A multidimensional poverty index based on the AROPE index.

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Abstract

Social exclusion prevents certain groups and individuals from fully participating in the economic, social, cultural, and political life of their communities. This exclusion can stem from various factors, including poverty, lack of education, discrimination, unemployment, limited access to basic services, and a lack of opportunities. To address this issue, governments and organizations implement policies and programs aimed at reducing poverty and improving household well-being. Measuring household poverty is crucial for designing and evaluating effective policies. This paper introduces a multidimensional poverty family index based on the AROPE index, which considers income, material deprivation, energy access, and employment status. Then, a household is classified as poor if it experiences deprivation in any of these four dimensions. Additionally, the framework allows for decomposition into these four sources of poverty, enabling more targeted policy interventions. Finally, we apply this measure to European countries to analyze the changes of multidimensional poverty in 2018, 2020, and 2022.

Keywords: Income Poverty, Material deprivation, Energy Poverty, Low Job.

1 Introduction

Poverty is a complex and persistent global challenge that hinders progress toward sustainable development. The Sustainable Development Goals (SDGs), adopted by all United Nations Member States in 2015 as part of the 2030 Agenda for Sustainable Development, recognize poverty eradication as a fundamental objective. The SDGs provide a comprehensive framework for tackling poverty in all its dimensions while promoting economic growth, social inclusion, and environmental sustainability.

Reducing poverty and implementing effective anti-poverty policies are essential components of social and economic development strategies worldwide. Poverty, defined by a lack of access to basic necessities such as food, employment, and even leisure, remains a major issue affecting millions globally. Addressing poverty not only improves individual well-being but also strengthens societal stability and fosters economic growth.

Household well-being and poverty are closely interconnected, with high poverty levels posing significant barriers to achieving a good quality of life. Governments and organizations implement policies and programs aimed at reducing poverty and enhancing household well-being, with the goal of improving living standards and providing opportunities for personal and economic development. Measuring and monitoring household well-being and poverty are crucial for designing and evaluating these policies effectively.

This paper aims to develop a multidimensional poverty index that assesses individuals' comfort levels based on four key factors: income level, material deprivation, energy poverty, and low household work intensity. The index specifically builds upon the AROPE index (At Risk of Poverty or Social Exclusion), which is a widely used measure in the European Union (EU) that evaluates economic and social vulnerability. The AROPE index is based on three main indicators: income poverty or social exclusion risk, severe material deprivation, and low work intensity. Some papers on this issue are Benítez et al. (2023) and Díaz et al. (2021).

By identifying those facing significant economic and social challenges, the AROPE index provides a valuable tool for assessing well-being. A higher AROPE index in a region or country indicates greater vulnerability and lower overall well-being. Consequently, governments and organizations often rely on this index to design public policies that combat poverty and social exclusion, increase access to quality employment, and improve living conditions for at-risk populations.

As mentioned, the multidimensional poverty measure proposed in this paper considers four dimensions: income poverty, material deprivation, energy poverty, and low employment. Notably, the variables used for this measure are the same as those in the AROPE index but combined differently.

The first key difference is that our framework is divided into four dimensions instead of three. This paper highlights the importance of energy poverty, which should be analyzed separately due to the growing body of research on the topic. Energy poverty significantly impacts people's quality of life, affecting their health, well-being, and ability to participate fully in society. Moreover, addressing energy poverty is essential for tackling climate change, as affected households often rely on polluting and inefficient energy sources. Given these factors, this paper argues that energy poverty should be treated as an additional dimension in multidimensional poverty analysis.

The second difference is that the presented measure goes beyond simply identifying the number of deprived individuals; it also assesses the intensity of multidimensional poverty and inequality among an affected population. To achieve this, we build on the unidimensional poverty index proposed by Bennett and Hatzimasoura (2011) and generalized by Yalonetzky (2012) for measuring poverty in ordinal variables. First, the unidimensional poverty is defined for each of the four dimensions; income, material, energy, and employment. Finally, these dimensions are aggregated into a comprehensive multidimensional poverty measure, following the framework of Bourguignon and Chakravarty (2003), as further characterized by Lasso de la Vega et al. (2011).

To measure income poverty, the Eurostat definition is followed, using household equivalent income, calculated as total household disposable income divided by the number of equivalent individuals, according to the modified OECD equivalence scale. This scale assigns a weight of 1 to the first adult, 0.5 to each additional adult (aged over 13), and 0.3 to children aged 13 and under.

Since the poverty indicator is designed for ordinal variables, income is categorized into seven groups based on the income gap, calculated using 60% of the median equivalent income as the poverty line. The greater the number of defined groups, the more closely the results approximate those obtained from a continuous measure. Individuals are considered at risk of income poverty if their household's equivalent income falls below this threshold. Based on their assigned group, each individual is given a corresponding intensity or gap value. Although the use of a continuous variable would provide more precise unidimensional results, this approach allows for a unified method of measuring multidimensional poverty across various types of variables as continuous, ordinal, and counting variables.

For severe material and social deprivation, the revised AROPE indicator proposed by Guio et al. (2016, 2017) and Guio & Marlier (2017) is adopted, which includes seven household-level and six personal-level items. This approach utilizes 11 of the original 13 items, along with a portion of another. The item "ability to keep the home adequately warm" is excluded from this dimension and instead classified under energy poverty. Furthermore, the variable "capacity to bear payment arrears (on mortgage or rental payments, utility bills, hire-purchase installments, or other loan payments)" is divided into two separate variables, increasing the total number of items in this dimension to 12, while the remaining two are allocated to the energy poverty dimension. Individuals are considered to be in severe material deprivation if they are deprived of six or more of these items.

For the measurement of energy poverty, the analysis focuses on subjective indicators commonly used in this domain. The first variable, "ability to keep the home adequately warm," was previously excluded from the material deprivation dimension. The second variable, "arrears on utility bills (electricity, water, gas)," was separated from the original AROPE material deprivation indicator.

Individuals are then classified into three categories based on their reported deficiencies: those with no deficiencies, those with one deficiency, and those with two deficiencies.

The fourth dimension, very low work intensity, follows the AROPE definition. Individuals in households where working-age members collectively work less than 20% of their potential working time are classified as having very low work intensity.

Then these four dimensions are aggregated into a multidimensional poverty index based on the Bourguignon and Chakravarty (2003) framework. Under this measure, a household experiencing deprivation in any of the four aspects is considered multidimensionally poor, with a fuzzy poverty value between 0 and 1. This measure enables the assessment of the individual multidimensional gap, offering insights into the intensity of multidimensional poverty and facilitating more nuanced analyses that account for inequality among the poor.

Furthermore, a key feature of this index family is its decomposability by dimension, which allows for the identification of the relative contribution of each of the four aspects—income, material, energy, and employment—to overall multidimensional poverty. This property supports the design of targeted policy interventions for households affected by one or more essential dimensions of poverty.

The paper is structured as follows: Sections 1 and 2 provide the introduction and literature review, respectively. Section 3 outlines the methodology, while Section 4 presents results using the proposed measure across different European countries. Section 5 identifies the most vulnerable groups, and Section 6 concludes with policy implications.

2 Literature review

To effectively analyze social exclusion, it is essential to understand its sources and scope. Sen (1976) identified two key aspects of poverty measurement: identifying the poor and aggregating their characteristics into a comprehensive indicator. Traditionally, poverty has been determined by setting an income or expenditure threshold, and classifying individuals as poor if their income falls below this level. Early poverty measures included the percentage of poor individuals and the average income gap among them. However, Sen (1976) criticized these approaches for failing to account for income redistribution among the poor, thereby overlooking inequality within this group. He proposed a more sophisticated, axiomatic poverty index, which was later expanded by researchers such as Foster (1983), Foster et al. (1984), and Zheng (1997).

However, well-being, and by extension, poverty, cannot be assessed solely through monetary variables. Defining income as the only indicator of individual well-being is inadequate and must be supplemented with other measures, such as access to energy, car and computer ownership, or the ability to afford annual vacations. Recognizing this, Atkinson (2003) pioneered the multidimensional approach to deprivation, distinguishing between social well-being and a counting-based method. Measuring poverty requires aggregating deprivations across multiple dimensions, as advocated by Alkire and Foster (2011a, 2011b), Tsui (2002), Bourguignon and Chakravarty (2003), Lasso de la Vega et al. (2011), Bossert et al. (2009), and Bosmans et al. (2018), among others.

Since Boardman's (1991) work, energy poverty has received increasing attention in both academic research and public policy. Access to modern and cleaner energy is widely regarded as a key indicator of social well-being, highlighting the strong link between societal welfare and access to energy services and modern technologies. Numerous definitions of energy poverty, both unidimensional and multidimensional, have been proposed by researchers such as Pachauri et al. (2004), Pachauri and Spreng (2011), Li et al. (2015), Day et al. (2016), Nussbaumer et al. (2012), Sadath and Acharya (2017), Okushima (2017), Bouzarovski and Petrova (2015), and Aristondo and Onaindia (2018).

Similarly, studies on material deprivation have increasingly recognized the limitations of relying solely on income and have shifted focus toward non-monetary measures of deprivation, as highlighted by Guio (2009) and Nolan and Whelan (2011). The AROPE index (At Risk of Poverty or Social Exclusion) exemplifies this approach, serving as a multidimensional measure that considers material deprivation alongside other factors such as low work intensity. The AROPE rate is the primary indicator for tracking the EU's poverty and social exclusion targets for 2030 and was central to monitoring the Europe 2020 Strategy. Some interesting results for European countries and Spain can be found in Díaz et al. (2021) and Benítez and Tapia (2023), respectively.

In this study, we focus on the AROPE index while differentiating key dimensions of poverty related to income, energy, material deprivation and low job intensity.

3 Methodology

3.1 Unidimensional poverty

In this paper, the methodology proposed by Bennett and Hatzimasoura (2011) is followed to measure poverty for ordinal data. Let define a population consisting of $n \geq 1$ individuals. Suppose that a dimension is divided in S categories $y = (y_1, y_2, ..., y_S)$, with $y_j < y_i$ if and only if the status i is preferred to status j. In fact, the y_1 represents the worst status and y_S the best.

Now q is defined as the number of categories in a deprived situation. Hence, $y_1, y_2, ..., y_q$ are the deprived categories and the rest the non-deprived ones. Then, Bennett and Hatzimasoura (2011) propose the class of ordinal FGT measures as:

$$\pi^{\alpha}(y; q) = \sum_{j=1}^{q} p_j \left(\frac{q - j + 1}{q}\right)^{\alpha} \tag{1}$$

where $p_j = \frac{n_j}{q \cdot n}$ and n_j are the share of population and the population in category y_j, respectively, and $\alpha \geq 0$ is a parameter. Notice that equation (1) can be interpreted as a weighted sum of the probabilities of being poor with weights determined by the number of deprived categories q and α the parameter.

For $\alpha = 0$, the standard poverty Headcount-ratio is found. When $\alpha > 0$, the poverty measure gives more weight to the most affected categories. Analogous to other measures of poverty, the ordinal FGT measures are sensitive to both the incidence and intensity of poverty when $\alpha > 0$.

Additionally, when $\alpha > 1$, the FGT measure is also sensitive to distribution, capturing the differences between the percentages of people in the various deprived categories.

This measure enables the computation of overall poverty across any ordinal dimension. However, the goal is to assign each individual a poverty level based on the category they fall into. The following proposition illustrates how individual poverty levels can be assigned using the ordinal FGT (Foster-Greer-Thorbecke) index.

Let define for each individual the *individual deprivation gap* as follows:

$$g_i(y; q) = \begin{cases} \dfrac{q - j + 1}{q} & i \in y_j, 1 \leq j < q \\ 0 & i \in y_j, q + 1 \leq j \leq s \end{cases} \tag{2}$$

Then, without loss of generality, the vector $g = (g_1, g_2, \dots, g_n)$ is defined ordered in a non-increasing way. Therefore, g is rewritten as follows:

$$g(y;q) = \left(\overbrace{\frac{q}{q}, \dots, \frac{q}{q}}^{n_1}, \overbrace{\frac{q-1}{q}, \dots, \frac{q-1}{q}}^{n_2}, \dots, \overbrace{\frac{2}{q}, \dots, \frac{2}{q}}^{n_{q-1}}, \overbrace{\frac{1}{q}, \dots, \frac{1}{q}}^{n_q}, \overbrace{0, \dots, 0}^{n_{q+1}+\cdots+n_S} \right)$$

(3)

where n_j for $j = 1, \cdots, S$ is the number of individuals in category i.

It should be noted that if there are *q* poor categories, individuals in the lowest (worst) category will be assigned a value of 1, those in the second worst category will be assigned a value of $\frac{q-1}{q}$, and so on, down to the last category of the poor. For individuals in the least affected category among the poor, they will take a value of $\frac{1}{q}$. Finally, individuals not considered poor, will be assigned a value of 0.

The following proposition shows that the class of ordinal FGT indices can be rewritten in terms of the *individual deprivation* gap.

Proposition 1. *The ordinal FGT index can be rewritten as follows*

$$\pi^{\alpha}(y;q) = \frac{1}{n}\sum_{i=1}^{n}(g_i)^{\alpha}$$

(4)

Proof of Proposition 1: Starting with equation (4) and taking into account equation (3) we have the proof.

$$\pi^{\alpha}(y;q) = \frac{1}{n}\sum_{i=1}^{n}(g_i)^{\alpha}$$

$$= \frac{1}{n}\left(n_1 \left(\frac{q}{q}\right)^{\alpha} + n_2 \left(\frac{q-1}{q}\right)^{\alpha} + \cdots + n_{q-1}\left(\frac{2}{q}\right)^{\alpha} + n_q \left(\frac{1}{q}\right)^{\alpha} \right)$$

$$= \sum_{j=1}^{q}\left(\frac{q-j+1}{q}\right)^{\alpha}\frac{n_j}{n}$$

$$= \sum_{j=1}^{q} p_j \left(\frac{q-j+1}{q}\right)^{\alpha} \blacksquare$$

This finding will enable the determination of each individual's deprivation, allowing for an assessment of whether the individual gap is influenced by various household characteristics.

3.1.1 Counting measures as ordinal FGT indices

In this subsection, it will be seen that this family of measures can also be applied to the counting poverty indices proposed by Chakravarty and D'Ambrosio (2006). Counting poverty measures are approaches used to assess poverty by counting the number of deprivations or deficits a person or household experiences across multiple dimensions. When measuring counting poverty we need to follow a dual cut-off approach. The first cut-off identifies whether individuals are poor in each dimension. Subsequently, each individual *i* is assigned a weighted sum of the dimensions in which they are deprived. In this case, the arithmetic mean is used, assigning to each individual a gap c_i that is the percentage of dimensions in which they are deprived. This value is called the individual deprivation count and takes values in $\left\{0, \frac{1}{s}, \frac{2}{s}, \dots, \frac{s-1}{s}, 1\right\}$, ranging from the least affected to the most affected. Then, the distribution of deprivation counts is defined as $c = (c_1, c_2, \cdots, c_n)$, ordered in a non-decreasing manner such that $c_i \leq c_j$ for every $1 \leq i \leq j \leq n$.

Finally, the second cut-off is applied to determine whether an individual is considered poor. This requires defining the minimum number of deprivations necessary to be considered poor. In this part, it is necessary to follow the union approach, which considers individuals as poor if they are deprived in at least one dimension. Thus, the distribution of individuals can be written from the poorest to the richest as follows:

$$c = (c_1, c_2, \cdots, c_n) = \left(\overbrace{1, \dots, 1}^{n_s}, \overbrace{\frac{s-1}{s}, \dots, \frac{s-1}{s}}^{n_{s-1}}, \dots, \overbrace{\frac{2}{s}, \dots, \frac{2}{s}}^{n_2}, \overbrace{\frac{1}{s}, \dots, \frac{1}{s}}^{n_1}, \overbrace{0, \dots, 0}^{n_0} \right) \tag{5}$$

where n_i for $i \in \{0,1,2,\dots,s\}$ is the number of individuals with *i* deprivations.

Then, a counting poverty measure for the union approach is defined as follows:

$$P^{\alpha}(c; s) = \frac{1}{n} \sum_{i=1}^{n} (c_i)^{\alpha} \tag{6}$$

The following proposition shows that the union approach of a counting poverty measure for equal weights can be also measured using the ordinal FGT poverty measure.

Proposition 2. *Let define a counting poverty measure of n individuals and a distribution of deprivation counts* $c = (c_1, c_2, \cdots, c_n)$ *with s dimensions. The counting poverty measures for the union approach and equal weights is exactly the ordinal FGT measure computed for c and s as follows:*

$$P^{\alpha}(c;s) = \pi^{\alpha}(c;s) \tag{7}$$

Proof of Proposition 2: Starting with equation (3) and taking into account equation (2) we have the proof.

$$\begin{aligned} P^{\alpha}(c;s) &= \frac{1}{n}\sum_{i=1}^{n}(c_i)^{\alpha} \\ &= \frac{1}{n}\left(n_s + n_{s-1}\left(\frac{s-1}{s}\right)^{\alpha} + \cdots + n_2\left(\frac{2}{s}\right)^{\alpha} + n_1\left(\frac{1}{s}\right)^{\alpha}\right) \\ &= \sum_{i=1}^{s}\left(\frac{s-i+1}{s}\right)^{\alpha} p_{s-i+1} \\ &= \pi^{\alpha}(c;s) \quad \blacksquare \end{aligned}$$

3.2 Multidimensional poverty

Let suppose now that K dimensions want to be analysed. In this case, $y^k = \left(y_1^k, y_2^k, \dots, y_{S^k}^k\right)$ needs to be defined for $k = 1,2,\cdots,K$, where S^k is the number of categories in which dimension k is divided and y_j^k for $1 \leq j \leq S_k$ are the categories in dimension k. Let define q^k for $1 \leq k \leq K$ *as* the number of deprived categories in dimension k. Then the multidimensional poverty measure for the K dimensions can be defined following Bourguignon and Chakravarty (2003) proposal as follows:

$$\begin{aligned} \Pi^{\alpha,\beta}(Y;Q) &= \frac{1}{n}\sum_{i=1}^{n}\Pi_i^{\alpha,\beta} = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{k=1}^{K} w_k \cdot \left(g_i(y^k;q^k)\right)^{\alpha}\right)^{\beta/\alpha} \\ &= \frac{1}{n}\sum_{i=1}^{n}\left(\left(w_1 \cdot \left(g_i(y^1;q^1)\right)^{\alpha} + \cdots + w_K \cdot \left(g_i(y^K;q^K)\right)^{\alpha}\right)\right)^{\beta/\alpha} \end{aligned} \tag{8}$$

where $\alpha > 0$ and for $\beta \geq 0$. $Y = (y^1,\cdots,y^K)$, $Q = (q^1,\cdots,q^K)$ are the matrices of categories of the K dimensions and the vector of number of deprived categories in the dimension, respectively. Then $w =$

$(w_1, w_2, \ldots, w_K)$ are the dimensions weights where $\sum_{j=1}^{K} w_j = 1$. Individual multidimensional gap can be defined in these cases as $\Pi_i^{\alpha,\beta}$.

The interpretations of the parameters are very similar to those proposed by Bourguignon and Chakravarty (2003). The degree of deprivation measure for each individual in Equation (8) depends on three different types of parameters. First, the weights w = (w_1,…,w_k) assigned to the different dimensions; and second and third, the parameters α and β. All the indices of the family are constructed in two stages. In the first stage, the deprivations of each individual are aggregated using a weighted mean of order α; the second stage proposes to combine the aggregated deprivations of individuals using a β-power function. Hence, it follows the union approach.

The parameter α permits to parameterize the elasticity of substitution between the gaps of the dimensions. The weighted means of order α, are non-decreasing in the parameter α. Thus, for α = 1, the arithmetic mean is obtained and the higher the value of α, the more sensitive the means of order α are to inequality between dimensions.

Finally, parameter β is a measure of sensitivity to poverty. That is, the higher the value of β, the more sensitive the index will be to the extreme deprivation of the individual. That is, the higher the value of β, the more sensitive the multidimensional index will be to the inequality among the poor. A detailed discussion on the interactions of these parameters and their implications for a deprivation index can be found in Atkinson (2003).

It should also be noted that the first concern when measuring multidimensional poverty is the identification of the poor. Following the definition of the proposed multidimensional measure, an individual will be considered poor if he/she is deprived in at least one of the dimensions. In other words, the identification of the poor corresponds to what is called the union procedure. Note that when $\beta = 0$ the multidimensional index becomes the multidimensional Headcount-ratio. For $\alpha = 1$, the dimensions are fully compensable. That is, a deprivation on one dimension can be compensated by another dimension. With $\beta = 1$, $\Pi^{\alpha,\beta}$ becomes a multimensional poverty gap obtained by some averaging of the poverty gaps in all the dimensions. Higher values for β may be interpreted, as in the one-dimensional case, as higher aversion towards extreme poverty.

In Table 1, an example has been added with two distributions of 5 individuals with their corresponding gaps in each of the dimensions. The gaps are shown in column 1. The second column, $\alpha = 1, \beta = 0$, shows whether each of the individuals is poor or not. Concluding that all individuals are poor, and therefore multidimensional poverty is 1 for the two distributions.

On the other hand, it can be observed that the first three individuals are exactly the same in the two distributions and that the arithmetic mean of their deprivations sum to 0.25. Therefore, for $\alpha = 1$, individual multidimensional poverty is exactly the same for the three individuals. However, for α values greater than 1, the variables will not be substitutes and individual poverty will be higher for those individuals who have more inequality among their dimensions, see column 5 of Table 1. On the other hand, when examining the last two individuals in distribution 2, it can be observed that these individuals have the same multidimensional deprivation value across all chosen parameters. It is important to note that the same amount of deprivation has been distributed among the dimensions. However, in the first distribution, the deprivations of the dimensions for the last two individuals have been allocated in such a way that one individual is completely deprived, while the other is almost not deprived. In other words, the deprivations of the two individuals have been distributed more unequally between them. Although the percentage of poor individuals and the intensity remain the same when dimensions can be compensated, greater inequality between dimensions is evident in distribution 2. This is because the differences between dimensions for individuals 4 and 5 in distribution 2 are virtually nonexistent. As a result, the multidimensional poverty for $\alpha = 2$ and $\beta = 1$ is greater in distribution 2 than in distribution 1. Nevertheless, it is very easy to see that the inequality between the multidimensional gap of the last two individuals in this case is greater for the first distribution than the second, concluding with higher multidimensional poverty for $\alpha = 1$ and $\beta = 2$.

Table 1 : Two distribution examples

Distribution 1	$\Pi_i^{\alpha,\beta}$				**Distribution 2**	$\Pi_i^{\alpha,\beta}$			
(IP ,MD, EP, LJ)	α=1 β=0	α=1 β=1	α=1 β=2	α=2 β=1	**(IP ,MD, EP, LJ)**	α=1 β=0	α=1 β=1	α=1 β=2	α=2 β=1
(0.5, 0.5, 0, 0)	1	0.25	0.06	0.35	(0.5, 0.5, 0, 0)	1	0.25	0.06	0.35
(0.25,0.25, 0.25, 0.25)	1	0.25	0.06	0.25	(0.25,0.25, 0.25, 0.25)	1	0.25	0.06	0.25
(1, 0, 0, 0)	1	0.25	0.06	0.50	(1, 0, 0, 0)	1	0.25	0.06	0.50
(0, 0.2, 0.2, 0)	1	0.10	0.01	0.14	(0, 0.2, 0.2, 0)	1	0.10	0.01	0.14
(1, 1, 1, 1)	1	1	1	1	(1, 1, 1, 1)	1	1	1	1
$\Pi^{\alpha,\beta}$	**1**	**0.4**	**0.2**	**0.5**	$\Pi^{\alpha,\beta}$	**1**	**0.4**	**0.2**	**0.5**

In addition, this multidimensional poverty measure when $\alpha = \beta = 1$, will allow to decompose the multidimensional poverty value in terms of the contributions of the K dimensions to the global poverty value.

Writing the measure for $\alpha = \beta = 1$:

$$\Pi^{\alpha=1,\beta=1}(Y;Q) = \sum_{i=1}^{n}\sum_{k=1}^{K} w_k \cdot g_i(y^k;q^k) = \sum_{k=1}^{K} w_k \cdot \pi^1(y^k;q^k) \tag{9}$$

The contribution of each dimension k can be easily written as follows:

$$C_k = \frac{w_k \cdot \pi^1\left(y^j;q^j\right)}{\Pi^{1,1}(Y;Q)} \quad for \;\; any\, k \in \{1,2,\cdots,K\} \tag{10}$$

where $C_1 + C_2 + \cdots + C_K \; = \; 1$.

3.3 Data description

The data used in this paper comes from the cross-sectional EU-SILC (European Union Statistics on Income and Living Conditions) survey for 25 European countries in the years 2018, 2020, and 2022. Conducted annually since 2004, the EU-SILC survey follows harmonized criteria across all EU countries and serves as a key reference for comparing income distribution and social exclusion across Europe (INE, 2023).

The database consists of four files containing household and individual level variables, along with corresponding weights, ensuring that the micro-data are representative at the national level. While the analysis focuses on households, individuals serve as the unit of analysis, whether they are adults or children. Therefore, we assign the same poverty level to all individuals within a given household. The variables used to compute multidimensional poverty are listed in Table 2.

As shown in Table 2, income poverty is measured based on a household's total equivalent income, calculated as disposable household income divided by the modified OECD equivalence scale to account for differences in household composition.

For severe material deprivation, a modified version of the standard Eurostat indicator is used, as proposed by Guio et al. (2016, 2017) and Guio and Marlier (2017). The variables considered in the AROPE indicator include M1, M2, M3 combined with E2 ("capacity to bear payment arrears on mortgage or rental payments, utility bills, hire-purchase instalments, or other loan payments"), as well as M4 to M12 and E1 from Table 2. In this study, 12 variables (M1 to M12) are used, with the original AROPE material deprivation variable split into two: "arrears on utility bills (electricity, water, gas)" (E2) and "capacity to bear payment arrears on mortgage or rental payments" (M3). While M3 remains part of the material deprivation dimension, E1 ("ability to keep the home adequately warm") has been moved to the energy poverty dimension. An individual is considered severely materially deprived if they lack at least six of these 12 items.

Table 2: Poverty variable description

POVERTY	VARIABLE	VALUES
Income Poverty	I1. Equivalent Income.	Continuous
Energy Poverty	E1. The ability to keep the home adequately warm. E2. The arrears on utility bills (electricity, water, gas).	- Yes -No
Material Deprivation	M1. Capacity to face unexpected financial expenses. M2. Capacity to afford paying for one-week annual holiday away from home. M3. Capacity to bear payment arrears on mortgage or rental payments. M4. Capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every two days.	- Yes -No
	M5. Access to a car/van for personal use. M6. Capacity to replace worn-out furniture. M7. Access to an internet connection. M8. Capacity to replace worn-out clothes with new. M9. Having two pair of properly fitting shoes (including a pair of all-weather shoes). M10. Spending a small amount of money each week on him/herself. M11. Having regular leisure activities. M12. Getting together with friend/family for a drink/meal at least once a month.	- Yes -No (cannot afford) -No (other reason)
Low Job Intensity	J1. Working-age members potential combined working time.	Continuous

For energy poverty, the consensus methodology is followed, using two widely recognized indicators for measuring subjective energy poverty, in line with the methodology established by Healy (2017) and Healy and Clinch (2004): “ability to keep the home adequately warm” (E1) and “arrears on utility bills (electricity, water, gas)” (E2). These variables were originally part of the AROPE material deprivation dimension but are treated separately in this analysis to specifically highlight energy poverty.

The fourth dimension, exclusion from the labour market (very low work intensity), follows the AROPE definition. An individual is classified as having very low work intensity if they live in a household where working-age members (18–64 years old) work less than 20% of their combined potential working time. This excludes students aged 18–24, retirees, and individuals over 60 whose primary income comes from pensions.

In summary, while the proposal uses the same variables as the AROPE index, the structure is redefined by dividing them into four dimensions instead of three, with greater emphasis placed on energy poverty.

4 Multidimensional poverty and social exclusion in European countries

4.1 European policies for multidimensional poverty

European policies for reducing poverty are structured through various measures and programs aimed at improving the economic and social situation of individuals and families in vulnerable situations. The Europe 2020 Strategy has been succeeded by the Europe 2030 Strategy, also known as the European Green Deal, and other frameworks associated with the UN Sustainable Development Goals (SDGs). This new strategy sets more ambitious targets to address the social, economic, and environmental challenges facing the European Union. These policies include the European Green Deal, the Action Plan of the European Pillar of Social Rights, Next Generation EU, the European Social Fund Plus (ESF+), the 2030 Agenda, and the SDGs, as well as monitoring and evaluation mechanisms.

The European Green Deal is a strategy to transform the EU economy into a sustainable economy while simultaneously addressing poverty and social exclusion. It includes initiatives to improve energy efficiency in housing and reduce energy costs for the most vulnerable households. The Action Plan of the European Pillar of Social Rights strengthens social rights and ensures equitable access to essential services such as education, health, and housing, including measures to guarantee adequate minimum incomes and fair working conditions. Next Generation EU is a post COVID-19 recovery fund that finances projects to enhance economic and social resilience by supporting investments in social housing, health, education, and training. The European Social Fund Plus (ESF+) merges several previous social funds to create a more effective mechanism to combat poverty and social exclusion. The 2030 Agenda and SDGs focus on integrating the Sustainable Development Goals into national and European policies to address poverty in all its dimensions. Monitoring and evaluation use indicators and tools to measure and monitor material deprivation and policy effectiveness.

All these policy strategies focus on the four fundamental aspects we aim to address in this work: income poverty, material deprivation, energy poverty, and low job intensity. It’s important to note that besides these European-level policy strategies, there are numerous anti-poverty measures in each European country.

These policies are implemented through a multidimensional approach that seeks not only to increase the income of people in poverty but also to improve their access to basic services, employment, housing, and education. Furthermore, there is collaboration between different levels of government (national, regional, and local) and non-governmental organizations to comprehensively address poverty and social exclusion.

Detecting multidimensionally poor individuals is an essential task. This measure will not only allow us to detect multidimensionally excluded individuals but also to understand the intensity of social exclusion for each of them. This means that this family will enable us to determine the poverty of each vulnerable individual. Moreover, this measure would be decomposable by type of poverty source, which will allow us to know which of the four poverty components have affected the multidimensional measure most. Therefore, once those affected by one or more essential aspects of poverty are identified, we can apply the most specific policies for each type of individual.

4.2 Unidimensional European results

This subsection is dedicated to computing unidimensional poverty for the four dimensions of study. The ordinal FGT indices for $\alpha = 0{,}1{,}2$ have been computed for income poverty (IP), material deprivation (MD), energy poverty (EP), and low job intensity (LJ) across the years 2018, 2020, and 2022 for 25 countries.

To measure ordinal IP, the gap for each individual i is first computed, defined as $g_i^1 = max\left\{0, \frac{z^1 - x_i^1}{z^1}\right\}$, where x_i^1 is the equivalent disposable income and z^1 represents the income poverty line. For this purpose, a relative poverty line is used, set at 60% of the median equivalent income for each year and country. Individuals are then categorized based on their income gap, forming seven groups, as shown in Table 3. All individuals with a gap greater than zero are classified as poor, resulting in six poverty groups, each assigned a weight according to its gap value in the ordinal FGT measure. It should be noted that in a unidimensional study, it would be more appropriate to use poverty measures for continuous variables. However, in this case, since the proposed multidimensional index combines different types of variables, the unified method proposed in the paper is followed. Material deprivation (MD) is measured using the AROPE methodology, considering the 12 material deprivation variables listed in Table 2. Individuals living in households with six or more deprivations are classified as poor, forming eight groups based on the number of deprivations, as shown in Table 3.

For energy poverty (EP), the two subjective variables previously mentioned are used. Individuals are classified as energy poor if they experience at least one deprivation and are further categorized based on the number of deprivations. The corresponding groups and weights are outlined in Table 3.

Table 3: Variable groups and their weights

INCOME		**MATERIAL**		**ENERGY**		**LOW JOB**	
Groups	**Weight**	**Groups**	**Weight**	**Groups**	**Weight**	**Groups**	**Weight**
0	0	0,1,2,...,5	0	0	0	0	0
(0, 0.2)	1/6	6	1/7	1	1/2	(0, 0.2)	1/6
[0.2, 0.4)	2/6	7	2/7	2	1	[0.2, 0.4)	2/6
[0.4, 0.6)	3/6	8	3/7			[0.4, 0.6)	3/6
[0.6, 0.8)	4/6	9	4/7			[0.6, 0.8)	4/6
[0.8, 1)	5/6	10	5/7			[0.8, 1)	5/6
1	1	11	6/7			1	1
		12	1				

Finally, to compute the ordinal low job intensity (LJ) dimension value, the low job intensity gap was calculated for each individual$i$ as $max\left\{0, \frac{z^4 - x_i^4}{z^4}\right\}$, where x_i^4 is the ratio of months worked by their household members of working age to their potential working time and z is the poverty line fixed as $z^4 = 0.20$. Then, individuals have been grouped based on their computed gap in seven groups. The groups can be seen in Table 3.

The unidimensional poverty results have been computed for all countries across the three years of study. Figures 1 and 2 present the unidimensional results for IP, MD, EP, and LJ, using the poverty measures π^0 and π^1.

In Figure 1, it is observed that income incidence remains consistently above 9.5 percent across all countries and years, while low work intensity remains below 20 percent for nearly all countries throughout the study period. However, material deprivation and energy poverty vary significantly across countries and years, with some recording very low values and others exceeding 40 percent.

Figure 1: Unidimensional Headcount-ratios (π^0)

Figure 2: Unidimensional π^1 values

Focusing on income incidence, values range between 9.5 and 23 percent. In 2022, the highest incidence rates are observed in Bulgaria, Romania, Estonia, Latvia, and Spain, all exceeding 20 percent. Examining the evolution of income incidence between 2018 and 2022, before and after the COVID-19 period, we find that it has worsened in the Czech Republic, Estonia, Finland, France, Luxembourg, the Netherlands, Germany, Bulgaria, and Slovakia. Conversely, countries such as Belgium, Cyprus, Croatia, Hungary, Poland, Romania, Serbia, Spain, and Sweden have seen a decline in income incidence over the entire period analyzed.

Regarding material deprivation, Bulgaria and Romania stand out with exceptionally high incidence rates, exceeding 25 percent, while most other countries report values below 10 percent.

Focusing now on energy incidence (Figure 1), the percentage of individuals affected by this dimension shows significant fluctuation, ranging from 3.24 percent in the Netherlands to 48.01 percent in Bulgaria in 2018. Notably, Bulgaria has reduced energy poverty by 15.11 percentage points over the study period.

Energy incidence has increased in Austria, Germany, Spain, Ireland, Luxembourg, the Netherlands, Romania, and Serbia across the two periods analyzed. The highest energy incidence rates are observed in Greece, Bulgaria, Romania, Spain, and Lithuania, while Austria, the Czech Republic, and Luxembourg report the lowest values.

Finally, regarding the incidence of the low job intensity dimension, the percentage of affected individuals ranges between 2 and 23 percent. The Netherlands and Belgium have the highest percentages of people experiencing low job intensity, whereas Poland and the Czech Republic have the lowest. While this indicator has improved between 2018 and 2022 in the Czech Republic, Greece, Spain, Croatia, Luxembourg, Portugal, Romania, and Slovakia, only the Czech Republic and Greece show consistent improvement in both periods: 2018–2020 and 2020–2022.

Turning to Figure 2, it shows the results for unidimensional intensity. In most countries, the trends in intensity closely mirror those of incidence. However, in some cases, incidence and intensity have followed opposite trajectories between 2018 and 2022. For example, in Austria and Serbia, income incidence has decreased, while intensity has increased. Conversely, Luxembourg has seen an improvement in income poverty intensity, despite an increase in the percentage of income-poor individuals.

In conclusion, the four dimensions of poverty do not exhibit uniform behavior across different countries. This suggests that social exclusion reduction policies should be tailored to the specific dimension most affecting each country. Notably, the study period coincides with the onset of the COVID-19 pandemic and subsequent lockdowns in 2020, and we believe that the varied trajectories among countries are directly linked to the anti-exclusion policies they implemented.

Nevertheless, multidimensional poverty analysis is widely regarded as superior to unidimensional analysis, as it provides a more comprehensive and realistic view of the multiple deprivations affecting households and individuals. While unidimensional measurements allow for more targeted policy responses, they fail to offer a holistic perspective on the overall socioeconomic situation of households, countries, or society as a whole. Therefore, in the following section, we will analyze multidimensional poverty using the measure proposed in this paper, which captures not only the incidence of poverty but also its intensity and inequality among those affected. Furthermore, as discussed in the previous section, one of the proposed measure is decomposable by dimensions, enabling us to determine the contribution of each dimension to overall multidimensional poverty.

4.3 Multidimensional European results

This section presents the computation of the multidimensional poverty index proposed in this paper for 25 European countries over the study years 2018, 2020, and 2022.

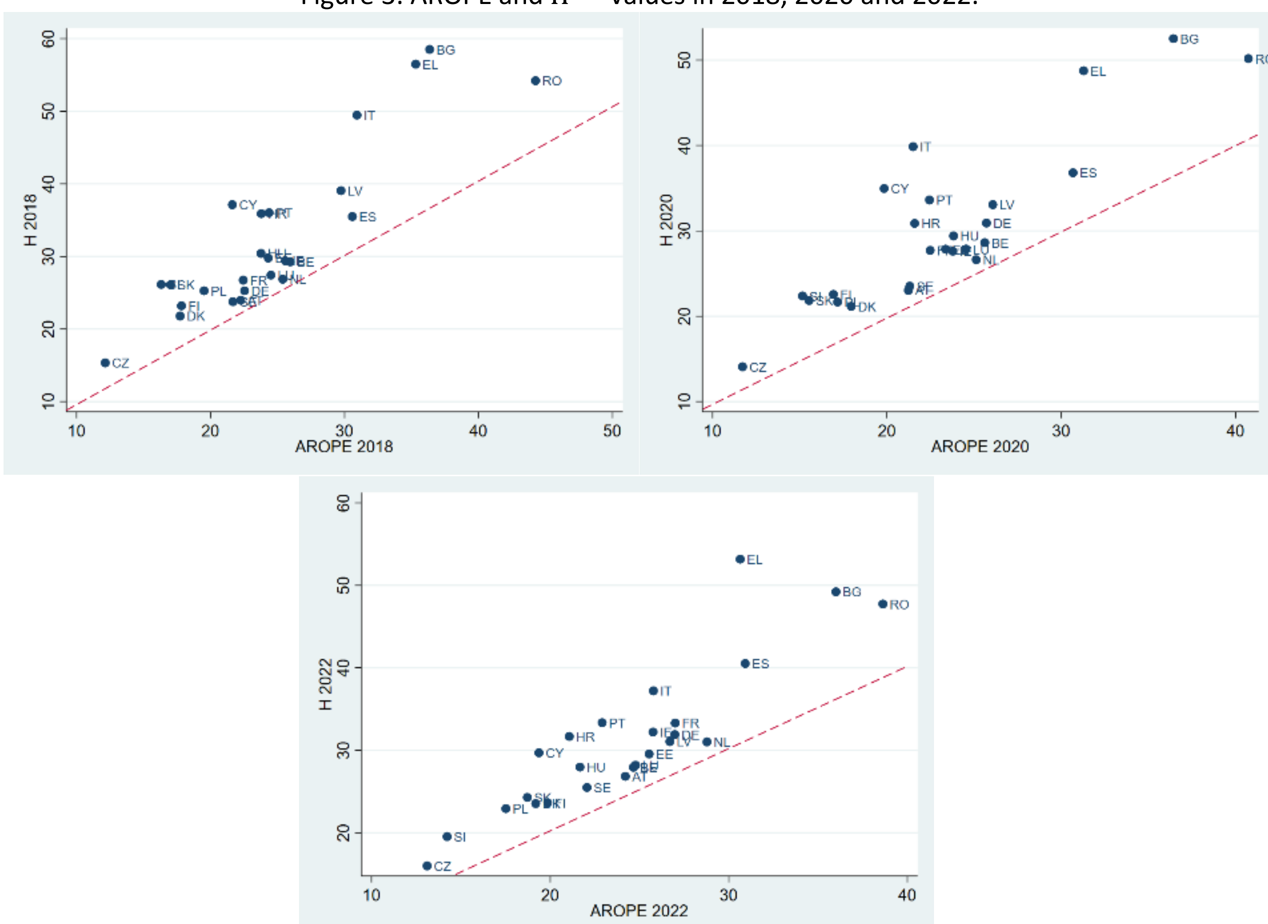
Our proposed Headcount-ratio is similar to the AROPE index, which is widely used by official statistical bodies to monitor poverty and social exclusion within the European Union. However, the analysis of this paper specifically focuses on four types of deprivation: income poverty, material deprivation, energy poverty, and low job intensity. Additionally, the framework not only measures multidimensional incidence but also accounts for the intensity and inequality in the distribution of poverty among those affected.

The first step in this application is to define the weights and select the value of α. First, all the dimensions are assigned equal importance, meaning that the weights applied will be $w_i = \frac{1}{4}$ for every $i \in \{1,2,3,4\}$. Secondly, $\alpha = 1$ is set, which implies that the deprivations across dimensions are fully compensable for each individual.

As mentioned earlier, the proposed multidimensional framework for $\beta = 0$, matches the multidimensional Headcount-ratio. For this index, the individuals are identified as multidimensionally poor if they experience deprivation in any of the four variables. In fact, it follows the union approach as in the AROPE index. Table 5 in the appendix presents the results for the multidimensional Headcount-ratio of our proposed index alongside the AROPE index, with comparisons illustrated in Figure 3.

Figure 3 shows that the proposed multidimensional Headcount-ratio consistently identifies a higher number of individuals as multidimensionally poor compared to the AROPE index, across all countries and study years. In some countries, such as the Czech Republic, Denmark, Finland, and Austria, the results are quite similar. However, in others, such as Bulgaria, Romania, and Greece, the discrepancy is much larger, with our index identifying more than 20 percent additional individuals as multidimensionally poor in some cases.

Figure 3. AROPE and $\Pi^{\alpha,0}$ values in 2018, 2020 and 2022.



In contrast, when considering measures for $\beta = 1$ and $\alpha = 1$, the index not only accounts for the percentage of vulnerable individuals but also incorporates the intensity of their deprivation. This means it evaluates the extent to which individuals experience multidimensional poverty. Furthermore, for $\beta = 2$ and $\alpha = 1$, the measure becomes sensitive to incidence, intensity, and inequality among those affected. In this case, it assigns greater weight to individuals in the most severely deprived groups within each dimension and captures disparities between different groups. Detailed numerical results for $\Pi^{1,1}$ and $\Pi^{1,2}$ can be found in Table 5 in the appendix, while Figures 4 to 6 illustrate the multidimensional results from 2018 to 2022.

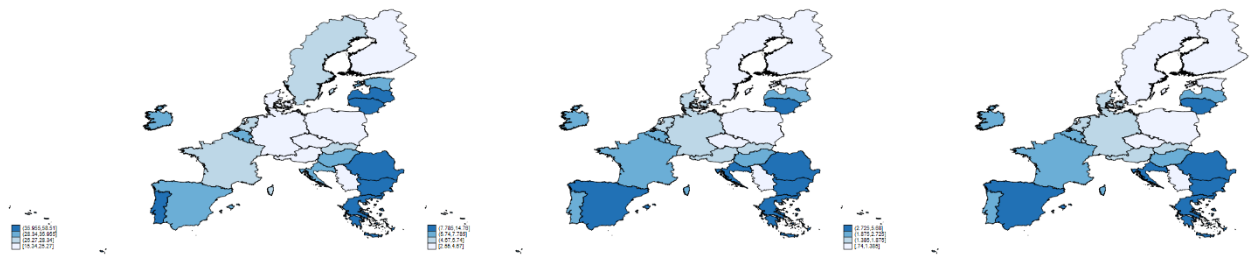
Focusing on Figure 4, it can be observed that the countries with the highest multidimensional values for the three indices in 2018 are Bulgaria, Greece, Romania, and Lithuania. Notably, in Spain and France, poverty measures that account for intensity and inequality among the poor show higher values than that for incidence when compared to other countries. In contrast, Latvia exhibits higher incidence values than intensity and inequality, meaning that while the percentage of multidimensional poverty is high, its severity and disparity are relatively lower. Conversely, when considering the intensity and inequality of poverty, Portugal's situation improves relative to its value for incidence. In other words, although Portugal has one of the highest percentages of multidimensional poverty, its intensity and inequality are more moderate.

Regarding 2020, most of the countries with the highest percentage of poor in 2018; Bulgaria, Greece, Romania, Lithuania, Latvia, Cyprus, and Portugal, continue to have the highest incidence of poverty. However, in 2020, Spain joins this group, while Latvia is no longer among the poorest (see Figure 5).

When considering intensity and inequality, it is noteworthy that in France, although the incidence of poverty is not particularly high in 2020, its intensity is higher, and its inequality is even more pronounced compared to other countries. Germany, on the other hand, records its highest values in terms of intensity. Meanwhile, Portugal follows the same pattern as in 2018.

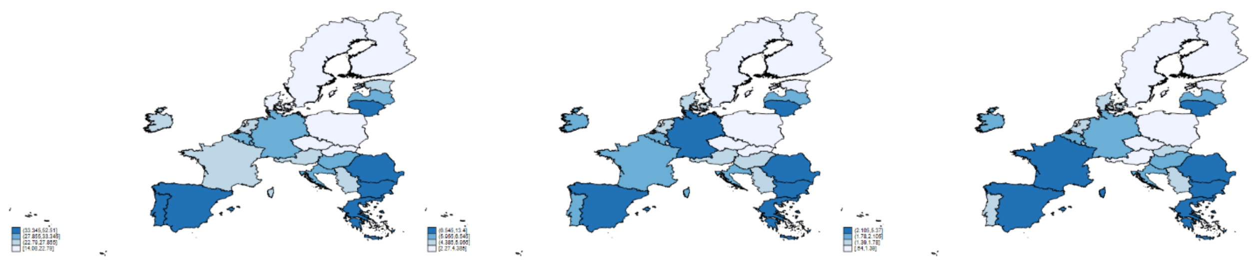
Finally, Figure 6 presents the results for 2022, showing that the countries with the highest incidence of poverty remain largely unchanged from previous years. This year, two countries are highlighted: France and Finland. In 2022, France recorded one of the highest intensity values, while Finland, which previously had low values, now shows a moderate level of poverty intensity.

Figure 4: Multidimensional results for 2018.



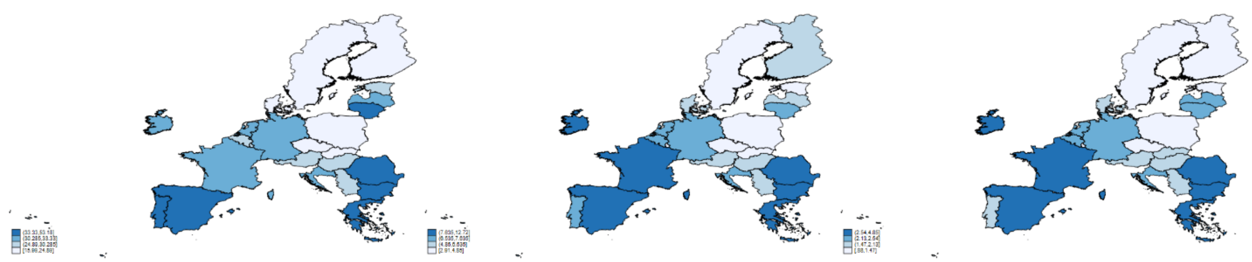
a) $\Pi^{\alpha,0}$ values in 2018 b) $\Pi^{1,1}$ values in 2018 c) $\Pi^{1,2}$ values in 2018

Figure 5: Multidimensional results for 2020.



a) $\Pi^{\alpha,0}$ values in 2020 b) $\Pi^{1,1}$ values in 2020 c) $\Pi^{1,2}$ values in 2020

Figure 6: Multidimensional results for 2022.



a) $\Pi^{\alpha,0}$ values in 2022 b) $\Pi^{1,1}$ values in 2022 c) $\Pi^{1,2}$ values in 2022

Examining changes from 2020 (see Table 5 in the appendix), it is found that multidimensional incidence has decreased in almost all countries, except for Germany, Spain, France, and Luxembourg. However, while Luxembourg has experienced improvements in intensity and inequality among the poor, these measures have worsened in the Netherlands and Serbia.

Table 5 also reveals that between 2020 and 2022, both the percentage of poor people and the intensity and inequality of their poverty have increased in several countries, including Austria, the Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Ireland, the Netherlands, Poland, Serbia, and Slovakia.

In summary, three countries, Bulgaria, Cyprus, and Sweden, have shown consistent improvements in multidimensional poverty across both study periods and all three indices. In contrast, Germany and France have worsened in at least one poverty measure in each period.

In the following section, the focus will be on identifying the key dimensions that have the most impact on multidimensional poverty.

4.4 Contributions of IP, MD and EP to multidimensional poverty

As shown in the methodology section, the proposed multidimensional family allows us to compute the contribution of each poverty dimension to the overall index when $\alpha = \beta = 1$.

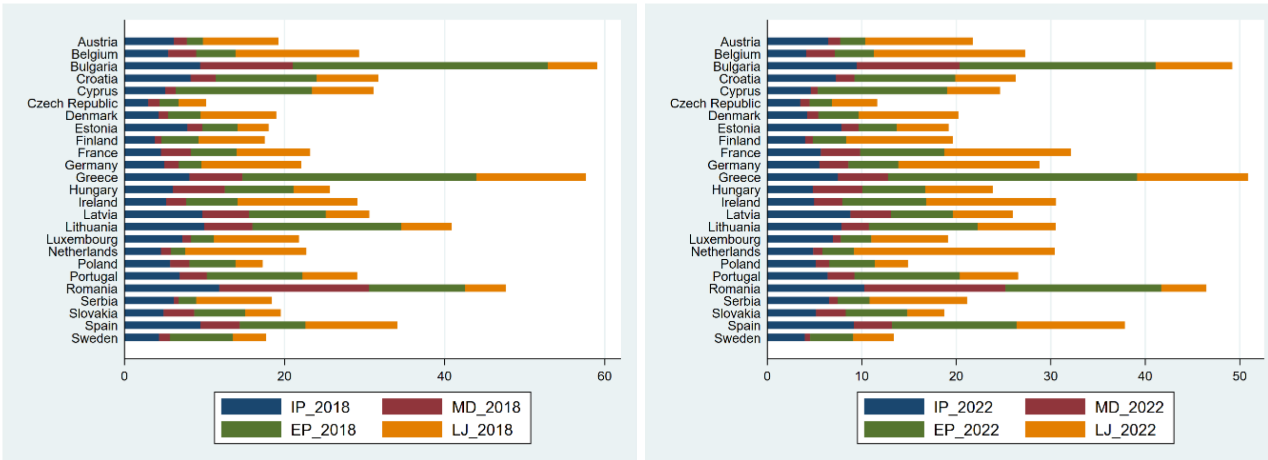
Understanding these contributions is essential for effectively implementing anti-poverty policies, as it provides insights into the key factors driving multidimensional poverty. This, in turn, enables the development of targeted strategies to alleviate poverty more effectively across different countries. Table 6 in the appendix presents the results of the $\Pi^{1,1}$ index for all countries in the years 2018, 2020, and 2022. Additionally, the table includes unidimensional poverty values for the four dimensions along with their respective contributions to overall multidimensional poverty. For better clarity, Figure 7 illustrates the contributions of IP, MD, EP, and LJ to the $\Pi^{1,1}$ index for 2018 and 2022, providing a clearer visual representation of these results.

Referring to Figure 7 or Table 6 in the appendix, it is observed that income poverty is the largest contributor to multidimensional poverty in Estonia, Latvia, and Poland. However, Romania stands out as the only country where material deprivation makes the highest contribution.

Additionally, energy poverty is the dominant factor in nine countries: Bulgaria, Cyprus, Croatia, Hungary, Lithuania, Portugal, Sweden, and Slovakia. For the remaining twelve countries, low job intensity is the primary driver of overall poverty levels.

While this aggregate indicator helps to identify poor households and the sources of multidimensional poverty, it is not sufficient for designing effective energy poverty policies. Developing targeted interventions requires identifying the most vulnerable households and understanding their specific characteristics. Therefore, the next section will analyze the characteristics of households most at risk of multidimensional poverty.

Figure 7: Contributions of the three dimensions to $\Pi^{1,1}$ in 2018 and 2022.



5 Identifying the most vulnerable groups

This study also aims to identify the key determinants of multidimensional poverty. Specifically, the objective is to estimate the impact of various household characteristics on multidimensional poverty and identify the factors most accurately predicted by the index.

To achieve this, two distinct estimations have been conducted. First, it will be determined whether an individual is multidimensionally deprived based on the four indicators by estimating $\Pi_i^{1,0}$. Next, the socioeconomic characteristics that significantly influence this deprivation level will be further analysed by estimating $\Pi_i^{1,1}$ and $\Pi_i^{1,2}$. For this purpose, we will use the following regression model:

$$\widehat{\Pi}_i^{\alpha,\beta} = \beta_0 + \beta X_i + u_i \quad for\ \ \alpha = 1\ \ and\ \ \beta = 0, 1, 2 \tag{11}$$

where $\widehat{\Pi}_i^{\alpha,\beta}$ is the endogenous variable representing the individual latent multidimensional gap. In addition, $X_i = (x_{i1}, x_{i2}, \dots, x_{il})$ is the vector of observed individual characteristics taking into account country fixed effects; β_0 is the constant of the estimation; $\beta = (\beta_1, \cdots, \beta_l)$ is the vector of parameters associated with X_i and u_i is the error term related to the individuals taking into account country-fixed effects. It should be noted that the estimates were computed using the data corresponding to the three years of study. In addition, robust standard errors have been used to avoid heteroscedasticity, and the inexistence of multicollinearity among the exogenous variables have been confirmed.

In the initial estimation, a logistic regression model is used, where the dependent variable is set to one if the individual is multidimensionally deprived, and zero otherwise. As mentioned, this corresponds to estimating the $\Pi_i^{1,0}$ values.

For the independent variables, key household characteristics are included, such as *Household Size* (number of individuals in the household), *Number of Rooms*, *Average Age*, *Highly Educated* (percentage of highly educated individuals), *Dwelling Type*, *Household Type*, *Tenure Status*, and *Degree of Urbanization*, as detailed in Table 4 (columns 1 and 2). Note that in the regressions the logarithm has been applied to the continuous variables *Household Size*, *Number of Rooms* and *Average Age.* Additionally, Table 4 presents the percentage of individuals in each category or, in the case of Household Size, Number of Rooms, Average Age, and Highly Educated, the mean values (column 3).

Table 4: The determinants of multidimensional deprivation between 2018-2022.

VARIABLE	GROUP	*Percent*	$\Pi^{1,0}$	OR	$\Pi^{1,1}$	$\Pi^{2,1}$
Household Size	Mean of Household Size *log*	*0.97*	1.062**	2.892	0.054**	0.072**
Number Rooms	Mean of Number of Rooms *log*	*1.31*	-0.799**	0.449	-0.046**	-0.062**
Average Age	Mean of Average Age *log*	*3.66*	0.138**	1.148	-0.007**	-0.007**
Highly Educated	Mean of Highly Educated percent	*0.43*	-1.550**	0.212	-0.061**	-0.088**
Dwelling Type	Detached house	*38.49*				
	Apart./flat with 10 or more dwellings	*27.81*	-0.201**	0.817	-0.017**	-0.021**
	Apart./flat with less than 10 dwellings	*16.98*	-0.103**	0.902	-0.011**	-0.013**
	Semi-detached or terraced house	*16.72*	-0.021	0.978	-0.004**	-0.003*
Household Type	Couple without any child(ren)	*35.66*				
	Couple with at least one child	*44.22*	-0.409**	0.664	-0.029**	-0.044**
	Lone parent with at least one child	*4.38*	1.095**	2.988	0.073**	0.105**
	One-person household	*14.93*	1.261**	3.531	0.053**	0.073**
	Other type of household	*0.81*	0.618**	1.856	-0.000	0.005
Tenure Status	Owner	*69.72*				
	Rental	*30.28*	0.022**	2.737	0.059**	0.081**
Degree of Urbanisation	Densely populated area	*42.88*				
	Intermediate area	*26.2*	0.044**	1.045	-0.001	-0.001
	Thinly populated area	*30.92*	0.198**	1.219	0.004**	0.006**
_cons			-1.991**	0.136	0.078**	0.114**

Note: Asterisks ** and * denote significance at the 95% and 90% levels, respectively.
Source: Own elaboration from EU-SILC data.

Table 4 presents the estimation results and the corresponding odds ratios in columns 4 and 5, respectively. It is important to note that while many results are statistically significant, odds ratios close to 1 indicate minimal differences between groups. Conversely, when the odds ratios are significantly greater or lower than 1, it suggests a higher or lower likelihood of being vulnerable compared to the reference household type.

As a result, significant correlations across all variables can be observed. Notably, households in sparsely populated areas are more frequently associated with being multidimensionally poor than those in densely or intermediately populated areas. Additionally, being a homeowner is negatively correlated with being poor compared to being a non-homeowner. Furthermore, individuals in larger households and those living in homes with fewer rooms show a higher likelihood of being associated with multidimensional poverty. And having a look at the logarithm of the average age of the household and the percentage of individuals with higher education in the household, it can be concluded that both variables show significant results, concluding that being multidimensionally poor is more associated with households with a higher average age and a lower percentage of individuals with higher education.

Regarding dwelling type, residing in a detached house is more often correlated with poverty than living in a flat. In terms of household type, single parents with at least one child appear most frequently associated with multidimensional poverty, whereas couples with at least one child are the least associated with it.

Secondly, we will assess whether individual multidimensional deprivation values or gaps, as measured by $\Pi^{1,1}$ and $\Pi^{1,2}$, are influenced by household socioeconomic characteristics. For these two cases, we employ multiple linear regression, a statistical technique used to model the relationship between a continuous dependent variable and two or more independent variables. We assume that $\Pi_i^{1,1}$ and $\Pi_i^{1,2}$ are continuous, as they can take on more than 120 different values. The definition of multiple linear regression follows a similar approach to the previous model, as shown in Equation (11).

In this case, columns 6 and 7 of Table 4 present the estimates for the two terms, $\Pi_i^{1,1}$ and $\Pi_i^{1,2}$, respectively. Here, we focus on changes in the intensity and inequality of multidimensional poverty. A higher estimated value indicates greater poverty intensity for the corresponding households. In a multiple linear regression, the coefficients of the independent variables represent the expected change in the dependent variable for each unit increase in the corresponding independent variable, while holding all other variables constant.

Table 4 shows that all classifications are statistically significant and exhibit patterns similar to those observed in incidence rates. The highest values are found within the Tenure Status category, where transitioning from homeownership to renting is correlated with an average increase of 5.9% in poverty intensity and 8.1% in squared intensity.

In the Household Type category, households formed by couples without any children are associated with lower levels of poverty intensity and inequality, on average, 7.3% and 10.2% lower, respectively, compared to households led by single parents with at least one child. Additionally, individuals living in intermediately and thinly populated areas are associated with an average poverty intensity that is 0.8% higher than that of individuals in densely populated areas.

To conclude, it is important to note the results obtained for the logarithm of the average age of the household. Although this measure shows a positive correlation with poverty for the multidimensional Headcount-ratio, the correlation regarding the gaps are negative. This leads to the conclusion that the increase in the logarithm of the average age of the household is positively associated with being multidimensionally poor but inversely associated with its intensity and inequality.

6 Conclusions and Policy Implications

Reducing poverty has become a primary objective for governments worldwide. Indeed, reducing social exclusion not only enhances individual well-being but also contributes to societal stability and economic growth. To this end, governments and organizations implement policies aimed at reducing poverty and improving household well-being. Measuring and monitoring these factors are crucial for the effective design and evaluation of such policies.

In this paper, a family of multidimensional measures of poverty has been proposed that consider income poverty, energy poverty, material deprivation and low job intensity. These measures allow identifying not only the percentage of vulnerable individuals but also the intensity of their vulnerability and the differences between them. Additionally, it is proved that for one of the indices, it is possible to determine the contribution of each of the four dimensions considered.

The findings indicate that in almost all the countries studied, vulnerability increased between 2018 and 2022. Among the components of the proposed multidimensional measure, material deprivation has the least impact on the final poverty index. However, the contributions of income poverty and energy poverty vary between countries.

In the final section, the characteristics of the most vulnerable individuals are identified, enabling the formulation of specific policies for these households. Concluding that both European and regional policies should focus on generating employment and providing retirement benefits. Additionally, there should be increased investment in training individuals both intellectually and in healthy living.

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Appendix

Table 5: Multidimensional Headcount-ratio and AROPE index.

	AROPE			$\Pi^{1,0}$			$\Pi^{1,1}$			$\Pi^{2,1}$		
	2018	**2020**	**2022**	**2018**	**2020**	**2022**	**2018**	**2020**	**2022**	**2018**	**2020**	**2022**
Austria	22.26	21.23	24.21	23.97	23.02	26.84	4.81	4.68	5.44	1.45	1.36	1.54
Belgium	25.95	25.61	24.66	29.26	28.62	27.94	7.32	6.46	6.82	2.68	2.09	2.27
Bulgaria	36.36	36.43	36.00	58.51	52.51	49.21	14.76	13.40	12.30	5.68	5.37	4.85
Cyprus	21.63	19.84	19.37	37.12	34.96	29.71	7.78	6.58	6.16	2.41	1.80	1.77
Czech Republic	12.14	11.72	13.11	15.34	14.08	15.99	2.55	2.27	2.91	0.74	0.64	0.88
Germany	22.54	25.71	26.98	25.27	30.92	31.90	5.52	6.63	7.20	1.67	1.99	2.26
Denmark	17.73	17.95	19.19	21.79	21.16	23.54	4.74	4.60	5.06	1.45	1.42	1.49
Estonia	24.31	23.36	25.54	29.78	27.85	29.55	4.50	4.04	4.80	1.12	0.94	1.26
Greece	35.32	31.28	30.64	56.48	48.75	53.18	14.42	12.25	12.72	5.44	4.71	4.52
Spain	30.59	30.67	30.92	35.49	36.80	40.52	8.52	8.78	9.45	3.25	3.17	3.34
Finland	17.83	16.93	19.86	23.20	22.56	23.64	4.38	4.16	4.90	1.20	1.11	1.45
France	22.44	22.48	27.00	26.73	27.72	33.31	5.80	6.30	8.04	1.90	2.12	2.82
Croatia	23.79	21.59	21.07	35.89	30.87	31.68	7.92	6.29	6.57	2.77	2.07	2.24
Hungary	23.77	23.82	21.67	30.41	29.40	27.96	6.42	5.69	5.97	2.15	1.84	1.99
Ireland	25.59	23.78	25.76	29.38	27.61	32.21	7.28	6.15	7.64	2.55	1.97	2.60
Lithuania	30.93	21.50	25.78	49.46	39.86	37.21	10.22	7.42	7.63	3.42	2.15	2.48
Luxembourg	24.51	24.54	24.78	27.42	27.86	28.19	5.45	5.32	4.79	1.61	1.48	1.23
Latvia	29.74	26.07	26.70	39.07	33.07	31.06	7.65	6.23	6.50	2.45	1.95	2.33
Netherlands	25.40	25.12	28.78	26.86	26.62	31.02	5.68	5.76	7.60	1.60	1.66	2.36
Poland	19.52	17.17	17.52	25.27	21.66	22.94	4.32	3.32	3.72	1.18	0.84	0.98
Portugal	24.37	22.44	22.91	36.02	33.62	33.35	7.27	6.15	6.63	2.24	1.72	2.02
Romania	44.26	40.73	38.63	54.21	50.18	47.73	11.90	10.92	11.62	4.17	3.78	4.30
Serbia	21.67	21.31	22.06	23.76	23.52	25.49	4.60	4.79	5.29	1.32	1.46	1.59
Sweden	16.32	15.16	14.23	26.14	22.37	19.54	4.42	3.71	3.35	1.14	0.97	0.89
Slovakia	17.01	15.53	18.72	26.09	21.84	24.29	4.88	4.17	4.69	1.85	1.47	1.62

Table 6: Multidimensional $\Pi^{1,1}$ values and the contributions of the four dimensions.

	2018					2020					2022				
	$\Pi^{1,1}$	IP	MD	EP	LJ	$\Pi^{1,1}$	IP	MD	EP	LJ	$\Pi^{1,1}$	IP	MD	EP	LJ
Austria	4.81	6.19	1.60	2.02	9.43	4.68	5.96	1.59	2.30	8.86	5.44	6.47	1.25	2.64	11.41
		32.2%	8.3%	10.5%	49.0%		31.9%	8.5%	12.3%	47.3%		29.7%	5.7%	12.1%	52.4%
Belgium	7.32	5.49	3.47	4.91	15.42	6.46	4.51	3.61	3.92	13.78	6.82	4.11	3.05	4.10	16.02
		18.7%	11.9%	16.8%	52.6%		17.5%	14.0%	15.2%	53.3%		15.1%	11.2%	15.0%	58.7%
Bulgaria	14.76	9.45	11.58	31.89	6.12	13.40	10.24	12.35	24.88	6.15	12.30	9.49	10.87	20.72	8.13
		16.0%	19.6%	54.0%	10.4%		19.1%	23.0%	46.4%	11.5%		19.3%	22.1%	42.1%	16.5%
Cyprus	7.78	5.09	1.31	17.04	7.66	6.58	4.83	0.87	15.07	5.55	6.16	4.60	0.76	13.65	5.62
		16.4%	4.2%	54.8%	24.6%		18.3%	3.3%	57.3%	21.1%		18.7%	3.1%	55.4%	22.8%
Czech Republic	2.55	3.00	1.39	2.37	3.44	2.27	2.91	1.05	2.06	3.07	2.91	3.48	1.00	2.36	4.78
		29.4%	13.6%	23.3%	33.8%		32.0%	11.5%	22.7%	33.8%		30.0%	8.6%	20.3%	41.1%
Germany	5.52	4.94	1.85	2.80	12.50	6.63	6.61	2.24	5.11	12.55	7.20	5.50	3.10	5.27	14.94
		22.4%	8.4%	12.7%	56.6%		24.9%	8.4%	19.3%	47.4%		19.1%	10.8%	18.3%	51.9%
Denmark	4.74	4.27	1.20	4.05	9.44	4.60	4.22	1.36	3.56	9.26	5.06	4.21	1.19	4.28	10.53
		22.5%	6.3%	21.4%	49.8%		22.9%	7.4%	19.3%	50.3%		20.8%	5.9%	21.2%	52.1%
Estonia	4.50	7.87	1.86	4.41	3.86	4.04	7.73	1.28	3.83	3.33	4.80	7.87	1.79	4.02	5.51
		43.7%	10.3%	24.5%	21.4%		47.8%	7.9%	23.7%	20.6%		41.0%	9.3%	20.9%	28.7%
Greece	14.42	8.12	6.65	29.19	13.70	12.25	7.62	6.52	22.66	12.17	12.72	7.48	5.28	26.38	11.73
		14.1%	11.5%	50.6%	23.8%		15.6%	13.3%	46.3%	24.9%		14.7%	10.4%	51.9%	23.1%
Spain	8.52	9.51	4.90	8.21	11.47	8.78	9.75	4.55	10.25	10.56	9.45	9.16	4.06	13.16	11.45
		27.9%	14.4%	24.1%	33.6%		27.8%	13.0%	29.2%	30.1%		24.2%	10.7%	34.8%	30.3%
Finland	4.38	3.78	0.83	4.64	8.26	4.16	3.72	0.71	4.46	7.74	4.90	4.00	0.81	3.54	11.26
		21.6%	4.7%	26.5%	47.2%		22.4%	4.3%	26.8%	46.5%		20.4%	4.1%	18.0%	57.4%
France	5.80	4.56	3.73	5.69	9.23	6.30	4.90	3.87	6.18	10.26	8.04	5.68	4.15	8.93	13.38
		19.6%	16.1%	24.5%	39.8%		19.4%	15.3%	24.5%	40.7%		17.7%	12.9%	27.8%	41.6%
Croatia	7.92	8.25	3.14	12.62	7.69	6.29	7.57	2.19	9.65	5.76	6.57	7.27	1.95	10.67	6.39
		26.0%	9.9%	39.8%	24.3%		30.1%	8.7%	38.3%	22.9%		27.7%	7.4%	40.6%	24.3%
Hungary	6.42	6.03	6.51	8.57	4.58	5.69	5.76	5.81	7.31	3.90	5.97	4.81	5.27	6.63	7.17
		23.5%	25.4%	33.4%	17.8%		25.3%	25.5%	32.1%	17.1%		20.1%	22.1%	27.8%	30.0%
Ireland	7.28	5.20	2.50	6.41	15.01	6.15	4.40	2.43	5.58	12.18	7.64	4.96	2.95	8.90	13.74
		17.9%	8.6%	22.0%	51.5%		17.9%	9.9%	22.7%	49.5%		16.2%	9.6%	29.1%	45.0%
Lithuania	10.22	9.95	6.04	18.58	6.29	7.42	5.90	4.04	14.71	5.04	7.63	7.87	2.88	11.51	8.25
		24.3%	14.8%	45.5%	15.4%		19.9%	13.6%	49.6%	17.0%		25.8%	9.5%	37.7%	27.0%
Luxemb.	5.45	7.27	1.03	2.89	10.60	5.32	6.33	1.06	3.24	10.64	4.79	6.96	0.83	3.23	8.13
		33.4%	4.7%	13.2%	48.6%		29.8%	5.0%	15.2%	50.0%		36.3%	4.3%	16.9%	42.5%
Latvia	7.65	9.75	5.82	9.58	5.44	6.23	8.63	3.93	7.15	5.22	6.50	8.81	4.29	6.55	6.35
		31.9%	19.0%	31.3%	17.8%		34.6%	15.8%	28.7%	20.9%		33.9%	16.5%	25.2%	24.4%
Nether.	5.68	4.56	1.22	1.81	15.13	5.76	4.69	0.93	1.95	15.49	7.60	4.87	0.94	3.38	21.22
		20.1%	5.4%	8.0%	66.6%		20.3%	4.1%	8.5%	67.2%		16.0%	3.1%	11.1%	69.8%
Poland	4.32	5.74	2.38	5.74	3.40	3.32	5.21	1.32	4.06	2.68	3.72	5.11	1.46	4.79	3.53
		33.3%	13.8%	33.3%	19.7%		39.3%	9.9%	30.6%	20.2%		34.3%	9.8%	32.2%	23.7%
Portugal	7.27	6.91	3.37	11.97	6.82	6.15	6.39	2.76	10.51	4.93	6.63	6.39	2.83	11.16	6.16
		23.8%	11.6%	41.2%	23.5%		26.0%	11.2%	42.7%	20.0%		24.1%	10.7%	42.1%	23.2%
Romania	11.90	11.84	18.73	11.95	5.09	10.92	11.21	16.55	11.96	3.96	11.62	10.27	14.94	16.48	4.79
		24.9%	39.3%	25.1%	10.7%		25.7%	37.9%	27.4%	9.1%		22.1%	32.1%	35.5%	10.3%
Serbia	4.60	6.19	0.55	2.23	9.44	4.79	6.27	0.83	2.55	9.52	5.29	6.51	0.92	3.39	10.34
		33.6%	3.0%	12.1%	51.3%		32.7%	4.3%	13.3%	49.7%		30.7%	4.4%	16.0%	48.9%
Sweden	4.42	4.33	1.32	7.87	4.16	3.71	3.99	1.09	6.11	3.67	3.35	3.97	0.58	4.54	4.30
		24.5%	7.5%	44.5%	23.5%		26.8%	7.3%	41.1%	24.7%		29.6%	4.3%	33.9%	32.1%
Slovakia	4.88	4.91	3.82	6.35	4.45	4.17	4.82	2.92	5.46	3.47	4.69	5.16	3.14	6.54	3.92
		25.2%	19.5%	32.5%	22.8%		28.9%	17.5%	32.8%	20.8%		27.5%	16.7%	34.9%	20.9%