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Social transfer policies and child poverty in European countries: Evaluating policy alternatives through a multiobjective programming model

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ABSTRACT

Child poverty remains a significant concern across Europe and citizens regard policy interventions that effectively address this issue to be of utmost importance. In this work, we analyse the potential of social transfer policy alternatives to alleviate child and overall poverty simultaneously in European countries. Using a logistic regression to define the objective functions and constraints, we rely on multiobjective programming to assess key features of national social transfer systems that can minimize child and overall poverty and tend to equal both levels downwards. Taking into account the starting levels of each country, the results underline the importance of finding an adequate combination of pro-child and pro-poor targeting of social transfer policies. For most European countries, an increase in the level of cash benefits for children is advisable – particularly universal benefits – except in Croatia, the Netherlands, and Norway. Nonetheless, in France, Greece, Italy, Ireland, the Netherlands, and Spain, the recommended proportion of GDP allocated to universal cash benefits is lower than the proportion allocated to means-tested benefits. In this regard, our research provides an innovative approach for policymakers to optimize poverty reduction strategies by contributing valuable insights for the design and implementation of effective social transfer policies to combat child and overall poverty in European countries.

1. Introduction

Childhood poverty constitutes one of the great challenges of our times, also in high-income countries, and has profound implications for individual well-being and societal development [1]. Sustainable Development Goal (SDG) 1 addresses poverty in all its forms everywhere and in Target 1.2 specifically encourages reducing by half child poverty (as measured according to national definitions) by 2030. In Europe, around one out of every five children lives in relative income poverty. This figure is higher than that of overall poverty in most countries of Europe, although with significant differences across countries [2]. This leads us to support that overall poverty levels, including those among different age groups, are influenced by a range of factors, including institutional settings and policy priorities over time ([3,4], among others).

Focusing on budgetary management, governments' decisions regarding public spending and revenue allocation are influenced by diverse objectives and circumstances. The level and composition of public spending, for example, are subject to numerous conditions: the levels reached in previous periods, the commitments acquired for future years, the greater or lesser expected availability of public revenue, and the budget balance and debt levels that are intended to be achieved, among others. In the short term, governmental room for determining the levels and composition of public spending is constrained by political priorities, although there is some flexibility to progressively refocus spending programmes towards specific objectives. In this context, social expenditure, particularly direct transfers to households, is widely recognized as a significant tool for reducing child and overall poverty, despite inherent trade-offs [5,6]. In particular, according to the literature, three specific key features of national social transfer systems should be examined to assess the effectiveness of social transfers: 1) the total expenditure on social transfers; 2) the distribution of spending by type of social benefits (i.e. retirement, survival, unemployment, illness, disability, family and children, social exclusion, housing, etc.); and 3) the nature of social transfers that are more or less conditional on the income level of the recipients (see, e.g., Ref. [7–13]).

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This paper aims to analyse the potential impact on overall and child poverty of different features of social transfers in 24 European countries through a combination of econometric and multiobjective techniques. To this end, we first estimate two logistic regression models controlling for household-level sociodemographic variables and country-level contextual variables that include some descriptive key features related to both the size and form of targeting of each country's social transfer system. In particular, the country-level policy decision variables consider the level of cash social benefits as a percentage of the gross domestic product (GDP), child and family cash benefits as a percentage of total cash benefits, the percentage of means-tested cash benefits over total cash benefits, and the percentage of cash benefits spent on poor children. Secondly, a multiobjective optimization problem with two objective functions is defined for each country using the previous models. The purpose is to obtain the combination of country-level indicators on key features of national social transfer systems that minimize the rate of child and overall poverty and tend to equal the levels of both rates downwards taking into account the starting context of each of the countries examined. To introduce realistic constraints, among other aspects, we consider potential changes in the size of social transfers close to the current levels for each country and the usual trade-off regarding how social transfers are targeted between pro-child and pro-poor targeting.

This paper makes several contributions. Although multiobjective programming tools have already been used to solve problems in different socioeconomic contexts (see Ref. [14–16], among others), this study is a first attempt to apply multiobjective programming to jointly minimize child and overall poverty by comparing key features of national social transfer systems. Several studies have combined logistic regressions with multiobjective optimization techniques. Pyo et al. [17] and Janagoudar et al. [18] utilized logistic regression solely for data categorization, followed by the resolution of a multiobjective optimization problem. This combination extends to machine learning, where training employs multiobjective optimization algorithms, followed by the exclusive use of logistic regressions for classification [19–21].

In contrast to the aforementioned studies, our approach diverges by employing logistic regression not for classification but to define the objective functions using estimated logistic regression coefficients within the overarching multiobjective optimization problem. These objective functions are incorporated into certain constraints. This differs from [22], which optimized only the parameters of a cost-sensitive logistic regression using a multi-objective particle swarm optimization algorithm, without utilizing the estimated coefficients to define the problem.

The rest of the paper is organized as follows. Section 2 describes the data, econometric estimation strategy, and the decision variables used to build the multiobjective optimization model developed in Section 3. Finally, some conclusions and policy recommendations are drawn in Section 4.

2. Econometric analysis

The proposed multiobjective programming model will employ the coefficients specified and estimated in this section to define the objective functions and constraints.

2.1. Data

We use the 2019 wave of the European Union Statistics on Income and Living Conditions (EU-SILC) as well as some significant contextual variables (see Appendix A) from Eurostat for 24 European countries (see Table B1 in Appendix B for the sample size and countries).

The analysis pools the data from the 24 countries into one merged file that contains information on individuals living in 106,429 households. When the analysis is confined to children (defined as those under 18 years of age living in the household unit, as in Ref. [24,25]; among others), the merged file contains information on 48,946 households with children.

Following Eurostat, our poverty measure is based on annual household disposable income (post-tax, post-transfer) adjusted for variations in household size and composition using the modified OECD (Organization for Economic Co-operation and Development) scale, which assigns a value of 1 to the household head, a value of 0.5 to each additional adult member, and a value of 0.3 to each child in the household. Income information corresponds to the year prior to the survey for all countries

Table 1
Results of the estimations (odds ratio estimates).

VARIABLES	Overall poverty		VARIABLES	Child poverty	
Lone parent	1.944[a]	(0.097)	Lone parent	1.128	(0.169)
Jobless	7.353[a]	(0.979)	Jobless	3.592[a]	(0.511)
Nch_2	1.176	(0.139)	Nch_2	1.226	(0.165)
Nch_3_5	1.214[a]	(0.055)	Nch_3_5	1.334[a]	(0.099)
Nch_6_11	1.220[a]	(0.063)	Nch_6_11	1.312[a]	(0.104)
Nch_12_17	1.455[a]	(0.086)	Nch_12_17	1.592[a]	(0.137)
Owner	0.903	(0.082)	Owner	1.062	(0.081)
Women head	1.063	(0.080)			
Young head	1.814[a]	(0.236)	Young father	1.329[c]	(0.203)
Old head	0.218[a]	(0.045)	Old father	0.430[a]	(0.115)
Secondary head	0.519[a]	(0.057)	Secondary father	0.747[b]	(0.087)
Tertiary head	0.188[a]	(0.026)	Tertiary father	0.326[a]	(0.049)
Work head	0.397[a]	(0.034)	Work father	0.390[a]	(0.047)
Health head	0.981	(0.051)	Health father	1.133	(0.093)
Immigrant (from EU) head	1.688[a]	(0.291)	Immigrant (from EU) father	1.467[b]	(0.258)
Immigrant (non-EU) head	2.451[a]	(0.468)	Immigrant (non-EU) father	1.724[a]	(0.304)
			Young mother	1.521[b]	(0.264)
			Old mother	0.419[b]	(0.145)
			Secondary mother	1.033	(0.078)
			Tertiary mother	0.478[a]	(0.048)
			Work mother	0.334[a]	(0.052)
			Health mother	0.868[b]	(0.060)
			Immigrant (from EU) mother	1.466[a]	(0.178)
			Immigrant (non-EU) mother	1.734[a]	(0.160)
Size	0.969	(0.024)	Size	0.934[a]	(0.023)
Child orientation	0.960	(0.030)	Child orientation	0.900[a]	(0.024)
Poor orientation of child benefits	1.003	(0.003)	Poor orientation of child benefits	1.001	(0.003)
Poor orientation of all benefits	0.970[a]	(0.007)	Poor orientation of all benefits	0.976[a]	(0.008)
Constant	1.119	(0.765)	Constant	3.979[b]	
Observations	106,429		Observations	48,946	
Number of groups	24		Number of groups	24	

Robust standard errors in brackets.
Note: Reference category for overall poverty is an individual living in a household with a man, middle-age, primary educated, non-working, in good health and native head, in a no lone-parent household where someone works and a member of the household is the outright owner of the dwelling. Reference category for child poverty is a child with a middle-age, primary educated, non-working, in good health and native father and mother, in a no lone-parent household where someone works and a member of the household is the outright owner of the dwelling.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.
Source: EU-SILC CROSS-SECTIONAL UDB [23].

except Ireland (where the income reference period refers to 12 months prior to the interview). The individual or child is classified as poor if he/she lives in a household with disposable household equivalent income below 60 per cent of the contemporary median equivalent income of the country where the individual or child lives. This poverty line, 60 per cent of the contemporary median equivalent income of the country, is the one used in the official poverty measures at the European level [26, 27][1].

We run two regressions, one for all individuals and another specifically for children. In both regressions the dependent variable is a binary variable that takes the value of 1 if the individual or child is poor.

2.2. Explanatory variables

As all individuals (children) in the same household share the same particular features, we control for these combined with the characteristics of the household head or of the father and mother in the children sample (Table B2 in Appendix B). We distinguish between fathers' and mothers' features because the literature has shown them to have a different effect on children's poverty (see, e.g. Ref. [12]). The characteristics are those commonly found in the related literature, namely parents' age, level of education, health status, labour market participation and immigration status (EU and non-EU) [7,8,24,25,28].

The statistics in Table B2 in Appendix B reveal well-known differences between the characteristics of households where children live and overall household characteristics. These include a higher incidence of poverty among children than in the overall population; a slightly lower level of education of fathers and mothers, on average, than in the general population; or a better health status of fathers and mothers than the health status of the head of the household in the overall sample.

The features of social benefits, such as the size, child orientation, poor orientation of child benefits, or overall benefits (see Table B3 in Appendix B and Appendix A for an extended definition), are the decision variables of our model. All of the decision variables are continuous for 2018, which is the reference period for the household income for all countries, including Ireland. The summary statistics of the variables are reported in Table B3 in Appendix B.

Note that to examine the role of benefits in reducing poverty in general and child poverty in particular, we consider expenditure on all benefits as a way of measuring the size of the social benefits system[2] by means of the variable *Size*. We evaluate the countries' intent to target lower incomes (in general and lower-income children) and children through three input indicators (defined in Table B3 in Appendix B): *Poor orientation of child benefits, Poor orientation of all benefits*, and *Child orientation*.

2.3. Estimation strategy

We estimate multilevel logit models for the overall sample and children sample for two reasons. Firstly, because conventional multivariate regression techniques do not account for the hierarchical structure of our data (individuals in level 1 and nested into countries in level 2) and the standard errors of variables at higher levels would be

[1] Note that the use of 60 % of median income as the poverty threshold dates back to the 1970s (see, for instance Ref. [40]). It is argued that this threshold represented a level of income below which individuals and households were at risk of being excluded from the ordinary living patterns, customs and activities of the society to which they belonged. In recent decades, this threshold has gained traction within the European context and has been widely adopted not only within the EU but also internationally.

[2] Social benefits include unemployment benefits, pensions, sickness benefits, disability benefits, education-related allowances, family- or child-related allowances, housing allowances, and other social assistance benefits not classified elsewhere.

Table 2
Decision variable values in the optimal solutions.

Country	Scenario	Size	Child orientation	Poor orientation of child benefits	Poor orientation of all benefits
Austria	Scenario 1	19.200	11.900	0.000	3.673
	Scenario 2	19.700	11.900	0.000	3.673
	Scenario 3	20.200	11.900	0.000	3.673
	Scenario 4	20.700	11.900	0.000	3.673
	Scenario 5	21.200	11.777	0.000	3.785
	Current value	19.200	9.900	9.050	5.491
Belgium	Scenario 1	18.500	11.190	0.000	4.180
	Scenario 2	19.000	11.190	0.000	4.179
	Scenario 3	19.500	11.190	0.000	4.180
	Scenario 4	20.000	11.005	0.000	4.348
	Scenario 5	20.500	10.759	0.000	4.572
	Current value	18.500	9.190	1.110	5.998
Bulgaria	Scenario 1	11.000	12.000	0.000	1.520
	Scenario 2	11.500	12.000	0.000	1.520
	Scenario 3	12.000	12.000	0.000	1.520
	Scenario 4	12.500	12.000	0.000	1.520
	Scenario 5	13.000	12.000	0.000	1.520
	Current value	11.000	10.000	30.690	3.338
Croatia	Scenario 1	13.700	10.760	82.554	3.701
	Scenario 2	14.200	10.760	71.683	3.701
	Scenario 3	14.700	10.760	60.724	3.701
	Scenario 4	15.200	10.760	49.674	3.701
	Scenario 5	15.700	10.760	38.528	3.701
	Current value	13.700	8.760	27.220	5.519
France	Scenario 1	20.000	8.941	0.000	9.802
	Scenario 2	20.500	8.694	0.000	10.027
	Scenario 3	21.000	8.447	0.000	10.251
	Scenario 4	21.500	8.201	0.000	10.475
	Scenario 5	22.000	7.954	0.000	10.700
	Current value	20.000	7.000	31.970	11.567
Greece	Scenario 1	20.100	7.470	0.000	9.127
	Scenario 2	20.600	7.229	0.000	9.395
	Scenario 3	21.100	6.982	0.000	9.667
	Scenario 4	21.600	6.733	0.000	9.941

(continued on next page)

Table 2 (*continued*)

Country	Scenario	Size	Child orientation	Poor orientation of child benefits	Poor orientation of all benefits
	Scenario 5	22.100	6.488	0.000	10.209
	Current value	20.100	7.960	71.620	8.591
Hungary	Scenario 1	11.100	15.510	0.000	0.769
	Scenario 2	11.600	15.510	0.000	0.769
	Scenario 3	12.100	15.510	0.000	0.769
	Scenario 4	12.600	15.446	0.000	0.809
	Scenario 5	13.100	15.219	0.000	1.033
	Current value	11.100	13.510	2.280	2.587
Ireland	Scenario 1	8.000	17.000	0.000	26.418
	Scenario 2	8.500	17.000	0.000	26.418
	Scenario 3	9.000	17.000	0.000	26.418
	Scenario 4	9.500	17.000	0.000	26.418
	Scenario 5	10.000	17.000	0.000	26.418
	Current value	8.000	15.000	30.970	28.236
Italy	Scenario 1	21.200	6.250	0.000	6.351
	Scenario 2	21.700	6.101	0.000	6.479
	Scenario 3	22.200	5.853	0.000	6.712
	Scenario 4	22.700	5.598	0.000	6.944
	Scenario 5	23.200	5.340	0.000	7.178
	Current value	21.200	4.250	50.990	8.169
Netherlands	Scenario 1	17.000	6.120	55.279	8.901
	Scenario 2	17.500	6.120	43.462	8.901
	Scenario 3	18.000	6.120	31.502	8.901
	Scenario 4	18.500	6.120	19.384	8.901
	Scenario 5	19.000	6.120	7.100	8.901
	Current value	17.000	4.120	35.640	10.719
Norway	Scenario 1	15.200	9.890	38.131	3.326
	Scenario 2	15.700	9.890	25.913	3.326
	Scenario 3	16.200	9.890	13.525	3.326
	Scenario 4	16.700	9.890	0.945	3.326
	Scenario 5	17.200	9.890	0.000	3.326
	Current value	15.200	7.890	13.660	5.144
Poland	Scenario 1	15.000	11.971	0.000	5.616
	Scenario 2	15.500	11.725	0.000	5.886
	Scenario 3	16.000	11.487	0.000	6.148
	Scenario 4	16.500	11.244	0.000	6.415
	Scenario 5	17.000	11.003	0.000	6.681
	Current value	15.000	12.670	34.170	4.847
Portugal	Scenario 1	16.500	6.850	0.000	4.133
	Scenario 2	17.000	6.850	0.000	4.133
	Scenario 3	17.500	6.850	0.000	4.133
	Scenario 4	18.000	6.850	0.000	4.133
	Scenario 5	18.500	6.805	0.000	4.174
	Current value	16.500	4.850	54.940	5.951
Romania	Scenario 1	10.000	12.847	0.000	2.642
	Scenario 2	10.500	12.593	0.000	2.873
	Scenario 3	11.000	12.333	0.000	3.109
	Scenario 4	11.500	12.077	0.000	3.342
	Scenario 5	12.000	11.818	0.000	3.577
	Current value	10.000	11.000	4.800	4.321
Serbia	Scenario 1	13.900	9.910	0.000	3.119
	Scenario 2	14.400	9.910	0.000	3.119
	Scenario 3	14.900	9.910	0.000	3.119
	Scenario 4	15.400	9.910	0.000	3.119
	Scenario 5	15.900	9.910	0.000	3.119
	Current value	13.900	7.910	24.060	4.937
Slovenia	Scenario 1	14.200	10.450	0.000	6.053
	Scenario 2	14.700	10.450	0.000	6.053
	Scenario 3	15.200	10.450	0.000	6.053
	Scenario 4	15.700	10.450	0.000	6.053
	Scenario 5	16.200	10.450	0.000	6.053
	Current value	14.200	8.450	46.410	7.871
Spain	Scenario 1	16.000	4.963	0.000	8.879
	Scenario 2	16.500	4.707	0.000	9.112
	Scenario 3	17.000	4.449	0.000	9.346
	Scenario 4	17.500	4.191	0.000	9.581
	Scenario 5	18.000	3.936	0.000	9.812
	Current value	16.000	3.130	11.480	10.545

Source: Authors' own calculations

Table 3
Optimal overall and child poverty rates.

Country	Scenario	Overall poverty	Child poverty	Country	Scenario	Overall poverty	Child poverty
Austria	Scenario 1	8.784	8.211	Netherlands	Scenario 1	8.239	9.242
	Scenario 2	8.660	7.958		Scenario 2	7.862	8.865
	Scenario 3	8.539	7.713		Scenario 3	7.498	8.500
	Scenario 4	8.418	7.474		Scenario 4	7.146	8.148
	Scenario 5	8.312	7.311		Scenario 5	6.806	7.809
	Current value	13.300	14.900		Current value	13.200	13.600
Belgium	Scenario 1	9.146	8.433	Norway	Scenario 1	7.285	8.286
	Scenario 2	9.018	8.174		Scenario 2	6.940	7.941
	Scenario 3	8.892	7.923		Scenario 3	6.608	7.608
	Scenario 4	8.788	7.788		Scenario 4	6.286	7.287
	Scenario 5	8.692	7.693		Scenario 5	6.179	7.055
	Current value	14.800	18.900		Current value	12.700	13.700
Bulgaria	Scenario 1	13.255	13.723	Poland	Scenario 1	10.070	9.075
	Scenario 2	13.078	13.325		Scenario 2	9.948	8.954
	Scenario 3	12.903	12.937		Scenario 3	9.827	8.830
	Scenario 4	12.729	12.559		Scenario 4	9.708	8.711
	Scenario 5	12.558	12.191		Scenario 5	9.589	8.592
	Current value	22.600	27.500		Current value	15.400	13.400
Croatia	Scenario 1	12.080	13.074	Portugal	Scenario 1	11.116	10.721
	Scenario 2	11.579	12.572		Scenario 2	10.964	10.399
	Scenario 3	11.092	12.087		Scenario 3	10.814	10.087
	Scenario 4	10.622	11.616		Scenario 4	10.665	9.783
	Scenario 5	10.166	11.160		Scenario 5	10.524	9.519
	Current value	18.300	17.100		Current value	17.200	18.500
France	Scenario 1	9.209	8.214	Romania	Scenario 1	17.304	16.309
	Scenario 2	9.108	8.113		Scenario 2	17.132	16.134
	Scenario 3	9.008	8.013		Scenario 3	16.964	15.967
	Scenario 4	8.909	7.914		Scenario 4	16.796	15.797
	Scenario 5	8.812	7.817		Scenario 5	16.629	15.632
	Current value	13.100	14.100		Current value	23.800	30.800
Greece	Scenario 1	12.130	11.132	Serbia	Scenario 1	17.814	18.600
	Scenario 2	11.985	10.983		Scenario 2	17.588	18.090
	Scenario 3	11.843	10.841		Scenario 3	17.365	17.592
	Scenario 4	11.703	10.703		Scenario 4	17.144	17.104
	Scenario 5	11.564	10.562		Scenario 5	16,925	16.628
	Current value	17.900	21.100		Current value	23.200	28.900
Hungary	Scenario 1	9.067	8.417	Slovenia	Scenario 1	7.271	7.314
	Scenario 2	8.940	8.158		Scenario 2	7.167	7.087
	Scenario 3	8.815	7.907		Scenario 3	7.065	6.866
	Scenario 4	8.702	7.704		Scenario 4	6.964	6.652
	Scenario 5	8.600	7.594		Scenario 5	6.864	6.444
	Current value	12.300	11.500		Current value	12.000	10.500
Ireland	Scenario 1	6.048	5.641	Spain	Scenario 1	16.134	15.138
	Scenario 2	5.961	5.462		Scenario 2	15.972	14.976
	Scenario 3	5.874	5.289		Scenario 3	15.812	14.817
	Scenario 4	5.789	5.122		Scenario 4	15.654	14.659
	Scenario 5	5.705	4.959		Scenario 5	15.496	14.500
	Current value	13.100	14.100		Current value	20.700	27.400
Italy	Scenario 1	14.753	13.852				
	Scenario 2	14.587	13.598				
	Scenario 3	14.434	13.440				
	Scenario 4	14.287	13.292				
	Scenario 5	14.141	13.148				
	Current value	20.100	24.500				

Source: Authors' own calculations.

underestimated. Secondly, because we require a model in which we can explore information beyond clustering.

Unlike linear regression, the purpose of logistic regression is not to predict the value of variable y_{ic} for individual or child i in country c from one or several predictor variables (X_{ic}), but rather to predict the probability that y_{ic} will occur when the values of the variables X_{ic} are known. These probabilities are known as odds ratios. $\pi_{ic} = P(y_{ic}=1|X_{ic})$ is the probability of individual or child i in country c being in poverty. The general equation is defined as follows:

$$\pi_{ic} = P(y_{ic}=1|X_{ic}) = \frac{e^{\beta_0+\beta_1 X_{ic}}}{1+e^{\beta_0+\beta_1 X_{ic}}} \quad (1)$$

where X_{ic} denotes the explanatory variables (household and country level variables). Applying logarithms to both members of the equality and considering their properties, we can linearize:

$$log\left(\frac{\pi_{ic}}{1-\pi_{ic}}\right) = \beta_0 + \beta_1 X_{ic} \quad (2)$$

where β_1 is a vector of coefficients. Each coefficient is interpreted as the effect that an additional unit of the corresponding variable in X_{ic} would have on the log-odds of poverty (it can be positive or negative). e^{β_1}, which is always positive, is interpreted as an odds ratio. Thus, values greater than 1 indicate that for every one-unit increase in the predictor, the odds of poverty increase by a factor of e^{β_1}. For e^{β_1} lower than 1, a one-unit increase in the predictor will reduce the odds of poverty by a factor of e^{β_1}.

Alternatively, we can consider a latent variable conceptualization. Let us assume a latent continuous response, y^*_{ic}, that represents the propensity of an individual or child i in country c being poor as compared to not poor such that:

$$y_{ic} = \begin{cases} 1 \ if \ y^*_{ic} > 0 \\ 0 \ otherwise \end{cases} \tag{3}$$

A linear regression model is specified for the latent response y^*_{ic}.

$$y^*_{ic} = \beta_0 + \beta_1 X_{ic} + \xi_c + \varepsilon_{ic} \tag{4}$$

where ξ_c is the random intercept representing the difference between the mean of poverty risk in a given country c and the overall mean and ε_{ic} are the individual level residuals, that is, the difference between the poverty risk of individual i and the average poverty risk in individual i's country c.

2.4. Results of the estimation

Table 1 shows the results of the estimation where our variables of interest are the context variables. One of the main advantages when using multilevel models is that we gain precision compared to using only aggregate (country-level) data because micro-level mechanisms are considered. Moreover, macro-level studies can only control for individual characteristics such as family structure at the aggregate level.

The results shown in Table 1 are in line with the literature ([11–13, 29], among others). First, regarding household characteristics, both regressions (i.e., the overall sample and the children sample) indicate that an individual or child living in a lone-parent household, in a household where no one works, or in a household with a larger number of children (even more if the child is 12–17 years old), the higher the likelihood of being poor.

As regards the characteristics of the household head for the regression on the overall sample and parents' characteristics for the children sample, our results are also aligned with previous results. Specifically, individuals or children living with a younger household head or parent, a less educated household head or parent, or an unemployed household head or parent are more likely to be poor. A household head or parent with bad health is not associated with a higher likelihood of being poor.[3] Finally, individuals and children with an immigrant household head or parent are more likely to be poor and even more so in the case of those living with a non-EU immigrant head or parent.

Our main interest is to examine different features of the social transfer systems because they are the decision variables of our multiobjective optimization model. For the sample of overall individuals, the results show that only pro-poor targeting is significantly associated with overall poverty risk, such that the higher the pro-poor targeting, the lower the risk of poverty. On the other hand, for children, the higher the size and targeting, (either pro-child or pro-poor targeting), the lower the risk of child poverty, with pro-child targeting showing a stronger association with child poverty risk.

This result can be explained as follows. Pro-poor transfers are distributed to individuals in the lower part of the distribution and therefore help children and individuals in general to exit poverty. Additionally, child-oriented transfers reinforce the reduction in child poverty because children are not uniformly spread across the entire income distribution but are predominantly found in lower deciles. Therefore, transfers targeting children seem to increase children's incomes above the poverty threshold and eventually make them less vulnerable to poverty.

Finally, the non-significant association between the size of the social benefits system and the risk of poverty for individuals overall may be due to the fact that lower deciles are, to a larger extent, composed of households without children, as shown in [12]. Therefore, these individuals are further away from the poverty line than children, who require greater effort to exit poverty. Consequently, the size of the transfer system would only have a significant effect for these individuals if it were large enough, while it has an effect for children who, despite being poor, are closer to the poverty line.

3. Multiobjective optimization problem

Multiobjective programming problems involve several criteria to be optimized (maximized or minimized) simultaneously. In such problems, the criteria and the constraints that determine the feasible set of alternatives can be mathematically expressed by functions. Since the criteria, also known as objective functions, are usually conflicting, there is no solution where all the objectives can reach their individual optimal solution at the same time. Instead, it is possible to identify some compromise solutions. These are known as Pareto optimal solutions, non-dominated objective vectors, or efficient solutions, where none of the objectives can improve without detriment to at least one of the others.

3.1. Concepts and notation in multiobjective optimization

In order to model and solve the multiobjective optimization model proposed in this study, let us firstly see the basic definitions and notations on multiobjective optimization. Considering the following general multiobjective problem:

$$\begin{array}{c} \min f(\mathbf{x}) = \left(f^1(\mathbf{x}), \ldots, f^k(\mathbf{x})\right) \\ s.t. : \mathbf{x} \in X \end{array} \tag{5}$$

involving k (≥ 2) conflicting objective functions $f^j : X \to \mathbb{R}$, $j = 1, \ldots, k$, which must be minimized simultaneously and where $\mathbf{x} = (x_1, \ldots, x_m)^T$ is the vector of the decision variables. Without loss of generality, all functions are minimized and to maximize them, the opposite function is simply minimized. The decision vector $\mathbf{x}$ belongs to the feasible region $X \subset \mathbb{R}^n$, which is a nonempty compact set. The image of any $\mathbf{x} \in X$, $\mathbf{z} = f(\mathbf{x})$ is called the objective vector and $Z = f(X)$ is called a feasible objective region. Usually, it is impossible to find a feasible solution to simultaneously minimize all objective functions due to the degree of conflict among the objectives. A decision vector $\mathbf{x}' \in X$ can be defined as efficient or a Pareto optimal solution of the problem (5) if there does not exist another $\mathbf{x} \in X$ such that $f^j(\mathbf{x}) \leq f^j(\mathbf{x}')$ for all $j = 1, \ldots, k$, with at least one strict inequality. When this occurs, $\mathbf{z}' = f(\mathbf{x}')$ is called a nondominated objective vector. The efficient set is denoted by E and $f(E)$ is the nondominated objective set.

The vector formed by the optimal individuals of each objective function is called the ideal vector $z^* = (z^*_1, \ldots, z^*_k)$, where $z^*_j = \min_{x \in E} f^j(x) = \min_{x \in X} f^j(x)$ for all $j = 1, \ldots, k$. On the one hand, lower bounds are set by the nadir vector $z^{nad} = (z^{nad}_1, \ldots, z^{nad}_k)$, where $z^{nad}_j = \max_{x \in E} f^j(x)$ for all $j = 1, \ldots, k$. While the ideal objective vector can be easily obtained, the nadir objective vector is usually approximated [30].

3.2. Multiobjective optimization model

3.2.1. Objective functions and variables

As mentioned in Section 2, to predict overall poverty (f^1) and child poverty (f^2), we first estimate two logistic regression models with independent micro-level variables (i.e., sociodemographic characteristics) and country-level variables.

[3] This non-significant effect is the net of other characteristics. Unsurprisingly, higher poverty among those suffering from health problems can be accounted for by other variables introduced in the model, such as labour status or age.

To define our multiobjective optimization model, the objective functions f^1 and f^2 are defined as a function of *Size* (x_1), *Child orientation* (x_2), *Poor orientation of child benefits* (x_3), and *Poor orientation of all benefits* (x_4). The sociodemographic features are incorporated in the objective functions through their mean values. Therefore, for each country, a specific multiobjective optimization problem is defined since it depends on the country's own characteristics.

For country c ($c = 1, 2, \ldots, 24$), the objective functions of the multiobjective optimization problem are given by:

$$f_c^1(x_1, x_2, x_3, x_4) = \widehat{\beta}_{0c}^1 + \widehat{\beta}_1^1 x_1 + \widehat{\beta}_2^1 x_2 + \widehat{\beta}_3^1 x_3 + \widehat{\beta}_4^1 x_4$$

$$f_c^2(x_1, x_2, x_3, x_4) = \widehat{\beta}_{0c}^2 + \widehat{\beta}_1^2 x_1 + \widehat{\beta}_2^2 x_2 + \widehat{\beta}_3^2 x_3 + \widehat{\beta}_4^2 x_4$$

where $\widehat{\beta}_r^j$ ($r = 1, \ldots, 4$; $j = 1, 2$) are the regression coefficients (log-odds) and the constants $\widehat{\beta}_{0c}^1$ and $\widehat{\beta}_{0c}^2$ include both the fixed effect and the current sociodemographic features of each country.

3.2.2. Bounds and constraints

To make our multiobjective optimization model more realistic, it is necessary to define a set of constraints that allows us to define different policies or strategies to be carried out based on the current situation. Specifically, for each country c ($c = 1, 2, \ldots, 24$), several constraints and bounds are defined considering the current rate of poverty (overall and child poverty) and the current values of the decision variables. Let us consider in our model:

I. It seems desirable for child and overall poverty rates to not differ significantly, ensuring that all age groups exhibit similar levels of poverty. In formal terms, we can determine that the absolute difference between π_c^1 and π_c^2 must not exceed one percentage point. Hence, the difference between the overall and child poverty rate cannot be higher than one percentage point:

$$|\pi_c^1 - \pi_c^2| \leq 0.01 \Longrightarrow$$

$$\left| \frac{e^{f_c^1(x_1,x_2,x_3,x_4)}}{1 + e^{f_c^1(x_1,x_2,x_3,x_4)}} - \frac{e^{f_c^2(x_1,x_2,x_3,x_4)}}{1 + e^{f_c^2(x_1,x_2,x_3,x_4)}} \right| \leq$$

$$\leq \left| \frac{e^{\hat{\beta}_{0c}^1 + \sum_{r=1}^4 \hat{\beta}_r^1 x_r}}{1 + e^{\hat{\beta}_{0c}^1 + \sum_{r=1}^4 \hat{\beta}_r^1 x_r}} - \frac{e^{\hat{\beta}_{0c}^2 + \sum_{r=1}^4 \hat{\beta}_r^2 x_r}}{1 + e^{\hat{\beta}_{0c}^2 + \sum_{r=1}^4 \hat{\beta}_r^2 x_r}} \right| \leq 0.01$$

II. For each country, the current levels of child and overall poverty are taken as a starting point with the objective of reducing both rates below the lower of the two rates. In other words, the optimal poverty rates must not be greater than the minimum of both the current overall and child poverty rates.

$$\pi_c^1 \leq \min\{\overline{p}_{1c}, \overline{p}_{2c}\}$$

$$\pi_c^2 \leq \min\{\overline{p}_{1c}, \overline{p}_{2c}\}$$

where $\overline{p}_{1c}$ and $\overline{p}_{2c}$ are the current overall and child poverty rates of country c, respectively.

III. In policy terms, given certain presupposed budgetary constraints of governments, we can consider alternative scenarios with different types of social transfer targeting, such as pro-child *versus* pro-poor targeting. Thus, considering the current values for *Child orientation* (x_2) and *Poor orientation of all benefits* (x_4), we assume that, to some extent, increases in the decision variable x_2 must come at the expense of decreases in x_4:

$$(x_2 - \overline{x}_2)(x_4 - \overline{x}_4) \leq -0.01$$

where $\overline{x}_2$ and $\overline{x}_4$ are the current values of x_2 and x_4, respectively. In addition, the range of improvement or worsening of both decision variables cannot be greater than two percentage points, so the lower and upper bounds (*lb* and *ub*, respectively) are defined as follows:

$$lb_r = \overline{x}_r - 2, r = 2, 4$$

$$ub_r = \overline{x}_r + 2, r = 2, 4$$

IV. Defining the above restriction, the trade-off between pro-child (x_2) and pro-poor (x_4) targeting would not necessarily nullify either one. Thus, we propose scenarios in which the modification of each type of orientation is not drastic. Specifically, we impose the restriction that the increase with respect to the starting situation in one type of orientation does not exceed the reduction in another type of orientation by more than 10 percentage points. Thus, the absolute value of the trade-offs cannot be less than 1.10:

$$\left| \frac{x_2 - \overline{x}_2}{x_4 - \overline{x}_4} \right| \leq 1.10 \text{ and } \left| \frac{x_4 - \overline{x}_4}{x_2 - \overline{x}_2} \right| \leq 1.10$$

which is equivalent to

$$\frac{1}{1.10} \leq \left| \frac{x_2 - \overline{x}_2}{x_4 - \overline{x}_4} \right| \leq 1.10$$

V. Finally, to consider potential, reasonable changes in the total cash benefits over the GDP in each country, we set that *Size* (x_1) is bounded around its current value ($\overline{x}_1$). In particular, we consider several scenarios where this decision variable is bounded until two points, both above and below:
   Scenario 1: $x_1 = \overline{x}_1$.
   Scenario 2: $\overline{x}_1 - 0.5 \leq x_1 \leq \overline{x}_1 + 0.5$.
   Scenario 3: $\overline{x}_1 - 1 \leq x_1 \leq \overline{x}_1 + 1$.
   Scenario 4: $\overline{x}_1 - 1.5 \leq x_1 \leq \overline{x}_1 + 1.5$.
   Scenario 5: $\overline{x}_1 - 2 \leq x_1 \leq \overline{x}_1 + 2$.

These scenarios can be written as: $|x_1 - \overline{x}_1| \leq t$, where $t = 0, 0.5, 1, 1.5, 2$.

3.2.3. Model and results

The resulting multiobjective optimization problem is formed by two objective functions, five constraints, and two bound constraints. For each country $c = 1, 2, \ldots, 24$ and each scenario $t = 0, 0.5, 1, 1.5, 2$ can be defined as follows:

$$Min \left(\widehat{\beta}_{0c}^1 + \sum_{r=1}^4 \widehat{\beta}_r^1 x_r, \widehat{\beta}_{0c}^2 + \sum_{r=1}^4 \widehat{\beta}_r^2 x_r \right)$$

$$\text{Subject to}: \left| \frac{e^{\hat{\beta}_{0c}^1 + \sum_{r=1}^4 \hat{\beta}_r^1 x_r}}{1 + e^{\hat{\beta}_{0c}^1 + \sum_{r=1}^4 \hat{\beta}_r^1 x_r}} - \frac{e^{\hat{\beta}_{0c}^2 + \sum_{r=1}^4 \hat{\beta}_r^2 x_r}}{1 + e^{\hat{\beta}_{0c}^2 + \sum_{r=1}^4 \hat{\beta}_r^2 x_r}} \right| \leq 0.01 \quad (6)$$

$$(x_2 - \overline{x}_2)(x_4 - \overline{x}_4) \leq -0.01$$

$$\frac{1}{1.10} \leq \left| \frac{x_2 - \overline{x}_2}{x_4 - \overline{x}_4} \right| \leq 1.1$$

$$\pi_c^1 \leq \min\{\overline{p}_{1c}, \overline{p}_{2c}\}$$

$$\pi_c^2 \leq \min\{\overline{p}_{1c}, \overline{p}_{2c}\}$$

$$|x_1 - \overline{x}_1| \leq t$$

$$lb_r \leq x_i \leq ub_r, r = 2, 4$$

$0 \leq x_3 \leq 100$

In total, 120 multiobjective optimization problems are solved (5 scenarios for 24 countries) using the preference-based evolutionary multiobjective optimization algorithm called NSGA-III [31] by means of PlatEMO [32].

3.3. Brief description of NSGA-III

The NSGA-III algorithm is an extension of the famous NSGA-II algorithm [33]. It was designed to overcome some of the limitations of the NSGA-II algorithm and improve the diversity and convergence of solutions. NSGA-II uses an elite preserving strategy and a diversity preserving mechanism that stands out for its fast non-dominated sorting procedure to rank the solutions into several non-dominated fronts for the selection of the best individuals. NSGA-III also ranks individuals according to the Pareto dominance relation but includes a diversity strategy that considers a set of reference points and emphasizes the closest individuals to each of these reference points considering an achievement scalarizing function. In practice, the distribution of reference points affects both the convergence and the diversity of the approximation generated by NSGA-III.

Many methods have been proposed to generate Pareto optimal solutions in multiobjective optimization problems. One group of techniques is based on the reference point methodology, where some values for the objective functions constitute the preferential information considered in the multiobjective programming model. Given some reference values for the objective functions, $\mathbf{q} = (q_1, \dots, q_k)^T$, which constitute the so-called reference point, and given a vector of weights $\mu = (\mu_1, \dots, \mu_k)^T$ to reach them, an achievement scalarizing function is built and minimized over the feasible set. Wierzbicki [34] proposed one of the most widely used achievement scalarizing functions (ASF):

$$s(\boldsymbol{q}, f(\boldsymbol{x}), \boldsymbol{\mu}) = \max_{j=1,\dots,k} \{\mu_j (f^j(\boldsymbol{x}) - q_j)\} + \rho \sum_{j=1}^{k} \mu_j (f^j(\boldsymbol{x}) - q_i) \tag{7}$$

which must be minimized in the feasible region:

$$\begin{aligned} &\min s(\mathbf{q}, f(\mathbf{x}), \mu) \\ &\quad s.t. : \mathbf{x} \in X \end{aligned} \tag{8}$$

where $\mu_j > 0$ for $j = 1, \dots, k$ and $\rho > 0$ is a so-called augmentation coefficient, which must be a small value to ensure the efficiency of the solutions generated. The vector $\mu = (\mu_1, \dots, \mu_k)^T$ is formed by the weights assigned to reach the reference values and can have different meanings [35]. Problem (8) produces nondominated solutions and it has been demonstrated that any Pareto optimal solution can be found by solving (8) using the ideal objective vector as a reference point (or any objective vector that dominates it, such as a utopian vector) and varying the weight vector in the whole weight vector space (Wierzbicki, 1980 [36]). It has also been demonstrated that by fixing the weight vector and varying the reference point any Pareto optimal solution can be found by solving (8) [36]. These good properties of the reference point approach and the good results of the NSGA-II algorithm have led us to use NSGA-III.

Since a constraint is non-differentiable in our model, we will solve problem (6) using formulation (8). Moreover, as this is a non-convex problem and exact techniques do not usually work well, we have used non-exact methods that, in general, are able to generate good approximations of the Pareto optimal front. Specifically, we have used the PlatEMO platform [32], which has a wide variety of evolutionary multiobjective optimization (EMO) algorithms. PlatEMO is implemented in MATLAB and enables users to solve their optimization problems or to add new algorithms and problems, which in turn allows keeping the platform updated with the state-of-the-art.

In the models of some countries, the algorithm does not find feasible solutions, that is, the solutions do not satisfy all the restrictions defined. This set of countries includes Czechia, Cyprus, Germany, Latvia, Lithuania, Switzerland, and Slovakia. In order to find feasible solutions, we relax the bound constraints of the seven countries specified previously. In particular, the range of improvements or worsening of x_2 and x_4 is increased from 2 to 4 points.

$$lb_r = \overline{x}_r - 4, r = 2, 4$$

$$ub_r = \overline{x}_r + 4, r = 2, 4$$

Considering the previous adjustment, we find solutions for Cyprus, Germany, and Switzerland,[4] which are in line with the solutions obtained for the original model (5) shown in Table 2 (values of the decision variables and current values) and Table 3 (values of the objective functions and current values).

Overall, in analysing the values of the decision variables, we can infer various courses of action to reduce overall and child poverty. Firstly, according to our results, most countries would need to increase their current level of child benefits (as a proportion of GDP) instead of means-tested benefits to combat child and overall poverty. However, it is noteworthy that the opposite holds true in Greece and Poland. Secondly, when the size of benefits (i.e., all cash benefits relative to GDP) increases, a marginal rise in the proportion of means-tested benefits relative to GDP is required compared to child benefits. This trend is observed in all countries except Bulgaria, Ireland, Slovenia, and Serbia, where the proportion of child benefits relative to GDP and means-tested benefits relative to GDP remain unchanged as the size of the benefits increases. Thirdly, in all countries, the optimal solution points towards implementing universal child benefits instead of means-tested child benefits. The only exceptions are Croatia, the Netherlands, and Norway, where a significant portion of resources would be allocated to children based on income conditions. However, this percentage decreases as the size of overall benefits increases.

In summary, a recommended strategy for effectively reducing child and overall poverty is to implement a combination of universal child cash benefits and means-tested benefits. In most countries, increasing the level of universal cash benefits for children is advisable. However, it is important to note that in six specific countries – France, Greece, Italy, Ireland Netherlands, and Spain – the proportion of GDP allocated to universal cash benefits should not be higher than that allocated to means-tested benefits.

Regarding the objective function values, the rate of overall poverty and child poverty decreases while the cash social benefits as a percentage of GDP increase. This means that the Scenario 5 represents the best situation for each country. Focusing on the objective values, Ireland obtains the lowest overall and child poverty rates. However, Serbia and Romania achieve the highest rates of overall and child poverty. Compared to the current values, Bulgaria is the country with the most significant reduction in overall and child poverty rates, although it is not the country with the worst current poverty rates. On the other hand, Hungary has the lowest reduction in both poverty rates. On average, the improvement in the child poverty rate is larger than the improvement in the overall poverty rate.[5]

4. Conclusions

In this study we examine the potential of various social transfer policy alternatives to address both child and overall poverty concurrently. To this end, multiobjective programming is used to assess the effectiveness of these policy options in mitigating both child and overall

4 Results shown in Table B4.

5 Note that, in order to analyse the robustness of the results, we have increased the range of variation of the variables x_2 and x_4 from 2 to 4. The results obtained are in line with those obtained previously.

poverty levels in 24 European countries based on a previous economic analysis to define our objective functions and constraints.

The results reveal several potential courses of action to simultaneously reduce child and overall poverty in European countries. First, the majority of countries would benefit from increasing their current level of child benefits as a proportion of GDP by providing direct support to families with children rather than relying predominantly on means-tested benefits to combat child and overall poverty. However, Greece and Poland are exceptions to this trend, where a pro-poor targeting strategy should be implemented instead of a pro-child one. Second, as the size of benefits increases, a marginal rise in the proportion of means-tested benefits relative to GDP is generally required compared to child benefits. This trend is observed across most countries, with the exception of Bulgaria, Ireland, Slovenia, and Serbia, where the proportions of child and means-tested benefits relative to GDP remain unchanged despite the increase in benefits. Third, the optimal solution for most countries tends towards implementing universal child benefits instead of means-tested alternatives. Croatia, the Netherlands, and Norway deviate from this trend as these countries allocate a significant portion of resources to children based on income conditions. However, this percentage decreases as the size of overall benefits increases.

In a nutshell, social transfer policies involving a combination of pro-child and pro-poor targeting strategies are an effective way to combat child and overall poverty. Nevertheless, while an increase in the level of cash benefits for children is advisable for most countries, in others such as France, Greece, Italy, Ireland, the Netherlands, and Spain, the proportion of GDP allocated to (universal) cash benefits should not exceed the proportion allocated to means-tested benefits.

Our conclusions largely align with the results of previous literature. Similar to other analyses (see, e.g., Ref. [5,9,12,13,37]), our findings underscore the relevance of increasing child benefits as a proportion of GDP to tackle child and overall poverty, highlighting the importance of direct support to families with children as a crucial element in poverty reduction strategies. Likewise, the suggestion to lean towards universal child benefits in most cases resonates with positions supporting the efficiency and inclusivity of universal programs [38,39], widely implemented across countries. However, our study goes further and proposes differentiated strategies by country, suggesting different country-specific combinations of pro-poor and pro-child targeting strategies. In any event, from the policy point of view, countries should consider these policy recommendations within their existing welfare frameworks, balancing the enhancement of child benefits with means-tested approaches based on their socioeconomic contexts and political circumstances. Potential reforms of social transfer policies should be thus tailored to the specific needs and conditions of each country and period, as well the country's budgetary restrictions and political priorities, to assess their practical relevance and feasibility.

This research has some limitations. First, while economic models help us to simplify reality, they have the drawback of not usually capturing all the relevant variables and some conclusions may not fully reflect the reality. Second, although the multiobjective model based on logit regression is quite novel and offers promising results, we can go one step further in future work in terms of accuracy: instead of considering mean estimates for the coefficients of the linear function corresponding to the exponent of the exponential function, we can estimate confidence intervals for these coefficients and approach the model with interval multiobjective optimization.

CRediT authorship contribution statement

Sandra González-Gallardo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Elena Bárcena-Martín:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Salvador Pérez-Moreno:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mariano Luque:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

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Appendix

A. Definitions

The European System of integrated Social PROtection statistics (ESSPROS) defines the following concepts.

- Social protection encompasses all interventions from public or private bodies intended to relieve households and individuals of the burden of a defined set of risks or needs, provided that there is neither a simultaneous reciprocal nor an individual arrangement involved. The list of risks or needs that may give rise to social protection is, by convention, as follows: 1. Sickness/Health care; 2. Disability; 3. Old age; 4. Survivors; 5. Family/children; 6. Unemployment; 7. Housing; 8. Social exclusion not elsewhere classified.
- Means-tested social benefits are social benefits that are explicitly or implicitly conditional on the beneficiary's income and/or wealth falling below a specified level.
- Family/children benefits are transfers targeted at households with dependent children, including: maternity allowances, birth grants, parental leave benefits, family or child allowances, other periodic or lump-sum payments to support households and help them meet the costs of specific needs, shelter and board provided to pre-school children during the day or part of the day, financial assistance towards payment of a nurse to look after children during the day, shelter and board provided to children and families on a permanent basis, goods and services provided at home to children or to those who care for them, and miscellaneous services and goods provided to families, young people, or children. They are in cash or

kind, except health care, in connection with the costs of pregnancy, childbirth and adoption, bringing up children and caring for other family members. Note that family/children benefits provided through the fiscal system are not considered in the data.

B. Tables

Table B.1
Sample size by country (number of households)

	Observations	
	Overall	Children
Austria	3540	1279
Belgium	4031	1735
Bulgaria	2823	1140
Croatia	3309	1416
Cyprus	2151	1085
Czechia	3014	1951
France	6571	3081
Germany	6196	1952
Greece	6917	3024
Hungary	2843	1196
Ireland	2352	1355
Italy	9459	3421
Latvia	2690	1121
Lithuania	2657	967
Netherlands	4468	2910
Norway	3329	1805
Poland	9328	5003
Portugal	6812	3142
Romania	3152	932
Serbia	2188	1041
Slovakia	2735	1125
Slovenia	2901	2469
Spain	9120	4123
Switzerland	3843	1673
	106,429	48,946

Source: EU-SILC CROSS-SECTIONAL UDB [23].

Table B.2
Descriptive statistics of household and household head (or parents in the children sample) characteristics.

Micro variables		Overall		Child	
		Mean	SD	Mean	SD
Household characteristics					
Poverty	1 if the child is poor	0.1661	0.3722	0.1836	0.3871
Lone parent	1 if lone parenthood	0.0636	0.2440	0.1133	0.3169
Jobless	1 if household where no one works	0.0605	0.2383	0.0497	0.2174
Owner	1 if the outright owner of the dwelling is a member of the household	0.1428	0.3882	0.2751	0.4466
No. Children	Number of children in the household				
Nch_2	younger than 3	0.1658	0.4149	0.2672	0.5049
Nch_3_5	between 3 and 5	0.3647	0.6438	0.3312	0.5460
Nch_6_11	between 6 and 11	0.3495	0.6333	0.7421	0.7871
Nch_12_17	between 12 and 17	0.3523	0.4777	0.6479	0.7864

Household Head Characteristics		Overall		Parents' Characteristics		Child	
		Mean	SD			Mean	SD
Young head	1 if head is younger than 30	0.0707	0.2562	Young father	1 if father is younger than 30	0.0354	0.1848
Old head	1 if head is older than 65	0.0098	0.0983	Old father	1 if father is older than 65	0.0100	0.0997
Secondary head	1 if head has secondary education	0.5937	0.4911	Secondary father	1 if father has secondary education	0.4989	0.5000
Tertiary head	1 if head has tertiary education	0.3483	0.4764	Tertiary father	1 if father has tertiary education	0.3096	0.4623
Work head	1 if head works full or part time	0.8437	0.3631	Work father	1 if father works full or part time	0.7796	0.4145
Health head	1 if head's general health status is bad or very bad	0.2483	0.4320	Health father	1 if father's general health is bad or very bad	0.1483	0.3554
Immigrant (from EU) head	1 if head is immigrant from EU	0.0310	0.1734	Immigrant (from EU) father	1 if father is immigrant from EU	0.0281	0.1652
Immigrant (non- EU) head	1 if head is immigrant from outside EU	0.0923	0.2895	Immigrant (non- EU) father	1 if father is immigrant from outside EU	0.1020	0.3027
Women head	1 if head is a woman	0.3415	0.4742	Young mother	1 if mother is younger than 30	0.0747	0.2630
				Old mother	1 if mother is older than 65	0.0176	0.1316
				Secondary mother	1 if mother has secondary education	0.5368	0.4987
				Tertiary mother	1 if mother has tertiary education	0.3714	0.4832
				Work mother	1 if mother works full or part time	0.6504	0.4768
				Health mother	1 if mother's general health is bad or very bad	0.1957	0.3967
				Immigrant (from EU) mother	1 if mother is immigrant from EU	0.0370	0.1889
				Immigrant (non- EU) mother	1 if mother is immigrant from outside EU	0.1157	0.3199

Source: EU-SILC CROSS-SECTIONAL UDB [23].

Table B.3
Descriptive statistics of social transfers features in the overall sample and children sample.

Contextual Variables		Overall Mean	SD	Overall Mean	SD
Size	Cash benefits over GDP (%)	16.9333	3.2865	16.9229	3.3214
Child orientation	Cash child/family benefits over cash benefits (%)	8.3454	3.5090	8.3028	3.4849
Poor orientation of child benefits	Cash means-tested child/family benefits over cash child/family benefits (%)	23.0554	19.1917	23.6375	18.8471
Poor orientation of all benefits	Cash means-tested benefits over cash benefits (%)	7.9256	3.6995	8.0673	3.9501

Note: Mean and SD of social benefits characteristics differ in the overall and children sample given that the distribution of children across countries differs slightly with respect to the distribution of individuals across countries.
Source: EU-SILC CROSS-SECTIONAL UDB [23].

Table B.4
Results of Cyprus, Germany, and Switzerland

Country	Scenario	Overall poverty	Child poverty	Size	Child orientation	Poor orientation of child benefits	Poor orientation of all benefits
Cyprus	Scenario 1	9.572	10.569	13.700	11.300	95.198	12.660
	Scenario 2	9.150	10.148	14.200	11.300	83.799	12.660
	Scenario 3	8.742	9.740	14.700	11.300	72.281	12.661
	Scenario 4	8.348	9.346	15.200	11.300	60.638	12.661
	Scenario 5	7.968	8.965	15.700	11.300	48.859	12.661
	Current value	14.700	16.700	13.700	7.300	75.790	16.297
Germany	Scenario 1	8.807	7.814	17.300	9.552	0.000	9.679
	Scenario 2	8.699	7.711	17.800	9.302	0.000	9.954
	Scenario 3	8.603	7.628	18.300	9.029	0.000	10.217
	Scenario 4	8.486	7.493	18.800	8.831	0.000	10.472
	Scenario 5	8.380	7.386	19.300	8.596	0.000	10.731
	Current value	14.800	12.100	17.300	11.560	4.580	7.470
Switzerland	Scenario 1	11.490	12.562	16.500	11.270	100	0.254
	Scenario 2	11.121	12.064	17.000	11.270	93.559	0.618
	Scenario 3	10.563	11.564	17.500	11.270	82.501	0.618
	Scenario 4	10.109	11.110	18.000	11.270	71.342	0.618
	Scenario 5	9.670	10.671	18.500	11.270	60.080	0.618
	Current value	16.000	18.100	16.500	7.270	6.540	4.254

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