Probabilities of Being Satified 0, 7, and 10 for any level of MEPIs*



$MEPI_{obj}$ refers to the intensity measure of EP that excludes the subjective ed, with equal weights. $MEPI4$ refers to the intensity measure of EP that excludes the ed4, with equal weights. $MEPI4_{ned5}$ refers to the intensity measure of EP that excludes ed4, with nested weights (half of the weight to the subjective ed, half to the objective eds). $MEPI4_{ned2}$ refers to the intensity measure of EP that excludes ed4, with nested weights (half of the weight to the ed2, half to the other eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. For each row, the first plot refers to being at the lowest level of satisfaction; the second refers to the level of satisfaction of the median individual; the third refers to the maximum level of satisfaction.
ITSILC data referring to 2013; Sample size: 23,193.

Table A1: *Multidimensional Headcount Ratios and Affordability Measures: additional information*

	Energy Poor				Non-Energy Poor			
	MHR	MHR_n	$10\%Rule$	$10\%Rule_{modified}$	MHR	MHR_n	$10\%Rule$	$10\%Rule_{modified}$
	Overlapping Degree with Income Poverty (%)							
Income								
Poor	31.23	36.71	27.17	17.54	68.77	63.29	72.83	82.46
Non-Poor	11.98	12.40	3.10	0.56	88.02	87.60	96.90	99.44
	Distribution across urban and rural areas (%)							
Urbanization								
Urban	13.15	13.42	5.07	2.65	86.85	86.58	94.93	97.35
Rural	16.98	19.00	9.02	4.31	83.02	81.00	90.08	95.69

MHR refers to the multidimensional headcount ratio with equal weights. MHR_n refers to the multidimensional headcount ratio with nested weights (half of the weight to the subjective ed, half to the objective eds). The energy poverty cut-off is set to d/3, where d is the number of the deprivations. The $10\%Rule$ considers an individual as energy poor if energy consumption equals or exceeds the 10% of household disposable income. The $10\%Rule_{modified}$ is a dual-threshold affordability measure, which considers an individual as energy poor if at least one condition holds between the electricity consumption equal or greater than 10% of household disposable income and the fuel consumption equal or greater than the 5% of household disposable income. The income poverty cut-off is set as the 60% of the median equivalised household income. Urban and Rural are defined on the base of the variable db100 of the survey, which indicates the degree of urbanization of the individuals' residence.
ITSILC data referring to 2013; Sample size:23,193.

Table A2: *Estimation Results: Robustness checks (I)*

	(1)		(2)		(3)	
	$10\%Rule_{modified}$ equation	SWB equation	$MEPI$ equation	SWB equation	$10\%Rule$ equation	SWB equation
	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
$10\%Rule_{modified}$		0.152 (0.092)*				
MEPI Level2				-0.256 (0.040)***		
MEPI Level3				-0.370 (0.056)***		
MEPI Level4				-0.627 (0.084)***		
MEPI Level5				-0.185 (0.232)		
10% Rule						0.057 (0.045)
Log Equivalized Income	-0.480 (0.050)***	-0.333 (0.154)**	-0.054 (0.008)***	0.038 (0.009)***	-0.492 (0.054)***	-0.390 (0.111)***
Richer than reference group	-0.906 (0.089)***	-0.674 (0.262)**	-0.217 (0.025)***	0.033 (0.020)	-0.769 (0.060)***	-0.619 (0.155)***
MMDI	0.437 (0.198)**	-0.470 (0.495)	1.904 (0.115)***	-0.659 (0.125)***	0.556 (0.155)***	-0.194 (0.417)
Male	-0.139 (0.043)***	-0.146 (0.042)***	0.002 (0.024)	-0.048 (0.015)***	-0.118 (0.035)***	-0.132 (0.032)***
Age	0.001 (0.009)	-0.019 (0.012)	0.007 (0.005)	-0.026 (0.003)***	0.005 (0.007)	-0.012 (0.010)
Age2	-0.001 (0.008)	0.019 (0.011)*	-0.020 (0.005)***	0.023 (0.003)***	0.002 (0.007)	0.019 (0.009)**
Unemployed	0.258 (0.071)***	-0.079 (0.205)	0.188 (0.038)***	-0.349 (0.034)***	0.232 (0.064)***	-0.037 (0.159)
Self-employed	0.373 (0.058)***	0.251 (0.126)**	-0.067 (0.039)*	-0.096 (0.024)***	0.321 (0.051***)	0.232 (0.087)***
Retired	-0.029 (0.057)	-0.012 (0.050)	-0.022 (0.035)	0.002 (0.023)	0.086 (0.044)*	0.078 (0.042)*
Pre-Primary	0.241 (0.165)	0.027 (0.192)	0.543 (0.078)***	-0.105 (0.065)	0.354 (0.119) ***	0.163 (0.164)
Primary	0.272 (0.099)***	0.093 (0.149)	0.456 (0.053)***	-0.082 (0.040)**	0.369 (0.078)***	0.204 (0.131)
Low-Secondary	0.192 (0.086)**	0.033 (0.122)	0.352 (0.045)***	-0.102 (0.031)***	0.207 (0.070)***	0.068 (0.103)
Upper-Secondary	0.170 (0.081)**	0.072 (0.096)	0.135 (0.043)***	-0.074 (0.023)***	0.146 (0.065)**	0.066 (0.076)
Post-Secondary	0.237 (0.129)*	0.204* (0.119)	0.140 (0.077)*	0.046 (0.044)	0.223 (0.106)**	0.203 (0.102)**
Married	-0.125 (0.065)*	0.036 (0.114)	-0.044 (0.035)	0.187 (0.023)***	-0.273 (0.053)***	-0.120 (0.113)
Separeted	0.279 (0.104)***	0.115 (0.146)	0.019 (0.059)	-0.132 (0.042)***	0.099 (0.094)	0.007 (0.100)
Divorced	0.190 (0.103)*	0.084 (0.114)	0.090 (0.068)	-0.071 (0.046)	0.191 (0.086)**	0.110 (0.094)
Widowed	0.299 (0.081)***	0.195 (0.113)*	0.038 (0.050)	-0.062 (0.034)*	0.183 (0.066)***	0.116 (0.075)
Children	-0.109 (0.057)*	0.013 (0.090)	0.008 (0.031)	0.144 (0.020)***	-0.100 (0.048)**	-0.004 (0.071)
Good Health	0.028 (0.081)	-0.139 (0.107)	0.098 (0.041)**	-0.193 (0.027)***	-0.083 (0.065)	-0.202 (0.076)***
Fair Health	0.047 (0.087)	-0.342* (0.201)	0.407 (0.046)***	-0.427(0.041)***	-0.117 (0.071)*	-0.416 (0.145)***
Poor	0.086 (0.098)	-0.562* (0.322)	0.608 (0.053)***	-0.714 (0.056)***	0.018 (0.078)	-0.502 (0.256)**
Very Bad Health	0.095 (0.140)	-0.793* (0.439)	0.850 (0.074)***	-1.008 (0.085)***	-0.046 (0.114)	-0.771 (0.350)**
Dwelling Quality	0.040 (0.009)***	0.047 (0.008)***	-0.029 (0.007)***	0.015 (0.004)***	0.018 (0.007)**	0.028 (0.008)***
Owner	-0.099 (0.049)**	0.005 (0.079)	-0.320 (0.026)***	0.036 (0.026)	-0.071 (0.041)*	0.014 (0.061)
No urban area	0.241 (0.052)***	0.242 (0.056)***	0.028 (0.028)	0.067 (0.018)***	0.228 (0.040)***	0.233 (0.040)***
N. Rooms	-0.001 (0.022)	0.020 (0.021)	-0.007 (0.011)	0.026 (0.008)***	0.040 (0.017)**	0.052 (0.015)***
Semi-detached	-0.031 (0.052)	0.013 (0.049)	-0.143 (0.031)***	0.018 (0.022)	-0.119 (0.040)***	-0.070 (0.050)
Flat-less10	-0.184 (0.060)***	-0.132 (0.078)*	-0.152 (0.032)***	-0.013 (0.024)	-0.313 (0.047)***	-0.253 (0.075)***
Flat-more10	-0.315 (0.066)***	-0.261 (0.099)***	-0.148 (0.036)***	-0.053 (0.025)**	-0.560 (0.054)***	-0.492 (0.105)***
2010-2013	-0.144 (0.159)		-0.841 (0.210)***		-0.167 (0.114)	
2000-2009	-0.042 (0.064)		-0.489 (0.048)***		-0.094 (0.062)	
1990-1999	0.002 (0.029)		-0.455 (0.048)***		-0.063 (0.033)*	
1980-1989	0.015 (0.026)		-0.371 (0.041)***		-0.051 (0.028)*	
1970-1979	0.031 (0.025)		-0.270 (0.036)***		-0.037 (0.021)*	
1960-1969	-0.001 (0.031)		-0.248 (0.036)***		-0.065 (0.040)*	
1950-1959	0.088 (0.046) *		-0.067 (0.038)*		0.010 (0.020)	
1900-1949	0.089 (0.055)					
ρ	0.733		0.224***		0.822**	
Regional residence	Yes		Yes		Yes	
AIC	92513.653		102003.130		89375.364	
BIC	93238.297		102761.206		90085.562	
Log-Likelihood	-46166.826		-50906.565		-44598.682	
Observation	23193		21585		21585	

*Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the significance level of ρ refers to a Wald test of independent equations. The 10% rule considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. The $10\%Rule_{modified}$ is a dual-threshold affordability measure, which considers an individual as poor if at least one condition holds between electricity consumption equal or greater than 10% of household disposable income and the fuel consumption equal or greater than 5% of household disposable income. MEPI refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations. MMDI is the multidimensional material deprivation index. ITSILC data referring to 2013; Sample size: 23,193.*