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Misperceiving Inequality and Its Roots Cross-Country Evidence from Europe

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Abstract

We contribute to the growing evidence that inequality is often misperceived and that personal experience plays a more significant role than objective conditions in shaping beliefs and attitudes toward it. In this study, we examine whether people's views about fairness and inequality align with empirical measures. Specifically, we compare individuals' perceptions of the relative importance of various factors in determining success in life with objective estimates of how education, hard work, family wealth, and gender predict income inequality across 27 EU countries. We find little correlation between perceptions and reality. People tend to more accurately recognize the importance of education in contributing to inequality, while the role of family wealth and gender is more strongly perceived by those directly affected by it. Women, for instance, exhibit greater awareness of gender-based disparities, and individuals in disadvantaged economic conditions display perceptions that correspond more closely to the observed role of family wealth. In contrast, those who are employed, upwardly mobile, or financially stable tend to attribute outcomes more strongly to hard work. These distorted perceptions, in turn, shape attitudes toward redistribution: beliefs about the importance of hard work and the overall level of inequality of opportunity emerge as key predictors of support for redistributive policies.

Keywords: Inequality, perceptions, opportunity, redistribution
JEL Classification: D63

1 Introduction

Inequality is often misperceived. A growing body of research shows that individuals' understanding of inequality and their own position within the income distribution frequently diverges from objective measures. People tend to misestimate both the overall extent of inequality and their relative position in terms of income or wealth within their society (Bavetta et al., 2020; Chambers et al., 2014; Cruces et al., 2013; Engelhardt & Wagener, 2014, 2018; Gimpelson & Treisman, 2018; Hauser & Norton, 2017; Karadja et al., 2017; Knell & Stix, 2020; Norton & Ariely, 2011). Importantly, these subjective perceptions have been found to predict people's political behaviour, including their support for redistribution, more accurately than objective measures of inequality (Bussolo et al., 2021; Engelhardt & Wagener, 2014; Gimpelson & Treisman, 2018). The extent and nature of such misperceptions, and their implications for redistributive preferences, therefore constitute a central question in the study of political economy and social fairness.

Traditional models, such as the one developed by Meltzer and Richard (1981), assume that individuals correctly perceive inequality and act out of self-interest, demanding more redistribution as their income falls relative to the mean. Yet, empirical evidence has long challenged this assumption (Dallinger, 2010; Dion & Birchfield, 2010; Kenworthy & McCall, 2007; Schmidt-Catran, 2016). Two main lines of research have emerged as critiques: one highlighting the importance of fairness beliefs and another emphasizing inequality misperceptions.

One strand of the literature has focused on the idea that not all inequalities are the same, nor are they perceived as such. As theories of distributive justice highlight, differences in outcomes are not inherently unjust, what matters is the process by which they arise (Roemer & Trannoy, 2016). This idea seems to be to a large extent shared by people. Experimental evidence from ultimatum and dictator games, for example, confirms this: people tend to accept income differences when they are proportional to effort (Cappelen et al., 2013). Most individuals are neither strict libertarians nor outcome-egalitarians, they support compensating individuals for disparities caused by factors beyond their control, such as luck or family background (Almås et al., 2020).

Thus, inequalities stemming from different sources are perceived as more or less acceptable. There is widespread consensus on promoting equality of opportunity, while opinions are more divided on achieving equality of outcomes. For example, in a 2022 State Policy Network poll, 78% of Americans agreed that society should aim for equality of opportunity rather than equality of outcomes. Similarly, a 2012 Gallup poll found that 70% of U.S. respondents viewed enhancing opportunities for advancement as "extremely" or "very important," while only 46% felt the same about reducing the income gap (Pew Research Center, 2012). These findings suggest that individuals' fairness beliefs, how they evaluate the sources of inequality, may drive misperceptions of inequality itself. People might perceive unfairness more acutely than inequality.

The second strand of the literature has documented the tendency of individuals to misperceive inequality. Perceptions are shown to be often biased and only weakly related to objective measures (Brunori, 2017; Engelhardt & Wagener, 2014;

Gimpelson & Treisman, 2018). People systematically misjudge their own position within the income distribution and often identify as "middle class", regardless of their actual economic status (Cruces et al., 2013; Karadja et al., 2017). These systematic misperceptions are shaped by personal characteristics and social environments: people's education, income, and intergenerational mobility experiences influence how they interpret inequality (Alesina et al., 2018; Amiel et al., 2015; Hoy & Mager, 2021b). As a result, perceptions of fairness and opportunity are filtered through individual reference groups and lived experiences rather than objective measures of the phenomenon.

This paper builds on these insights by investigating whether individuals are able to correctly identify the sources of inequality and the extent of inequality of opportunity in their societies. Specifically, we assess the relationship between subjective perceptions of fairness and objective measures of inequality of opportunity (IOp hereafter) across European countries. To do so, we need to merge information from two sources.

First, using the Special Eurobarometer 529 and 471 on "Fairness, Inequality, and Intergenerational Mobility" (collected in 2022 and 2017), we measure fairness beliefs as perceived inequality of opportunity and beliefs about the relative importance of various factors, hard work, education, gender, and family wealth, in getting ahead in life. These data, covering 37,488 observations across all 27 EU countries, allow us to construct indicators of perceived meritocratic and structural determinants of success.

Although some covariates describing individual success are available in Eurobarometer, the sample size and coverage of the survey is insufficient to properly benchmark beliefs and reality. Therefore, to complement these perceptions with objective data, we employ the European Union Statistics on Income and Living Conditions (EU-SILC) surveys from 2005, 2011, and 2019, focusing on intergenerational transmission of disadvantage. We compute objective measures of inequality of opportunity and of the relative importance of individual (hard work, education) versus structural (gender, family wealth) factors using a variable importance analysis borrowed from supervised machine learning.

By merging the two data sources, we obtain a panel structure in which individuals born in different countries and at different points in time report beliefs about inequality. These can be compared with the estimated levels of IOp and the relative importance of different factors, both calculated by country and cohort. The first contribution of our analysis is therefore to describe the relationship between the two. The cohort-panel structure allows us to address potential endogeneity and reverse causality between perceptions, inequality, and redistribution, including country and survey fixed effects in the analysis.

The second contribution of the analysis consists in testing whether subjective perceptions of fairness, together with individual experiences of economic success or hardship, affect preferences for redistribution. In doing so, we contribute to both strands of the literature: research on fairness beliefs as drivers of redistribution (Alesina & Angeletos, 2005; Almås et al., 2020; Benabou & Tirole, 2006; Cappelen et al., 2013; Piketty, 1995) and research on inequality misperception and its behavioral consequences (Alesina et al., 2018; Bastani & Waldenström, 2021; Brunori, 2017; Haaland & Roth, 2023; Hoy & Mager, 2021a; Settele, 2022).

Our findings can be summarized as follows. Individuals' perceptions of inequality of opportunity are not systematically related to objective measures of inequality of opportunity. However, perceptions of education are positively associated with their actual relative importance, while perceptions of hard work, family wealth and gender are not. Individuals who have experienced financial hardship tend to attribute more importance to structural factors and less to meritocratic ones, indicating that personal experience and cultural narratives may shape fairness beliefs. Furthermore, not all perceptions have the same political implications: perceiving hard work as important decreases support for redistribution, while perceiving high inequality of opportunity increases it.

The remainder of the paper is organized as follows. Section 2 presents the empirical strategy, Section 3 describes the data, Section 4 reports the main findings, and Section 5 concludes.

2 Empirical strategy

To assess the relationship between objective inequality, subjective perceptions, and preferences for redistribution, we construct a longitudinal dataset with cohort-level measures of inequality calculated for individuals born at different points in time across countries. The objective indicators measure the extent to which different individual characteristics can predict future incomes. The ability to predict is our measure of the importance of a given factor in providing access to opportunity. We then evaluate the extent to which these relative importances are correctly perceived by individuals. Finally, we assess how perceptions as well as measured indicators are predictive of redistributive preferences.

2.1 Model specifications

We consider three variables of interest: the perceived relative importance of different factors in determining success in life $PERC$, the perceived level of inequality of opportunity in the society PIO, and attitude toward redistribution RED.

To estimate the formation of perceptions, the following linear regression model is used:

$$PERC_{ictj} = \alpha + \beta RI_{jct} + \gamma X_{ict} + FE_i + \epsilon_{ict}, \tag{1}$$

Where $PERC_{ictj}$ stays for the perceived relative importance attached to factor j (sex, family wealth, education, or hard work) by individual i, residing in country c and belonging to birth cohort t. Hence, we estimate four different OLS regression models for each factor j[1].

[1]Ordered logistic regression models have not been applied since the proportional odds assumption does not hold (see Table 5 in Appendix).

RI_{jct} is the real importance of factor j in country c for birth cohort t, where β indicates the degree of correlation between measured and perceived j. While a significant positive correlation would point to a correct perception, a non-significant or negative correlation would point to a misperception. X is the vector of individual-specific controls. FE is the vector of country and survey year fixed effects. We include country fixed-effects to control for potential endogeneity. A country's institutional setting might be endogenous to individual perceptions. For our binary dependent variable of perceived inequality of opportunity, PIO, we run the same model using a logistic regression and calculating average marginal effects (AME).

Finally, to model support for redistribution, RED, we adopt a model specification in line with what is proposed by (Bussolo et al., 2021). The model developed by Bussolo and co-authors explains both, support for redistribution as well as subjective inequality perceptions, by self-interest, ideology and personal characteristics. Subjective inequality perceptions are further explained by the economic context (here our objective measures) and in turn influence support for redistribution. The following logistic regression model is estimated:

$$RED_{ictj} = \alpha + \beta RI_{jct} + \lambda PERC_{jct} + \gamma X_{ict} + FE_i + \epsilon_{ict}, \tag{2}$$

Where $PERC_{jct}$ is the dependent variable of (1) and the other regressors are defined in the same way.

2.2 Objective measure of relative importance and inequality of opportunity

When referring to the relative importance of different factors, such as hard work, and circumstances like sex and family of origin, we acknowledge the inherent difficulty in causally disentangling the effect of each variable on success in life. Therefore, we adopt a more pragmatic approach, framing our empirical exercise as a prediction problem.[2]

For this reason, objective measures of variable importance are obtained using a supervised machine-learning approach. Specifically, the relative importance of variable j in country c for cohort t is proxied by a measure of relative predictive importance $RI_{j,c,t}$, which is assessed by evaluating the reduction in predictive accuracy when variable j is excluded from the set of predictors of individual income.

We implement conditional inference random forests (Hothorn et al., 2006), a flexible algorithm that averages predictions from hundreds of overfitted regression trees. The relative importance of each variable is estimated by randomly shuffling predictor j, thereby breaking its relationship with the response variable (income). The change in prediction accuracy before and after shuffling - averaged across all

[2]This approach is increasingly adopted in the literature measuring IOp (see for example the recent OECD report (OECD, 2025) or the GEOM database published in 2024 (Ferreira et al., 2024).

trees - serves as the measure of variable importance (Breiman, 2001). To address key limitations of traditional variable importance estimation, we apply the conditional variable importance framework introduced by Strobl et al. (2009). This method corrects for two main biases: the tendency to favor variables with more categories or continuous values, and the overestimation of importance for correlated predictors.

The output of our analysis is, therefore, an estimate of the relative importance of the same factors about which individuals are asked in the questionnaire used to survey perceptions (or what we consider to be good proxies for them). The estimation is performed at the country-cohort level to obtain a panel of relative importance measures for each country and cohort. This panel can then be used as an explanatory variable to explain individuals' perceptions.

Moreover, to study the determinants of the inequality of opportunity perceived we apply the exact same method predicting income using the set of observed circumstances beyond individual control (sex and socioeconomic background). Consistent with what is suggested by (Brunori et al., 2023) and largely adopted by the empirical literature, this results in a summary index measuring the level of inequality observed in the predicted income distribution (OECD, 2025).

3 Data

After a careful review of existing harmonized data about perceptions and actual inequalities we excluded the possibility to use a single survey to perform the empirical analysis. For this reason, our empirical exercise relies on two different data sources Eurobarometer and European Union Statistics on Income and Living Conditions survey.

3.1 Dependent variables

Individuals' subjective perceptions of inequality of opportunity and of the relative importance of sex, family wealth, education, and hard work for getting ahead in life are taken from the Special Eurobarometer 471 (2017) and 529 (2022) on fairness, inequality and intergenerational mobility (EBS hereafter), a national representative survey targeting the general population aged 15 and above in all 27 EU Member States. The survey covers over 37,488 individuals, with approximately 1,400 respondents per country (small countries like Malta and Cyprus have around 700, while Germany has 2,000 observations). The post-stratification survey weights we use are based on income, age, sex, urbanization, region of residence at NUTS2 regional level to match country's population statistics in terms of these demographic characteristics. The EBS further contains a rich set of individual-specific demographic and socio-economic characteristics. However, it does not contain sufficient information on parental background and detailed personal net income data to be used to directly measure inequality and its determinants in the same sample of individuals[3].

[3]For further details, see https://europa.eu/eurobarometer/surveys/detail/2652 and https://europa.eu/eurobarometer/surveys/detail/2166.

The perceived relative importance of different factors in determining success in life are operationalized by a battery of questions asking "How important is family wealth/sex/education/hard work for getting ahead in life?". Respondents were asked to simultaneously assess the importance of each factor on a five-point Likert scale, ranging from "Essential" (value of 1) to "Not important at all" (value of 5). Because questions about wealth, sex, education, and hard work are presented simultaneously to respondents[4], we assume that their answers reflect the perceived relative importance of each factor compared to the other three. To facilitate the interpretation of the result we invert the individuals' answers in such a way that 0 indicates "Not important at all" and 4 stays for "Essential", and calculate the scores of factors' perceived relative importance according to the following formula:

$$PERC_j = a_j/(\sum_{j=1}^{n} a_j), \tag{3}$$

where a_j is the value assigned to the factor j. In the case of the sum being zero, we replace the value with 1/4 [5]. Just as the real relative importance, the resulting variable is taking values from 0 to 1. We are aware that such aggregation is only one of several possible approaches, therefore when discussing the results, we also consider estimates obtained in case answers are treated as cardinal, absolute measures of importance (see Table 6 in Appendix).

Besides the perceived importance of each factor we are also interested in understanding the overall perception of inequality of opportunity and individuals preferences for redistribution. EBS contains an explicit item about equal opportunity: "You have equal opportunities for getting ahead in life, like everyone else". Respondents choosing "Disagree" or "Strongly Disagree" on a Five-point Likert scale are subsumed under the category "perceiving inequality of opportunity", whereas those choosing "Strongly Agree", " Agree" or "Neither agree nor disagree" fall under the category "not perceiving inequality of opportunity".

Finally, to understand preferences for redistribution we construct a binary variable based on the agreement to the statement "The government should take measures to reduce differences in income levels". Respondents choosing "Strongly Agree" or " Agree" on a five-point Likert scale are subsumed under the category "Support redistribution", whereas those choosing "Neither agree nor disagree", "Disagree" or "Strongly Disagree" fall under the category "Do not support redistribution". We dropped observations with missing values in the dependent variables. We analyzed missing values across all dependent variables, which ranged from 0.3% for the perceived relative importance of education to 2.5% for that of gender. Logistic regressions predicting missingness from a wide set of covariates indicated that only survey year and country were significant predictors. Since these variables are included as controls in all models, we considered listwise deletion a relatively low-risk approach for handling item nonresponse. Table 1 reports mean values for perceived relative importance (columns 3 to 7), perceived inequality of opportunity

[4]The questionnaire page for 2022 is reported in Figure 4 in Appendix.

[5]We thank Gabriele Lombardi for suggesting this formula.

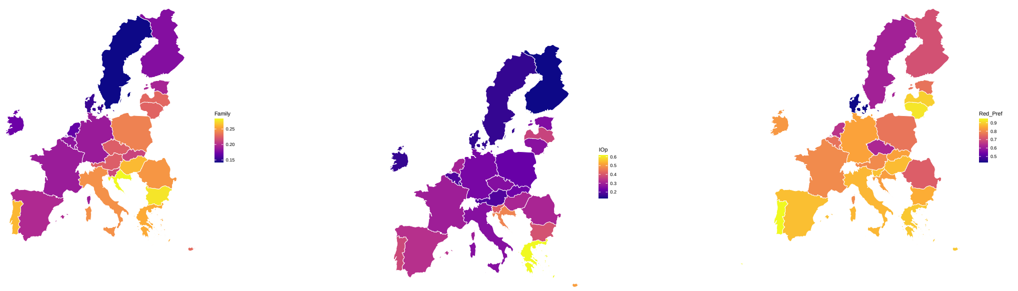
(8) and preference for redistribution (9) by country.

Table 1: Descriptive statistics by country: perceptions and redistributive preferences

Country	Sample	Sex	Family	Education	Hard Work	IOp	Red. Pref.
AT	1234	0.196	0.223	0.312	0.268	0.194	0.798
BE	1152	0.160	0.184	0.340	0.316	0.193	0.762
BG	1203	0.171	0.275	0.265	0.289	0.393	0.851
CY	436	0.133	0.230	0.348	0.290	0.509	0.884
CZ	1238	0.169	0.223	0.307	0.301	0.259	0.630
DE	1528	0.156	0.188	0.373	0.282	0.244	0.836
DK	540	0.130	0.154	0.369	0.347	0.158	0.433
EE	979	0.111	0.194	0.359	0.336	0.254	0.762
ES	1126	0.142	0.198	0.349	0.311	0.334	0.872
FI	771	0.146	0.180	0.340	0.334	0.130	0.704
FR	983	0.167	0.189	0.294	0.351	0.296	0.799
GR	1202	0.119	0.256	0.325	0.300	0.619	0.883
HR	1279	0.178	0.282	0.278	0.262	0.470	0.828
HU	792	0.190	0.261	0.264	0.284	0.313	0.869
IE	949	0.161	0.172	0.328	0.340	0.160	0.820
IT	1220	0.180	0.245	0.302	0.273	0.262	0.863
LT	942	0.114	0.226	0.351	0.309	0.265	0.920
LU	497	0.164	0.186	0.339	0.311	0.173	0.798
LV	1133	0.108	0.228	0.384	0.281	0.367	0.892
MT	270	0.152	0.194	0.357	0.297	0.191	0.845
NL	573	0.134	0.168	0.350	0.348	0.306	0.653
PL	1022	0.172	0.239	0.294	0.294	0.225	0.765
PT	1164	0.131	0.261	0.323	0.285	0.374	0.945
RO	1289	0.178	0.248	0.319	0.256	0.314	0.728
SE	822	0.157	0.143	0.350	0.350	0.159	0.613
SI	1156	0.168	0.214	0.304	0.314	0.409	0.874
SK	513	0.165	0.211	0.295	0.329	0.233	0.834
Total / Avg	27103	0.156	0.217	0.332	0.303	0.284	0.804

Source: EBS 2017 & 2022.

Overall, perceptions of IOp are rather low with an average across countries of 0.284, varying, however, considerably from 13% of the population in Finland to 61.9% in Greece, who (strongly) disagree with the statement that equal opportunities exist in their country. Sex is seen as least important factor on average (0.156) and with little variation over countries, whereas education is seen as most important factor (0.332), shortly after hard work (0.303). Interestingly, there is little variation over countries in the assessment of hard work, while the strongest variation can be observed for family wealth. A geographical pattern emerges: while individuals in Northern European countries perceive on average lower IOp and individual factors to be more important than structural factors, individuals in South Eastern countries on average ascribe a more important role to family background and show more perceived IOp (see Figure 1). For example, Croatia (HR) shows the second lowest perceived relative importance of hard work (0.262), which is only slightly smaller than the high score of perceived relative importance of family background (0.282), consistent with a relatively high perception of IOp (0.470). In contrast, Sweden shows a much lower relative importance score of family background (0.143) and higher perceived relative importance of hard work (0.350), consistent with one of the lowest IOp perceptions (0.159). This geographical pattern is consistent with support for redistribution. While Northern countries with lower perceptions of IOp and the relative importance of structural factors show lower levels of support for redistribution (lowest in Denmark with 0.433), South Eastern countries show higher support for redistribution with highest support in Portugal (0.945). However, support is generally quite high with an average value of 0.804.



(a) Perceived relative importance of family wealth

(b) Perceived IOp

(c) Support for redistribution

Figure 1: Perceptions and preferences across the EU

3.2 Control variables

Individual characteristics included as controls are: sex of the respondent (0 = male, 1 = female), location of residence (rural area/town = 0, city = 1), own education (0 = no education completed or primary school, 1 = secondary education, 2 = post-secondary education (non-tertiary, Bachelor, Master or Doctoral), parental education (coded as in "educational level"; taking the educational level of the parents, which is higher) and employment status (1 = employed, 0 = not employed). We also include a dummy indicating whether the respondent has faced financial difficulties (based on the question "*Difficulties to pay bills at the end of the month during last year*"; 1 = "*Most of the time*" or "*From time to time*", 0 = "*Almost never*" or "*Never*"). These variables typically determine whether individuals will be on the "benefiting" or "contributing" side of redistribution. Moreover, to account for the presence of a self-esteem bias (Bavetta et al., 2019; Brunori, 2017), we add two dummy variables: upward mobility and downward mobility. Due to data limitations, mobility could only be assessed in educational terms, i.e., whether a respondent obtained a higher or lower educational level compared to the parent with the highest education. We also control for the survey year and included country fixed effects. Summary statistics are added in Table 8 in the Appendix.

3.3 Objective measures of relative importance and inequality of opportunity

To obtain our objective measures of inequality and to assess the relative importance of its sources, we use data from the European Union Statistics on Income and Living Conditions survey (EU-SILC) conducted by Eurostat.[6] We draw on individual-level data from three ad-hoc modules on the intergenerational transmission of disadvantages and poverty, collected in 2005, 2011, and 2019. These modules include a rich battery of questions regarding the individual's demographic and socio-economic characteristics, parental background, and other important factors, as well as detailed data on personal net income. In this exercise, we restrict our sample to employed and unemployed individuals aged 25-65 with positive personal disposable net income. Retired individuals and those still in education are excluded from the analysis. Yearly personal disposable net income is constructed as the sum of four components: net non-cash employee income, net cash employee income, net self-employed income, and net social benefits, as reported in EU-SILC[7]. The relative advantage of the EU-SILC dataset compared to other potential data sources, such as the Luxembourg Income Survey (LIS) or the EU Labour Force Survey (EU-LFS), is that it offers the largest possible coverage in terms of countries and individual-specific circumstances (Commission, 2020).

However, the EU-SILC does not provide personal net income for seven countries: Cyprus, Denmark, Finland, Hungary, Malta, the Netherlands, and Slovakia. For Germany, such information is available for 2005 only. To complete our dataset, we therefore use EUROMOD (version I6.39) to impute personal net incomes for these countries (European Commission. Joint Research Centre. & European Commission. Statistical Office of the European Union., 2024). EUROMOD is an open-source tax-benefit microsimulation model for the European Union that applies user-defined tax and benefit policy rules to harmonized microdata, thereby estimating their impact on net incomes. Because EUROMOD does not provide input microdata for 2005 or 2011, we impute missing personal net incomes for the aforementioned countries for 2019 only. Specifically, to obtain the imputed personal disposable net income, we first apply the given income tax to the proportion of labor income out of all income and then subtract this newly generated income tax variable together with social contributions from gross labor income. For Cyprus, Denmark, Finland and Hungary there have been multiple income tax rates (e.g. different tax rates for self-employed), which has been considered accordingly. The final sample comprises 329,835 individuals across all 27 EU member states observed in at least one of the three waves. Further manipulations of the data include: the trimming of income at the 99.99 percentile of the country's distribution to replace few outliers. All values are reported in 2018 PPP-adjusted euros.

To quantify the extent to which different factors predict income later in life, we consider a range of individual and background characteristics. As a proxy for "family wealth" we use the retrospective self-reported information on the father's

[6]For further details, see https://ec.europa.eu/eurostat/web/income-and-living-conditions/database/modules.

[7]Net income components correspond to gross income components net of the tax at source and social insurance contributions.

and mother's educational attainment and occupational status when the respondent was 15 years old. Parental education is categorized into three groups: "low" (less than primary, primary education, or lower secondary education), "middle" (upper secondary education and post-secondary non-tertiary education), and "high" (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level).[8] Parental occupation is coded into eleven categories corresponding to the ten ISCO-08 1-digit occupational groups, plus an additional category for parents outside the labour force. "Hard work" is proxied by the total number of hours usually worked per week in the respondent's main job. For "sex" and "education", we rely on self-reported information on individuals' sex and the highest level of education achieved. Finally, "inequality of opportunity" is measured by applying the Gini index to the income distribution predicted by circumstances (i.e. sex and family background). We use a random forest of five subsamples of 600 observations drawn from each cohort. The resulting variable is equally ranging from 0 to 1. This is a standard approach in the measurement of inequality of opportunity (Ferreira et al., 2024; OECD, 2025).

Since the cross-sectional waves of the EBS and EU-SILC were collected in different times, the only possibility to obtain longitudinal data to analyze the phenomenon consists in measuring both "objective" and "subjective" measures by birth cohort in each country. Measuring inequality of opportunity and the objective relative importance within birth cohort has the additional advantage of accounting for generational effects, which could otherwise confound the influence of circumstances (Andreoli et al., 2021).

We define 35 rolling cohorts containing nine year-cohorts each. For example, the first cohort, 1955, includes respondents born between 1951 and 1959, the latter, 1989, includes all respondents born between 1985 and 1993. Cohorts start from 1955 (1951-1959), to guarantee a minimum sample size to each cohort. Descriptive statistics for the data used by country are reported in Tables 10 and 9 in the Appendix.

4 Results

4.1 Objective relative importance and inequality

The first results we present are the objective measures of the relative importance of different factors in predicting income variability. Table 2 reports, for each country: sample size, total inequality (Gini), mean personal net disposable income, the relative importance of each predictor, and the estimated inequality of opportunity. All values are weighted averages across cohorts based on the relative sample size.

In most countries, hard work is the strongest predictor of income variability; it is especially dominant in Denmark and Germany (hours worked explain around 65% and 62%, respectively). The explanatory power of hard work ranges widely, with some countries showing a value as low as 11% (Romania). Own education is

[8]The 2005 ad hoc module reports five separate levels of parental education. These were reclassified to ensure comparability across all modules.

Table 2: Descriptive statistics by country: objective measures

Country	Sample	Total Ineq.	Income	Family	Education	Hard Work	Sex	IOP
AT	11711	0.32	26596.09	0.11	0.25	0.49	0.16	0.15
BE	11841	0.25	27198.31	0.08	0.32	0.49	0.13	0.12
BG	10033	0.43	4723.22	0.34	0.44	0.13	0.10	0.20
CY	3981	0.36	20530.95	0.20	0.40	0.30	0.10	0.16
CZ	12341	0.30	8969.00	0.15	0.40	0.22	0.24	0.14
DE	12813	0.37	25193.17	0.04	0.20	0.62	0.15	0.19
DK	1838	0.23	36886.57	0.05	0.22	0.65	0.12	0.08
EE	10008	0.38	9957.69	0.07	0.46	0.22	0.25	0.14
EL	16275	0.31	14649.77	0.15	0.35	0.40	0.10	0.13
ES	34400	0.34	17808.54	0.08	0.41	0.37	0.14	0.13
FI	4522	0.35	24173.38	0.35	0.19	0.34	0.12	0.12
FR	20666	0.33	25200.79	0.10	0.35	0.44	0.11	0.15
HR	8842	0.32	8566.75	0.07	0.41	0.39	0.13	0.12
HU	3329	0.34	5794.14	0.07	0.56	0.19	0.21	0.13
IE	7309	0.33	31240.19	0.09	0.28	0.56	0.08	0.15
IT	44277	0.31	21520.80	0.09	0.29	0.47	0.16	0.12
LT	9174	0.41	6373.99	0.13	0.48	0.28	0.12	0.15
LU	10409	0.35	46073.15	0.08	0.56	0.22	0.15	0.18
LV	8371	0.39	8979.65	0.07	0.56	0.20	0.18	0.16
MT	2772	0.30	19259.80	0.05	0.60	0.30	0.06	0.12
NL	3968	0.28	33687.86	0.08	0.26	0.53	0.13	0.13
PL	30838	0.38	7015.61	0.13	0.52	0.19	0.16	0.15
PT	17611	0.35	12249.79	0.07	0.65	0.19	0.10	0.14
RO	9255	0.35	4001.11	0.29	0.55	0.11	0.05	0.18
SE	2726	0.23	28346.39	0.12	0.26	0.51	0.11	0.09
SI	10523	0.29	13715.40	0.08	0.58	0.24	0.09	0.11
SK	1280	0.22	8519.50	0.17	0.14	0.23	0.60	0.07
Total / Avg	329835	0.33	17486.67	0.13	0.39	0.36	0.14	0.14

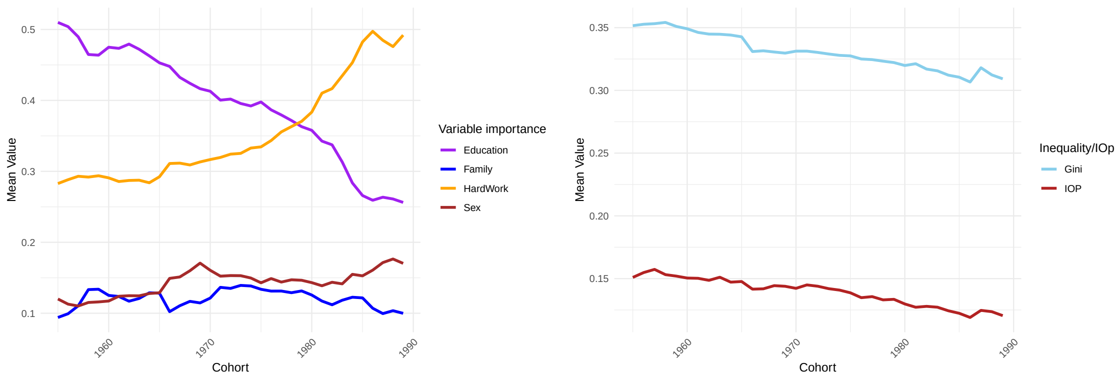
Source: EU-SILC 2005, 2011, 2019.

often the second-most important factor, but it is the most important predictor in Portugal and Malta (exceeding 60%). Family background and sex are generally less influential than hard work and education, although family background is relatively strong in South-Eastern Europe (e.g., Bulgaria 34%, Romania 29%). Sex is modest in most countries but exceptionally large in Slovakia (60%)[9], the country showing the lowest level of IOp in the continent, and notably high in Czechia and Estonia (above 20% in both). Inequality of opportunity (IOp) varies across countries with a well-known North-South gradient.

It is important to interpret this cross-country variation with caution. The values reported in Table 2 are obtained by averaging across cohorts that exhibit substantial heterogeneity in relative importances. As shown in Figure 2, while Sex and Family display, on average, relatively small and stable relative importance, the opposite

[9] Since this value appears extraordinarily high, we performed several checks. First, we examined the distribution of each income component separately for men and women and found no evidence that any single factor drives a pronounced gender imbalance. Men and women also display similar patterns in working hours and employment status. According to the (European Commission. Statistical Office of the European Union., 2021), the gender wage gap in Slovakia is close to the EU average. Although we do not have a definitive explanation for the unusually large role of gender in our results, (Filauro et al., 2023) and (Mogila et al., 2022) report similarly high estimates.

Figure 2: Continental trends in inequality, IOp and relative factors importance



Note: averages across countries are not weighted by population. Source EU-SILC 2005, 2011, 2019.

holds for own education and hours worked. These variables exhibit clear opposing trends, with a notable increase in the role of hours worked and a decline in the predictive power of respondents' education, effectively reversing their relative importance for younger cohorts. The second panel, instead, suggests an almost stable or slightly declining trend for both total inequality and IOp across birth cohorts.

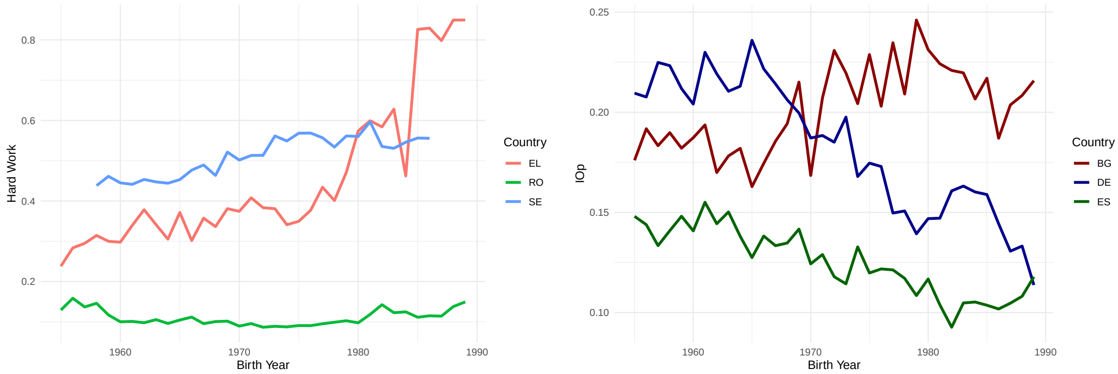
Moreover, these patterns are common to most countries, but not all. To give an example of cross-country variability the first panel of Figure 3 shows the relative importance of hours worked in three countries: Greece, Romania, and Sweden. Greece exhibits a clear monotonic trend, while Sweden shows a high but stable level. In Romania, the predictive power of hours worked also remains stable, but at much lower levels. Similarly, as shown in the second panel, IOp in Bulgaria, Germany, and Spain follows diverging trends: Germany and Spain show a decline, whereas Bulgaria experiences an increase in IOp for younger cohorts. This descriptive evidence highlights substantial variation across countries and cohorts, both in the relative importance of different predictors of income inequality and in the level of inequality of opportunity. Because each cohort is observed at three points in time during its working life, we can exclude the possibility that life-cycle dynamics alone drive this heterogeneity. This variability suggests that analyses aggregating information from respondents observed at the same time but at different ages may fail to fully capture the relationship between perceptions and the objective conditions individuals have experienced over their lives.

4.2 Explaining perception of inequalities

We merge information about objective measures of relative importance, based on EU-SILC, with information about perceived relative importance based on EBS. The level of correlation between the two measures is low, slightly positive and significant for "hard work" and "family wealth", not different from zero for the other variables.

Table 3 presents estimates from model (1), which relates individuals' perceived

Figure 3: Relative importance of hours worked and level of IOp in selected countries



Source EU-SILC 2005, 2011, 2019.

importance of each factor to its corresponding objective measure, controlling for personal characteristics as well as country and survey year fixed effects. All perceived and objective variables were standardized before estimation. Since the original dependent variables were ordinal, an ordered logit model would have been appropriate. However, since the necessary proportional odds assumption (Brant, 1990) did not hold (see Table 5 in the Appendix), ordinary least squares (OLS) was used for our modified perceived relative importance variables. Since the perception of inequality of opportunity is modelled as binary, a logistic regression model was employed with relative coefficients and average marginal effects (AME).[10]

Once personal characteristics, country and survey year fixed effects are accounted for, individual-level regressions show no systematic link between perceptions of inequality of opportunity and the relative importance of different factors and the corresponding objective measures. This finding is consistent with previous evidence on misperceptions of inequality and mobility (Alesina et al., 2018; Brunori, 2017; Bussolo et al., 2021; Hauser & Norton, 2017). Among the different factors considered, only "own education" exhibits a consistently positive and statistically significant relationship between its perceived and measured importance.

Individual characteristics and life experiences, rather than objective measures, play a more important role in shaping perceptions of inequality and its sources. Women tend to assign greater importance to a person's sex and less to hard work compared to men. Women also assign less importance to family background (consistent with what is shown by (Alesina et al., 2018)). Respondents with post-secondary education report, on average, 0.237 standard deviations higher perceived importance of education than those with at most primary education. Having more educated parents decreases the probability of perceiving inequality of opportunity by 28.2

[10]We recognize that country fixed effects have limited ability to account for heterogeneity in the data-generating process, since not only perceptions but also the covariance between perceptions and some regressors can vary across countries. For this reason, we also repeated the analysis separately by country. Sample sizes are small for some countries, resulting in many non-significant coefficients. However, the coefficients generally show consistent signs and magnitudes, suggesting that assuming a similar data-generating process net of a country fixed effect is a reasonable approach. Results are available upon request.

percentage points, and being employed by 54 percentage points, consistent with prior findings that the unemployed perceive greater IOp (Brunori, 2017; Bussolo et al., 2021).

Conversely, individuals who have experienced financial difficulties tend to attribute less importance to hard work and education, and more to family wealth and gender. They also show a 47.9 percentage points higher probability of perceiving inequality of opportunity, for the downwardly mobile, this likelihood increases by 19.6 percentage points. These results align with previous literature linking personal mobility experiences with meritocratic beliefs (Piketty, 1995), perceptions of inequality of opportunity (Brunori, 2017) and social mobility (Alesina et al., 2018).

Overall, more privileged or successful individuals (e.g., employed, from advantaged backgrounds) tend to endorse stronger meritocratic beliefs and perceive opportunities as more equal, whereas experiences of hardship or downward mobility are associated with perceiving greater structural inequality. This is consistent with self-serving attribution theory (Frank, 2017; Gilovich et al., 2002; Miller & Ross, 1975), whereby individuals ascribe success to internal effort and failure to external constraints. Thus, even within the same national context, individuals interpret inequality through their own experiences and project these interpretations onto society as a whole. Finally, the survey year fixed effects indicate changes in perceptions over time, with education playing an increasing role, family wealth declining in importance, and a rising perception of IOp between 2017 and 2022.

We then turn to the analysis of support for redistribution. In this analysis, we include three types of variables to explain the probability of supporting redistribution: objective measures of relative importance and IOp, subjective measures of the same variables, and individual characteristics.

Table 4 reports AME of the determinants of support for redistribution for three alternative model specifications including and excluding objective and subjective measures respectively. Consistent with prior evidence (Bussolo et al., 2021; Engelhardt & Wagener, 2014; Gimpelson & Treisman, 2018; Hauser & Norton, 2017), perceptions are more strongly correlated with redistributive preferences than objective measures of inequality of opportunity. These results hold regardless of whether perceived or objective indicators are included in the model. When included, they sometimes even show counterintuitive signs; for example, although not significant, the AME for measured IOp suggests a reduction in the probability of supporting redistribution.

Perceiving inequality of opportunity is associated with a 53.4 percentage points increase in the probability of supporting redistribution. Conversely, a one-standard-deviation increase in the belief that hard work is important for success is associated with a 5.7 percentage point decrease in the likelihood of supporting redistribution. These findings align with the theoretical argument of (Piketty, 1995) that perceiving hard work as an important factor for success reduces redistribution support, as higher taxes may increase incentive costs. They also corroborate empirical evidence showing that perceiving society as unfair increases support for redistributive policies (Alesina & La Ferrara, 2005; Bjørnskov et al., 2013; Günther & Martorano, 2025; Hoy & Mager, 2021b). Taken together, the results support the argument that

Table 3: OLS and logistic regression models explaining perceptions

	Dependent variable: perception of				
	Hard Work	Education	Family	Sex	Inequality of Opportunity
	OLS	*OLS*	*OLS*	*OLS*	*Logit*
	(1)	(2)	(3)	(4)	(5)
Hard Work RI	0.014				
	(0.011)				
Education RI		0.048***			
		(0.009)			
Family RI			−0.005		
			(0.011)		
Sex RI				0.012	
				(0.011)	
IOp					−0.026
					(0.030)
Woman	−0.026**	0.046***	−0.106***	0.092***	0.035
	(0.012)	(0.014)	(0.012)	(0.013)	(0.030)
Employed	0.056***	−0.038**	−0.023	0.010	−0.540***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.038)
Own Edu = 2	−0.047	0.070*	0.025	−0.039	−0.124
	(0.037)	(0.037)	(0.037)	(0.039)	(0.096)
Own Edu = 3	−0.124**	0.237***	0.012	−0.107*	−0.168
	(0.061)	(0.056)	(0.058)	(0.059)	(0.145)
Parental Edu = 2	0.036	−0.013	−0.033	0.016	−0.194***
	(0.029)	(0.027)	(0.027)	(0.029)	(0.072)
Parental Edu = 3	0.140**	−0.038	−0.087	−0.011	−0.282**
	(0.056)	(0.053)	(0.054)	(0.055)	(0.138)
Experience Fin. Diff.	−0.121***	−0.214***	0.193***	0.136***	0.479***
	(0.016)	(0.014)	(0.015)	(0.015)	(0.034)
Mobility Up	0.068**	−0.020	−0.060*	0.012	−0.126
	(0.034)	(0.032)	(0.033)	(0.034)	(0.085)
Mobility Down	−0.025	0.035	0.035	−0.042	0.196**
	(0.041)	(0.040)	(0.040)	(0.040)	(0.093)
City	−0.022*	0.001	0.001	0.020	−0.020
	(0.013)	(0.014)	(0.014)	(0.014)	(0.032)
Year = 2022	−0.003	0.010***	−0.006**	−0.001	0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Constant	5.521	−19.981***	12.130**	1.501	−108.861***
	(5.339)	(5.130)	(5.241)	(5.418)	(12.735)
Country FE included	Yes	Yes	Yes	Yes	Yes
R^2/ Pseudo R^2	0.06	0.105	0.108	0.059	0.078
Observations	24,077	24,077	24,077	24,077	24,077

Note: RI = Relative Importance (measured). Standard errors clustered at country-cohort level in parentheses. Continuous variables are standardized. Coefficients in model 5 report AME. *p<0.1; **p<0.05; ***p<0.01.

perceived fairness shapes attitudes toward redistribution.

In terms of individual characteristics, we find that women are more likely to support redistribution than men, consistent with previous studies (Alesina & Giuliano, 2011; Bussolo et al., 2021; Fong, 2001). By contrast, employment and higher educational attainment are associated with lower support, possibly reflecting differences in self-interest (Alesina & Giuliano, 2011; Bussolo et al., 2021). Finally, residing in urban areas is associated with a 8.5 percentage point increase in the likelihood of supporting redistribution, potentially because exposure to more deprivation heightens inequality aversion (Kaplan et al., 2025).

Finally, the descriptive aggregated trends noted by (Berlingieri et al., 2023), that European citizens' perceptions of unfairness are increasing while their support for redistribution is declining over time, are confirmed by our multivariate analysis. Overtime, perceived IOp increased but support for redistribution declined. This raises important questions about how this inconsistency can be understood and whether reduced trust in institutions is a plausible explanation.

A number of robustness checks have been performed. First, models (1) and (2) were re-estimated using country-specific samples. As expected, given the smaller sample sizes, this led to a substantial reduction in the statistical significance of the coefficients but did not indicate systematic country-specific peculiarities in the data-generating processes, country-specific estimates are available upon request. Second, aware that our interpretation of perceptions in relative terms may be questionable, we repeated the analysis assigning cardinal meaning to the answers in EBS. For this purpose, we use the absolute values assigned to each factor on a five-point Likert scale and regress them on a measure of that factor's absolute importance in predicting income differences. The OLS regression results are reported in Table 6 in the Appendix. Third, because the transformation into a binary variable of the attitude toward redistribution is also questionable, we estimate an OLS model for support for redistribution in which again the Likert scale is interpreted as a cardinal variable. Results are reported in Table 7 in Appendix and are consistent with our preferred model specification. Finally, since the question about the importance of different factors in determining success is not formulated in the exact same manner in wave 2017 and 2022 (additional factors were included in the item in the 2017 wave), we re-estimated all analyses using data from the 2022 wave only. The results are robust and remain unchanged (tables are available upon request).

5 Conclusions

In this paper, we have shed light on the systematic misperceptions of inequality of opportunity and the relative importance of different factors explaining inequality. We benchmark individual perceptions from the EBS against objective measures of inequality of opportunity and the relative importance of education, hard work, gender, and family wealth in predicting income, estimated using machine learning on EU-SILC data. Harmonizing the two data sources by birth cohort and country allows for a panel analysis across 27 EU countries.

Table 4: Logistic regression models explaining redistribution support

	Baseline model	Perceptions only	Measure only
	(1)	(2)	(3)
Perc IOp	0.534***	0.533***	
	(0.045)	(0.044)	
Perc Hard Work	−0.057**	−0.056**	
	(0.023)	(0.023)	
Perc Education	0.032	0.031	
	(0.023)	(0.023)	
Perc Sex	−0.022	−0.022	
	(0.026)	(0.026)	
Hard Work RI	−0.091*		−0.095*
	(0.054)		(0.053)
Education RI	−0.095*		−0.087*
	(0.050)		(0.049)
Sex RI	−0.038		−0.040
	(0.045)		(0.046)
IOp	−0.038		−0.042
	(0.041)		(0.041)
Woman	0.292***	0.292***	0.295***
	(0.035)	(0.035)	(0.034)
Employed	−0.188***	−0.182***	−0.246***
	(0.047)	(0.048)	(0.047)
Own Edu = 2	−0.176	−0.166	−0.186
	(0.119)	(0.119)	(0.118)
Own Edu = 3	−0.488***	−0.472***	−0.490***
	(0.175)	(0.175)	(0.174)
Parental Edu = 2	−0.085	−0.081	−0.103
	(0.081)	(0.081)	(0.080)
Parental Edu = 3	−0.229	−0.228	−0.254*
	(0.153)	(0.153)	(0.152)
Experience Fin. Diff.	0.019	0.022	0.063
	(0.042)	(0.042)	(0.043)
Mobility Up	0.044	0.042	0.031
	(0.099)	(0.099)	(0.098)
Mobility Down	−0.162	−0.157	−0.149
	(0.109)	(0.109)	(0.108)
City	0.085**	0.084**	0.085**
	(0.038)	(0.038)	(0.037)
Year = 2022	−0.064***	−0.063***	−0.058***
	(0.008)	(0.008)	(0.008)
Constant	130.357***	130.108***	118.940***
	(15.477)	(15.465)	(15.321)
Country FE included	Yes	Yes	Yes
Pseudo R^2 (McFadden)	0.15	0.15	0.143
Observations	24,077	24,077	24,077

Note: Standard errors clustered at country-cohort level in parentheses. Continuous variables are standardized. Coefficients are reported as AME. *p<0.1; **p<0.05; ***p<0.01.

We provide evidence of substantial heterogeneity across countries and birth cohorts in both the absolute level of IOp and the relative importance of different factors in predicting income variability. At the European level, over cohorts, we observe a growing role of hours worked, the measure of "hard work", and a declining role of education. However, trends differ markedly by country, providing evidence that individuals in different cohorts and countries have indeed experienced different levels and types of inequality.

In our analysis, we explain perceptions of inequality and their determinants by modeling perception as a function of objective measures, country and survey year fixed effects, and other individual-specific variables. We find little correlation between perceptions and reality. Regressions of individual perceptions on objective measures show that the only significant positive association is between the perceived and measured relative importance of education. Rather than these objective conditions, personal characteristics and life experiences significantly shape perceptions. For example, individuals who have experienced upward mobility tend to attribute greater importance to hard work, whereas those who have faced financial hardship tend to perceive hard work and education as less important, and gender and family wealth as more important. These patterns suggest that experiences of personal "success" or "failure" are interpreted through a self-serving bias and then generalized to society as a whole.

We then study how perceptions covary with attitudes toward redistribution. We model support for redistribution as a function of subjective perceptions of the role of different factors, objective measures, individual characteristics, and country and survey year fixed effects. We find that redistributive preferences are significantly correlated with perceived inequality of opportunity and beliefs about the role of hard work, rather than with objective measures. Several individual characteristics also significantly predict the probability of supporting redistribution: women are more supportive, while individuals in better conditions (well-educated) are less supportive. Moreover, our analysis confirms the paradox of European citizens increasingly perceiving inequality as unfair, while at the same time becoming less supportive of redistributive policies.

Future research could explore ways to make perceptions of fairness less biased and more consistent with reality. For example, experiments could test the effect of providing information on measured inequality of opportunity and the relative importance of different factors on misperceptions and redistributive preferences. Our analysis focuses on predefined sources of inequality, but other unexamined factors may also shape perceptions. Future work could leverage open-ended survey responses to better capture individuals' understanding of inequality and its sources. Finally, we acknowledge the challenges of operationalizing the concept of "hard work." Due to data limitations, we proxy hard work with working hours, although individuals' understanding likely extends beyond this quantitative measure. Relatedly, our sample includes only employed and unemployed individuals, overlooking those outside the labor force who may still engage in substantial effort, such as homemakers or caregivers.

6 Appendix

6.1 Survey item dependent variables

How important do you think each of the following are for getting ahead in life?

*?PipinInstruction8 (M)

Rows: Random | Columns: Normal

Rendered as Dynamic Grid

		Essential	Very important	Fairly important	Not very important	Not important at all	*?PipinInDK99 (M) *Fixed* *Exclusive*
		1	2	3	4	5	999
Coming from a wealthy family	1	○	○	○	○	○	○
Having a good education	2	○	○	○	○	○	○
Working hard	3	○	○	○	○	○	○
Being born a man or a woman	4	○	○	○	○	○	○

Eurobarometer Standard - 97.4 (CAPI + CAWI) | version 6 | © Kantar79

Figure 4: Survey item 2022

6.2 Model specification: proportional odds assumption

Since our dependent variables are initially coded on a five-point Likert scale, we run an ordinal logistic regression model for each dependent variable. To verify whether this model is more appropriate for our data, we test the proportional odds assumption (POA) of parallel slopes using the built-in stata command oparallel (Buis, 2013). Oparallel conducts several tests (i.e. Likelihood Ratio, Wald, score, Brant, Wolfe Gould), testing the null hypothesis of constant coefficients across response levels.

As seen in Table 5, the null hypothesis is rejected in all tests, indicating that the POA does not hold and making the proportional odds model less appropriate[11].

[11]It should be noted that tests cannot be applied if data separation issues leading to perfect predictability of the response variable arise. Due to very small number of observations in the lowest response category ("Not important at all") of the variables *perceived relative importance*

Table 5: Testing the proportional odds assumption

	Wolfe Gould	Brant	Score	Likelihood Ratio	Wald
Perception IOp					
χ^2	948.3	935.9	952.3	944.5	960
df	114	114	114	114	114
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000
Perception Hard Work					
χ^2	620.8	572.7	600.4	613.5	581.1
df	111	111	111	111	111
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000
Perception Education					
χ^2	671.9	619.1	648.9	662.2	630.9
df	108	108	108	108	108
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000
Perception Family Wealth					
χ^2	616.2	605.4	620.5	615	612.9
df	114	114	114	114	114
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000
Perception Gender					
χ^2	559.9	585.9	595.1	559.3	592.6
df	114	114	114	114	114
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000
Redistributive Preferences					
χ^2	944.7	875.4	881.1	903.9	890.8
df	135	135	135	135	135
$P > \chi^2$	0.000	0.000	0.000	0.000	0.000

of hard work and *perceived relative importance of education* for Ireland, Spain and Italy, data separation issue has been present. Therefore, these countries have been removed temporarily to conduct the test.

6.3 Model specification: absolute importance

Table 6: OLS regression: perceived and measured absolute importance

	Dependent variables (1-5 Likert scale): perception of				
	Hard Work	Education	Family	Sex	Inequality of Opportunity
	(1)	(2)	(3)	(4)	(5)
Hard Work Abs	−0.021				
	(0.016)				
Education Abs		0.054***			
		(0.010)			
Family Abs			−0.008		
			(0.011)		
Sex Abs				0.004	
				(0.008)	
IOp					0.006
					(0.354)
Woman	−0.007	0.061***	−0.066***	0.088***	0.022*
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)
Employed	0.059***	−0.040**	−0.007	0.013	−0.237***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Own Edu = 2	−0.141***	−0.016	−0.069*	−0.073*	−0.116***
	(0.041)	(0.037)	(0.039)	(0.039)	(0.039)
Own Edu = 3	−0.215***	0.119**	−0.089	−0.135**	−0.183***
	(0.064)	(0.058)	(0.059)	(0.059)	(0.058)
Parental Edu = 2	0.053*	0.021	−0.027	0.010	−0.034
	(0.030)	(0.026)	(0.027)	(0.029)	(0.027)
Parental Edu = 3	0.191***	0.050	−0.056	−0.010	−0.066
	(0.059)	(0.053)	(0.055)	(0.055)	(0.054)
Experience Fin. Diff.	−0.108***	−0.179***	0.168***	0.119***	0.256***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Mobility Up	0.110***	0.038	−0.018	0.020	−0.012
	(0.036)	(0.033)	(0.033)	(0.035)	(0.033)
Mobility Down	−0.109**	−0.062	−0.015	−0.063	0.023
	(0.042)	(0.041)	(0.039)	(0.040)	(0.039)
City	0.028**	0.047***	0.035***	0.040***	−0.010
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Year = 2022	−0.012***	−0.002	−0.006**	0.001	0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	24.907***	3.909	12.912**	−1.078	−73.204***
	(5.391)	(5.347)	(5.284)	(5.460)	(5.241)
Country FE included	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.101	0.131	0.077	0.147
Observations	24,067	24,067	24,066	24,066	24,077

Note: Standard errors clustered at country-cohort level in parentheses. Continuous variables are standardized. *p<0.1; **p<0.05; ***p<0.01.

6.4 Model specification: OLS redistribution support

Table 7: OLS regression: support for redistribution

	Dependent variable:
	Support for redistribution (1-5 Likert Scale)
Perc IOp	0.234***
	(0.015)
Perc Hard Work	−0.033***
	(0.009)
Perc Education	−0.001
	(0.009)
Perc Sex	−0.014
	(0.010)
RI Hard Work	−0.028
	(0.020)
RI Education	−0.033*
	(0.017)
RI Sex	−0.014
	(0.015)
IOp	0.0003
	(0.013)
Woman	0.092***
	(0.013)
Employed	−0.078***
	(0.016)
Own Edu = 2	−0.020
	(0.036)
Own Edu = 3	−0.100*
	(0.057)
Parental Edu = 2	−0.062**
	(0.029)
Parental Edu = 3	−0.164***
	(0.054)
Experience Fin. Diff.	0.020
	(0.015)
Mobility Up	−0.026
	(0.033)
Mobility Down	−0.022
	(0.040)
City	0.016
	(0.014)
Year = 2022	−0.022***
	(0.003)
Constant	43.679***
	(5.553)
Country FE included	Yes
R^2	0.06
Observations	24,077

Note: Standard errors clustered at country-cohort level in parentheses. Continuous variables are standardized. *p<0.1; **p<0.05; ***p<0.01.

6.5 Summary statistics of EBS data

Table 8: Summary statistics by country (covariates): share of respondents in each category

Variable	**Category**	**AT**	**BE**	**BG**	**CY**	**CZ**	**DE**	**DK**	**EE**	**ES**	**FR**	**GR**	**HR**	**HU**	**IE**	**IT**
City	0	0.72	0.72	0.51	0.51	0.73	0.64	0.70	0.56	0.46	0.52	0.51	0.66	0.61	0.68	0.67
City	1	0.28	0.28	0.49	0.49	0.27	0.36	0.30	0.44	0.54	0.48	0.49	0.34	0.39	0.32	0.33
Own Education	1 (at most primary)	0.01	0.04	0.03	0.08	0.04	0.06	0.02	0.02	0.16	0.05	0.11	0.04	0.07	0.05	0.05
Own Education	2 (secondary)	0.14	0.42	0.58	0.43	0.72	0.52	0.12	0.27	0.33	0.50	0.50	0.72	0.67	0.32	0.63
Own Education	3 (post-secondary)	0.85	0.54	0.39	0.49	0.24	0.42	0.86	0.71	0.50	0.45	0.39	0.24	0.27	0.63	0.31
Parental Education	1 (at most primary)	0.07	0.21	0.18	0.47	0.06	0.26	0.13	0.09	0.65	0.39	0.53	0.26	0.23	0.24	0.32
Parental Education	2 (secondary)	0.43	0.45	0.55	0.41	0.74	0.44	0.06	0.26	0.24	0.37	0.37	0.61	0.61	0.54	0.54
Parental Education	3 (post-secondary)	0.51	0.33	0.27	0.12	0.20	0.30	0.81	0.65	0.11	0.23	0.10	0.13	0.16	0.22	0.14
Employment Status	0 (not employed)	0.17	0.27	0.19	0.20	0.18	0.22	0.12	0.20	0.29	0.31	0.24	0.28	0.08	0.20	0.18
Employment Status	1 (employed)	0.83	0.73	0.81	0.80	0.82	0.78	0.88	0.80	0.71	0.69	0.76	0.72	0.92	0.80	0.82
Experience Financial Difficulties	0	0.75	0.62	0.35	0.42	0.68	0.78	0.93	0.70	0.68	0.58	0.14	0.45	0.68	0.59	0.40
Experience Financial Difficulties	1	0.25	0.38	0.65	0.58	0.32	0.22	0.07	0.30	0.32	0.42	0.86	0.55	0.32	0.41	0.60
Mobility	0 (not mobile)	0.59	0.56	0.59	0.35	0.73	0.60	0.72	0.65	0.34	0.45	0.37	0.58	0.61	0.41	0.54
Mobility	1 (upwardly mobile)	0.38	0.38	0.32	0.63	0.16	0.33	0.17	0.21	0.65	0.50	0.61	0.37	0.32	0.57	0.43
Mobility	2 (downwardly mobile)	0.03	0.06	0.09	0.02	0.11	0.07	0.11	0.14	0.02	0.05	0.02	0.05	0.06	0.03	0.03
Woman	0	0.50	0.49	0.48	0.49	0.51	0.50	0.52	0.48	0.49	0.49	0.49	0.50	0.50	0.47	0.50
Woman	1	0.50	0.51	0.52	0.51	0.49	0.50	0.48	0.52	0.51	0.51	0.51	0.50	0.50	0.53	0.50
Year	2017	0.50	0.48	0.48	0.54	0.49	0.51	0.49	0.48	0.51	0.48	0.49	0.47	0.49	0.50	0.49
Year	2022	0.50	0.52	0.52	0.46	0.51	0.49	0.51	0.52	0.49	0.52	0.51	0.52	0.51	0.50	0.51

Variable	**Category**	**MT**	**NL**	**SK**	**FI**	**LU**	**LT**	**PL**	**PT**	**RO**	**SE**	**LV**	**SI**
City	0	0.53	0.45	0.82	0.61	0.79	0.60	0.63	0.58	0.65	0.54	0.62	0.81
City	1	0.47	0.55	0.18	0.39	0.21	0.40	0.37	0.42	0.35	0.46	0.38	0.19
Own Education	1 (at most primary)	0.04	0.01	0.06	0.03	0.07	0.00	0.05	0.30	0.08	0.00	0.04	0.04
Own Education	2 (secondary)	0.31	0.23	0.77	0.31	0.30	0.35	0.66	0.51	0.66	0.30	0.34	0.53
Own Education	3 (post-secondary)	0.65	0.76	0.17	0.66	0.63	0.65	0.29	0.19	0.26	0.70	0.61	0.43
Parental Education	1 (at most primary)	0.27	0.05	0.13	0.27	0.35	0.22	0.25	0.64	0.28	0.15	0.16	0.25
Parental Education	2 (secondary)	0.47	0.43	0.77	0.35	0.35	0.39	0.64	0.30	0.54	0.30	0.33	0.57
Parental Education	3 (post-secondary)	0.26	0.52	0.10	0.38	0.29	0.39	0.11	0.06	0.18	0.55	0.51	0.18
Employment Status	0 (not employed)	0.11	0.10	0.12	0.24	0.28	0.27	0.15	0.16	0.25	0.10	0.24	0.25
Employment Status	1 (employed)	0.89	0.90	0.88	0.76	0.72	0.73	0.85	0.84	0.75	0.90	0.76	0.75
Experience Financial Difficulties	0	0.76	0.82	0.61	0.75	0.86	0.59	0.78	0.40	0.46	0.91	0.60	0.71
Experience Financial Difficulties	1	0.24	0.18	0.39	0.25	0.14	0.41	0.22	0.60	0.54	0.09	0.40	0.29
Mobility	0 (not mobile)	0.45	0.65	0.78	0.46	0.43	0.52	0.57	0.51	0.57	0.58	0.56	0.48
Mobility	1 (upwardly mobile)	0.53	0.30	0.18	0.46	0.52	0.43	0.39	0.46	0.34	0.32	0.31	0.47
Mobility	2 (downwardly mobile)	0.01	0.05	0.04	0.09	0.04	0.06	0.04	0.03	0.08	0.10	0.13	0.05
Woman	0	0.51	0.49	0.50	0.51	0.54	0.47	0.50	0.46	0.51	0.51	0.46	0.51
Woman	1	0.49	0.51	0.50	0.49	0.46	0.53	0.50	0.54	0.49	0.49	0.54	0.49
Year	2017	0.45	0.50	0.50	0.45	0.50	0.48	0.48	0.51	0.45	0.46	0.44	0.49
Year	2022	0.55	0.50	0.50	0.55	0.50	0.52	0.52	0.49	0.55	0.54	0.56	0.51

Source: EBS 2017 & 2022.

6.6 Summary statistics of EU-SILC data

Table 9: Summary statistics by country (continuous variables)

Country	Income (Mean)	Income (Var)	Age (Mean)	Age (Var)	Hrs Worked (Mean)	Hrs Worked (Var)
AT	24153.18	171.63	41.79	0.10	35.80	0.18
BE	24603.41	183.99	40.70	0.09	35.55	0.16
BG	4597.12	97.97	42.03	0.11	37.48	0.15
CY	16571.68	317.52	40.82	0.17	36.32	0.24
CZ	8177.03	56.12	40.76	0.09	39.07	0.14
DE	21948.24	205.42	41.22	0.09	33.02	0.17
DK	34819.98	508.55	42.86	0.27	36.06	0.45
EE	8801.69	93.44	41.15	0.13	38.40	0.15
ES	16236.81	87.83	40.41	0.06	34.16	0.12
FI	23309.86	258.15	41.77	0.20	36.36	0.29
FR	23496.92	168.08	40.72	0.08	35.63	0.13
EL	13605.40	118.77	40.33	0.09	38.37	0.17
HR	8302.70	70.43	41.26	0.12	36.83	0.18
HU	5836.70	112.73	44.40	0.21	35.56	0.32
IE	29495.21	420.39	41.56	0.15	32.77	0.25
IT	19765.38	105.40	41.31	0.06	36.36	0.08
LT	5609.07	81.80	41.34	0.14	38.33	0.18
LU	41610.54	504.47	40.37	0.12	37.97	0.20
LV	6213.77	91.52	41.20	0.12	37.00	0.20
MT	18883.18	266.46	37.45	0.22	39.99	0.24
NL	32490.21	457.37	41.28	0.20	33.99	0.22
PL	6262.19	38.65	40.12	0.06	40.52	0.09
PT	11170.24	100.08	40.51	0.09	36.21	0.16
RO	3957.81	39.33	40.77	0.12	39.03	0.15
SE	26997.76	270.86	41.11	0.22	37.44	0.28
SI	12756.88	91.26	40.63	0.11	38.87	0.16
SK	7325.11	90.61	43.85	0.24	38.33	0.34

Source: EU-SILC 2005, 2011, 2009.

Table 10: Summary statistics by country (categorical variables): share of respondents in each category

Variable	**Category**	**AT**	**BE**	**BG**	**CY**	**CZ**	**DE**	**DK**	**EE**	**ES**	**FI**	**FR**	**GR**
Female	0 (= No)	0.54	0.53	0.52	0.54	0.50	0.52	0.52	0.50	0.56	0.53	0.51	0.60
	1 (= Yes)	0.46	0.47	0.48	0.46	0.50	0.48	0.48	0.50	0.44	0.47	0.49	0.40
Own Education	1 (= Primary education)	0.00	0.04	0.02	0.08	0.00	0.01	0.01	0.00	0.12	0.00	0.05	0.12
	2 (= Lower secondary education)	0.12	0.11	0.11	0.07	0.05	0.05	0.07	0.06	0.24	0.07	0.10	0.10
	3 (= (Upper) secondary education)	0.51	0.33	0.56	0.37	0.73	0.39	0.39	0.43	0.24	0.41	0.45	0.35
	4 (= Post-secondary non-tertiary education)	0.08	0.03	0.00	0.04	0.01	0.15	0.00	0.08	0.01	0.02	0.00	0.08
	5 (= 1st stage & 2nd stage of tertiary education)	0.29	0.50	0.30	0.43	0.21	0.40	0.53	0.43	0.39	0.50	0.38	0.35
Occupation Mother	0 (= Armed forces occupations)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
	1 (= Managers)	0.01	0.02	0.01	0.00	0.01	0.02	0.06	0.06	0.01	0.05	0.02	0.02
	2 (= Professionals)	0.03	0.10	0.14	0.06	0.09	0.07	0.15	0.19	0.03	0.14	0.05	0.04
	3 (= Technicians and associate professionals)	0.01	0.04	0.04	0.03	0.13	0.12	0.12	0.15	0.02	0.13	0.07	0.01
	4 (= Clerical support workers)	0.09	0.09	0.11	0.06	0.16	0.12	0.17	0.09	0.03	0.10	0.14	0.05
	5 (= Service and sales workers)	0.18	0.09	0.18	0.11	0.17	0.12	0.13	0.12	0.09	0.18	0.12	0.06
	6 (= Skilled agricultural, forestry & fishery workers)	0.10	0.02	0.12	0.03	0.06	0.02	0.02	0.07	0.03	0.04	0.05	0.21
	7 (= Craft and related trades workers)	0.05	0.03	0.11	0.02	0.11	0.03	0.04	0.06	0.04	0.03	0.04	0.04
	8 (= Plant and machine operators & assemblers)	0.01	0.02	0.06	0.04	0.08	0.05	0.01	0.09	0.01	0.09	0.03	0.01
	9 (= Elementary occupations)	0.11	0.07	0.16	0.18	0.13	0.04	0.13	0.11	0.11	0.08	0.12	0.05
	10 (= No occupation)	0.40	0.53	0.07	0.46	0.06	0.40	0.17	0.06	0.62	0.14	0.36	0.51
Occupation Father	0 (= Armed forces occupations)	0.01	0.02	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.03	0.02	0.01
	1 (= Managers)	0.04	0.09	0.03	0.02	0.04	0.07	0.19	0.10	0.06	0.08	0.09	0.07
	2 (= Professionals)	0.05	0.13	0.09	0.09	0.08	0.15	0.16	0.11	0.05	0.12	0.09	0.06
	3 (= Technicians and associate professionals)	0.09	0.10	0.09	0.08	0.14	0.15	0.10	0.07	0.07	0.14	0.11	0.03
	4 (= Clerical support workers)	0.06	0.11	0.02	0.03	0.03	0.06	0.02	0.02	0.06	0.02	0.07	0.10
	5 (= Service and sales workers)	0.14	0.07	0.07	0.15	0.04	0.05	0.06	0.02	0.10	0.05	0.04	0.08
	6 (= Skilled agricultural, forestry & fishery workers)	0.13	0.04	0.11	0.11	0.04	0.05	0.09	0.03	0.12	0.10	0.09	0.28
	7 (= Craft and related trades workers)	0.29	0.21	0.22	0.27	0.35	0.28	0.22	0.27	0.23	0.20	0.19	0.21
	8 (= Plant and machine operators & assemblers)	0.07	0.10	0.18	0.12	0.21	0.12	0.06	0.29	0.13	0.14	0.09	0.09
	9 (= Elementary occupations)	0.09	0.08	0.15	0.10	0.05	0.04	0.06	0.06	0.13	0.02	0.18	0.07
	10 (= No occupation)	0.01	0.05	0.01	0.02	0.01	0.03	0.03	0.02	0.02	0.09	0.02	0.01
Education Mother	1 (= Low level)	0.56	0.57	0.38	0.59	0.51	0.26	0.37	0.29	0.86	0.33	0.76	0.76
	2 (= Medium level)	0.37	0.26	0.48	0.31	0.43	0.59	0.34	0.42	0.07	0.43	0.14	0.18
	3 (= High level)	0.07	0.17	0.14	0.10	0.06	0.15	0.28	0.29	0.06	0.24	0.10	0.06
Education Father	1 (= Low level)	0.38	0.52	0.39	0.55	0.47	0.15	0.32	0.32	0.80	0.34	0.72	0.71
	2 (= Medium level)	0.45	0.25	0.48	0.33	0.43	0.51	0.35	0.43	0.09	0.42	0.15	0.18
	3 (= High level)	0.16	0.23	0.13	0.12	0.11	0.35	0.33	0.25	0.11	0.24	0.13	0.11

Variable	**Category**	**HR**	**HU**	**IE**	**IT**	**LT**	**LU**	**LV**	**MT**	**NL**	**PL**	**PT**	**RO**	**SE**	**SI**	**SK**
Female	0 (= No)	0.54	0.48	0.50	0.58	0.49	0.55	0.49	0.60	0.54	0.53	0.52	0.59	0.56	0.51	0.56
	1 (= Yes)	0.46	0.52	0.50	0.42	0.51	0.45	0.51	0.40	0.46	0.47	0.48	0.41	0.44	0.49	0.44
Own Education	1 (= Primary education)	0.01	0.00	0.06	0.04	0.00	0.16	0.03	0.00	0.01	0.06	0.34	0.01	0.01	0.04	0.00
	2 (= Lower secondary education)	0.09	0.11	0.12	0.30	0.05	0.10	0.07	0.39	0.07	0.00	0.21	0.13	0.08	0.07	0.05
	3 (= (Upper) secondary education)	0.65	0.52	0.19	0.42	0.30	0.35	0.46	0.24	0.34	0.59	0.21	0.58	0.42	0.57	0.68
	4 (= Post-secondary non-tertiary education)	0.00	0.06	0.07	0.04	0.26	0.02	0.11	0.05	0.00	0.04	0.01	0.05	0.08	0.02	0.02
	5 (= 1st stage & 2nd stage of tertiary education)	0.25	0.30	0.56	0.20	0.39	0.38	0.33	0.32	0.57	0.31	0.22	0.23	0.42	0.31	0.25
Occupation Mother	0 (= Armed forces occupations)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
	1 (= Managers)	0.01	0.01	0.03	0.02	0.04	0.03	0.05	0.01	0.01	0.02	0.02	0.00	0.02	0.01	0.01
	2 (= Professionals)	0.08	0.07	0.09	0.04	0.19	0.08	0.16	0.04	0.13	0.09	0.04	0.06	0.22	0.08	0.09
	3 (= Technicians and associate professionals)	0.05	0.09	0.01	0.04	0.05	0.05	0.11	0.01	0.06	0.08	0.03	0.03	0.06	0.12	0.10
	4 (= Clerical support workers)	0.08	0.14	0.06	0.04	0.06	0.07	0.10	0.02	0.08	0.08	0.04	0.04	0.12	0.10	0.14
	5 (= Service and sales workers)	0.11	0.14	0.05	0.06	0.11	0.08	0.13	0.06	0.15	0.11	0.09	0.10	0.26	0.10	0.20
	6 (= Skilled agricultural, forestry and fishery workers)	0.03	0.05	0.03	0.03	0.06	0.04	0.06	0.01	0.01	0.23	0.13	0.20	0.02	0.05	0.05
	7 (= Craft and related trades workers)	0.05	0.10	0.03	0.05	0.11	0.03	0.08	0.01	0.01	0.08	0.07	0.12	0.01	0.06	0.08
	8 (= Plant and machine operators and assemblers)	0.01	0.07	0.02	0.03	0.03	0.02	0.03	0.01	0.00	0.02	0.04	0.06	0.03	0.07	0.06
	9 (= Elementary occupations)	0.13	0.15	0.07	0.07	0.26	0.13	0.20	0.02	0.06	0.11	0.16	0.09	0.05	0.15	0.16
	10 (= No occupation)	0.45	0.16	0.63	0.62	0.10	0.48	0.07	0.80	0.47	0.18	0.36	0.29	0.21	0.25	0.10
Occupation Father	0 (= Armed forces occupations)	0.01	0.01	0.01	0.02	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00
	1 (= Managers)	0.05	0.04	0.15	0.07	0.06	0.08	0.06	0.10	0.11	0.05	0.07	0.01	0.08	0.05	0.04
	2 (= Professionals)	0.06	0.08	0.10	0.06	0.10	0.12	0.11	0.08	0.20	0.06	0.04	0.06	0.17	0.08	0.08
	3 (= Technicians and associate professionals)	0.11	0.06	0.06	0.09	0.05	0.11	0.06	0.12	0.15	0.07	0.07	0.05	0.13	0.12	0.11
	4 (= Clerical support workers)	0.05	0.02	0.04	0.06	0.02	0.07	0.01	0.04	0.05	0.03	0.05	0.03	0.04	0.04	0.02
	5 (= Service and sales workers)	0.09	0.05	0.19	0.07	0.03	0.04	0.03	0.14	0.09	0.04	0.09	0.02	0.08	0.06	0.08
	6 (= Skilled agricultural, forestry and fishery workers)	0.05	0.09	0.06	0.09	0.07	0.10	0.06	0.04	0.05	0.21	0.15	0.19	0.06	0.08	0.02
	7 (= Craft and related trades workers)	0.21	0.30	0.11	0.26	0.26	0.25	0.26	0.24	0.19	0.28	0.29	0.33	0.24	0.26	0.28
	8 (= Plant and machine operators and assemblers)	0.12	0.22	0.10	0.13	0.23	0.15	0.28	0.10	0.07	0.17	0.13	0.17	0.13	0.14	0.24
	9 (= Elementary occupations)	0.20	0.09	0.12	0.12	0.17	0.06	0.10	0.10	0.04	0.06	0.08	0.11	0.02	0.13	0.11
	10 (= No occupation)	0.06	0.03	0.05	0.04	0.01	0.01	0.02	0.03	0.04	0.02	0.02	0.03	0.03	0.04	0.03
Education Mother	1 (= Low level)	0.61	0.48	0.51	0.82	0.46	0.63	0.37	0.41	0.56	0.42	0.91	0.55	0.41	0.57	0.59
	2 (= Medium level)	0.32	0.43	0.35	0.15	0.37	0.25	0.47	0.52	0.25	0.51	0.04	0.41	0.29	0.33	0.35
	3 (= High level)	0.07	0.10	0.13	0.03	0.17	0.12	0.16	0.07	0.18	0.08	0.05	0.04	0.29	0.10	0.06
Education Father	1 (= Low level)	0.46	0.40	0.56	0.76	0.50	0.52	0.41	0.39	0.46	0.37	0.90	0.51	0.43	0.47	0.63
	2 (= Medium level)	0.43	0.47	0.29	0.18	0.36	0.30	0.45	0.49	0.25	0.54	0.05	0.44	0.28	0.41	0.27
	3 (= High level)	0.10	0.13	0.15	0.06	0.14	0.18	0.14	0.12	0.29	0.09	0.05	0.06	0.29	0.12	0.09

Source: EU-SILC 2005, 2011, 2009.

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