Acta Politica
https://doi.org/10.1057/s41269-026-00418-9

ORIGINAL ARTICLE

Conceptualizations of socio-economic status and preferences for redistribution

Antonio M. Jaime-Castillo[1] · **Juan J. Fernández**[2]

Received: 6 March 2025 / Accepted: 3 March 2026

Abstract
The self-interest approach to preferences for redistribution draws upon the idea that socio-economic conditions influence policy preferences via personal interests. Following this principle, a burgeoning interdisciplinary literature has examined the influence of socio-economic status (SES) on redistributive preferences. Yet this body of research is quite fragmented because it includes a plethora of understandings of SES and there is still no consensus on which conceptualization best accounts for variation in these preferences. We fill this gap in the literature through an analysis of the predictive validity of seven conceptualizations of SES: (i) income as a linear measure; (ii) income measured in deciles; (iii) skills specificity; (iv) ESeC schema; (v) Oesch class schema; (vi) risk of unemployment; and (vii) routine task intensity. Using data from the European Social Survey for 24 countries in 2012–2022, we determine the predictive power of each conceptualization through different measures of goodness of fit. The results show that income measured in deciles is the conceptualization with highest predictive power and parsimony.

Keywords Preferences for redistribution · Socio-economic status · Income · Goodness of fit

The relationship between socio-economic status (SES) and political preferences is a foundational concern in political science and political economy. Classical theories of political behavior, particularly those rooted in Marxist (Wright 1985) and rational choice (Meltzer and Richard 1981) traditions, presume that individuals' political preferences align with their material interests. From this perspective, individuals with

✉ Antonio M. Jaime-Castillo
amjaime@poli.uned.es

1 Universidad Nacional de Educación a Distancia, C/ Obispo Trejo 2, 28012 Madrid, Spain

2 Universidad Carlos III de Madrid, 28903, C/ de Madrid 126, Getafe, Spain

Published online: 21 March 2026

low SES should prefer parties and policies that promote redistribution, labor protections, and welfare benefits, while individuals with high SES should support market liberalism, low taxation, and limited state intervention. Across democratic societies, a vast literature supports this expectation, showing that socio-economic position is a significant predictor of political behavior (Lindh and McCall 2020). Nevertheless, the specific processes and dimensions of SES that shape political preferences are complex and remain insufficiently understood. We address this question by focusing on the paradigmatic case of preferences for redistribution, a domain that lies at the heart of political economy, connecting individual attitudes with broader questions about inequality, democracy, and the role of the state (Persson and Tabellini 2000).

Scholarly research on socio-economic divides in redistribution preferences is both burgeoning and fragmented. Over the last decades many studies in the social sciences have examined attitudes towards the role of the state in economic redistribution, an interest in part stemming from income inequality trends in high-income democracies. Based on the tenet that objective socio-economic conditions influence policy preferences via personal interests (Kumlin 2007; Lindh and McCall 2020; Manza and Crowley 2018), many of these studies focus on micro-level divides in redistribution preferences. Yet there is still no consensus on which conceptualization of SES provides the highest analytical leverage. Indeed in this deeply interdisciplinary literature many conceptualizations of socio-economic standing have been linked to redistribution preferences (Mccall et al. 2011). Extant studies on these preferences conceptualize and operationalize socio-economic location in terms of income (Beramendi and Rehm 2016), large occupational groups linked to employment relations (Fernández and Jaime-Castillo 2018) or work logics (Kitschelt and Rehm 2014), levels of skills specificity (Iversen and Soskice 2001), risks of unemployment (Rehm 2009, 2011) and routine task intensity (Thewissen and Rueda 2019) among others. Substantive findings using different conceptualizations tend to go in same direction, indicating a robust negative relationship between SES and preferences for redistribution. However, this overall pattern may be influenced by publication bias against null findings and the literature reveals considerable variation in the magnitude of the effects, as well as disagreement about the significance of certain effects. For instance, while Steele et al. (2022) find a consistent effect of income in English-speaking OECD countries, Bonnet et al. (2024) show that for six advanced economies the effect of income is non-significant after controlling for financial security and risk aversion.

Prior analyses shed light on our understanding of which socio-economic groups prove more committed towards redistribution. Yet in seeking to advance (yet another) politically-relevant conceptualization of SES, several of these studies display two main limitations. First, many of them talk past each other. They commonly control for just one alternative conceptualization and rarely consider most or (at least several) alternative conceptualizations—especially those generated in other disciplines. As a result, the robustness of effects associated with most factors remains under-documented. Second, extant studies uniformly discount costs of additional model complexity. The standard strategy of these studies involves assessing solely whether the variable(s) tapping the proposed conceptualization has(have) a significant and/or substantial impact after controlling for a range of conditions independent from model complexity. This approach thus ignores the role of parsimony.

This large degree of fragmentation in scholarly production on pro-redistribution divides means that there are no comprehensive studies addressing the critical matter of which conceptualization of SES constitutes the most efficient and effective predictors of redistribution attitudes. In other words, we do not yet know which SES conceptualization provides the best balance between parsimony and explanatory power. This manuscript seeks to fill the gap. It follows an eclectic and agnostic approach to determine the predictive validity—also called construct validity—of seven major conceptualizations of SES for redistribution preferences. Within this general goal, we tackle two concrete questions: First, which conceptualization attains the highest explanatory power? Second, which conceptualization provides the best trade-off between explanatory power and parsimony?

We seek to answer these two questions without preconceptions. Our aim in this study is to identify the predictive validity of these indicators in comparative terms. We specifically focus on seven conceptualizations with especially large recognition in the social sciences: (i) net income in linear terms (Beramendi and Rehm 2016); (ii) a set of dummy variables for household's income decile (Guillaud 2013); (iii) the degree of skills specificity (Iversen and Soskice 2001); (iv) the European Socio-economic Classification (ESeC) (Paskov and Weisstanner 2022); (v) the class typology devised by Oesch (2006) and revised by Kitschelt and Rehm (2014); (vi) the risk of unemployment (Rehm 2009, 2011); and (vii) task routine intensity (Thewissen and Rueda 2019). A few studies compare the predictive power of SES conceptualizations (Carriero 2021; Kevins et al. 2019; Mccall et al. 2011; also Van den Berg and Coffé 2012), however all of them only consider two SES alternatives and none but one (Kevins et al. 2019) assess their predictive power across a variety of European countries.[1]

To assess the predictive validity of each of these seven conceptualizations, we conduct multivariate analyses of the determinants of redistribution preferences in 24 European countries during 2012–2022. We utilize rounds six to eleven of the European Social Survey (ESS) (2012–2022). In the following analysis, we assess the predictive validity of each indicator by taking into account both the explanatory power and parsimony of the models. For this purpose, we conduct comparisons of statistical goodness of fit—specifically, measures based on explanatory power such as R^2 and measures based on predictive power and parsimony such as BIC—across models including each of the conceptualizations (Claeskens and Hjort 2008). We focus on the predictive validity of each conceptualization (rather than sheer statistical significance) because predictive validity reveals the proportion of variation in the outcome accounted by the explanatory factor. The results show that overall income-based models (especially dummies for income deciles) fit the data better than the rest of the models. On the other hand, class based conceptualizations, such as ESeC or the typology proposed by Oesch (2006) do worse than other approaches, such as the risk of unemployment and skill specificity.

[1] Nevertheless, Kevins et al. (2019) focus on subjective social class and analyze only ten countries and smaller samples in each country.

Conceptualizations of socio-economic status and redistribution preferences

A central theme in the interdisciplinary literature on redistribution preferences revolves around the role of socio-economic divides. Many works in this area assess whether objectively-defined, socio-economic locations of individuals affect their redistribution preferences. Despite extensive differences in the theoretical models underpinning their claims and their ultimate predictions—which we review briefly below -, studies in this area share a commitment to rational-action assumptions (Meltzer and Richard 1981). They build on the tenets that (a) objective socio-economic locations determine personal economic interests and (b) that these self-interests determine political preferences. The self-interest approach is certainly not the only model of political attitude formation—in recent decades it has been challenged by a growing scholarship on other-regardingness (Dimick et al. 2018). Yet the self-interest model remains clearly prevalent in the literature on pro-redistribution divides, to a large extent because extensive research using very diverse operationalizations and indicators reports robust associations between indicators of individual SES and redistribution preferences (Kumlin 2007).

Seven conceptualizations of SES have proven to have particularly large resonance in accounting for redistribution preferences: (i) a continuous linear measure of income; (ii) a set of dummy variables for household's income decile; (iii) the degree of skills specificity; (iv) the ESeC schema; (v) the Oesch class schema and versions of it; (vi) the risk of unemployment; and (vii) the routine task intensity. Seminal studies leveraging each of these conceptualizations have been widely cited in the social sciences. What are the main similarities and differences across these seven conceptualizations?

Individual or household *income* has for long been a central economic dimension affecting political attitudes (especially in economy and political science). It is even a prevalent indicator in the sociology of stratification (Barone et al. 2021) and "the most common strategy for operationalizing the class location of individuals" (Manza and Crowley 2018: 370) in studies on political attitudes. Income offers a popular operationalization as this single dimension discriminates well among relative locations in the socio-economic hierarchy and people care deeply about their purchasing power. From this perspective, since individuals in the lowest half of the income distribution have lower resources than individuals in the highest half, they have more to gain from state-driven redistribution and are disproportionately likely to support redistributive policies (Lipset and Martin 1960; Meltzer and Richard 1981; Roberts 1977). Despite the simplicity of this model, it has proven fruitful: whether measured in linear terms or in categorical levels, a long list of studies in economics (Guillaud 2013), political science (Doherty et al. 2006; Walter 2017) and sociology (Brady and Bostic 2015) report direct and positive associations between individual (and household) income and redistribution preferences.

There are strong reasons to believe that individual income is a particularly robust predictor of pro-redistribution preferences. First, recent research shows that permanent income over the life course is actually better predicted by contemporary household income than measures of occupations or social class (Brady et al. 2018;

Shahbazian and Bihagen 2022). Second, income constitutes a culturally-preeminent category of classification (rich/poor; high/middle/low income). Children as young as 4–5 use the concepts rich/poor person and prefer rich groups (Horwitz et al. 2014). Adults hold widely-shared conceptions about personality differences between rich and poor individuals, with the former perceived as more competent and the latter more warm (Fiske et al. 2018). Approximately, one in every three Europeans perceive that there is “a lot of tension” between “poor and rich” individuals and perceptions of tensions between “managers and workers” are slightly less common (Van Drunen et al. 2021). Moreover, individuals perceive that income is a major source of differences between the “middle” and “upper middle” class (Stubager et al. 2018).

Three continuous conceptualizations of SES have been proposed since the early 2000s. Formulated by political scientists and political economists, they identify axes of objective socio-economic differentiation around occupational features, which are theorized as consequential for political preference formation. The three models have not been suggested as substitutive, but as complementary to the income dimension. They refer to the *skills specificity* (Iversen and Soskice 2001), *unemployment risk* (Rehm 2009, 2011) and *task routine intensity* (Thewissen and Rueda 2019) of occupations. The three models, moreover, build on the principle that redistribution constitutes a form of individual insurance against potentially substantial drops in income during the life cycle due to ill health, job loss or old age. Iversen and Soskice (2001) broke new ground in the self-interest approach by theorizing that beyond the amount of human capital, the asset or *skills specificity* of human capital is also politically consequential. Many occupations are filled with workers with specific skills whereas others comprise workers with general, portable skills. This approach argues that in the face of wage or employment loss, workers in occupations with high skills specificity have a smaller range of jobs they can transfer into and thus suffer higher risks of large declines in their purchasing power, which incentivizes them to be disproportionately supportive of redistribution. Operationalizing this as the inverse of the proportion of workers per occupation, Iversen and Soskice (2001) and latter studies have documented a positive effect of skills specificity (Cusack et al. 2006) on redistribution preferences.

Rehm (2009, 2011) has alternatively argued for the attitudinal relevance of variations in *unemployment risks* across occupations. He argues that in post-industrial societies, the largest individual risk is that of job loss, so that individuals at higher risk of unemployment support pro-redistributive policies to prevent sharp income losses. In determining their risk of unemployment, Rehm’s model states that the prevalent reference of comparison used by individuals is their occupation, because their own human capital is tied to their occupation—rather than their economic sector—and because occupations are major sites of normative and political socialization. Rehm’s general prediction that occupational-specific risks of unemployment shape redistributive preferences has been supported by his and latter empirical work (Rehm 2016; Vlandas 2021) and other studies have found a relationship between individual labor market shocks and political attitudes (Schraff 2018). More recently, Thewissen and Rueda (2019) have argued for a third occupational-based continuous divide in political attitudes: *routine task intensity*. According to their model, since technological change and work automation crowds-out routine occupations with intermediary skills, individuals in occupations susceptible to automation are more supportive of redistribution (Busemeyer and Sahm 2021). Importantly, these two latter models consider that unemployment and automation risk are orthogonal to skills specificity, because occupations with high skill specificity vary widely in unemployment risks and routine task intensity.

The *ESeC* and *Oesch* conceptualizations of SES constitute strict academic constructs. They also represent multicategorical conceptualizations capturing multiple dimensions of individual socio-economic standing. Both indicators have a strong sociological outlook. Designed as an improvement of the classic Erikson-Goltdhorpe and Portobello (EGP) class schema (Goldthorpe 2000), the ESeC schema classifies workers into 8–10 groups depending on combinations of their working conditions and the reward package offered by employers to meet firm needs (Rose and Harrison 2010). Taking the two classes in extreme positions, individuals in the upper salariat class fill jobs requiring task autonomy and skills in high demand, whereas individuals in the working class fill jobs with low autonomy and general skills. To ensure retention of the former, they are compensated with higher income, job security and promotion prospects. These differentials in economic conditions, the model goes, produce divides in life chances and political interests (Evans and Carl 2017). Recent studies relying on ESeC to predict redistribution preferences show that (controlling for individual income) unskilled workers are significantly more supportive of redistribution than all the other classes (Paskov and Weisstanner 2022).

The Oesch's (Oesch 2006) class schema classifies workers into large occupational groups based on the skills brought by workers to the labour market. It differs from the EGP and ESeC schemas in its reliance on a second dimension concerning the type of tasks commonly conducted by that large occupational group. It specifically identifies four logics of task structure: independent, interpersonal, organizational and technical. Drawing on Oesch's typology, Kitschelt and Rehm (2014), Kitschelt et al. (1994) specifically hypothesize that daily working routines in the interpersonal logic are characterized by recurring symbolic interaction and one-to-one negotiations, which induces workers in this logic to hold more compassion, egalitarian ethos and ultimately more support for redistribution than workers in other logics (also, Kriesi et al. 2008). Furthermore, Kitschelt et al. (1994) show that unskilled workers and workers in the interpersonal logic actually prove more supportive of redistribution.

A few recent studies have begun comparative exploration of the predictive power of conceptualizations of SES on political attitudes. Using US data, Mccall et al. (2011) and Weeden and Grusky (2012) assess the predictive power of, on the one hand, the EGP model versus, on the other, income and micro-classes, respectively. In both cases, the EGP schema fares worse than the alternative. Using data for European countries, Kevins et al. (2019) examines the predictive power of subjective social class versus income and find that income is a better predictor of attitudes towards the welfare state. Carriero (2021), instead, relies on ESS data to assess the predictive power of the ESeC versus the Oesch schema on redistribution attitudes and concludes that their predictive validity are practically indistinguishable. These latter comparative studies provide valuable insights but they have limitations because (a) they limit the comparison to only two conceptualizations—when at least seven exist—and (b) usually do not explore the parsimony of explanatory models.[2]

Data and methods

We use the European Social Survey (ESS), which contains information on all necessary variables to build each SES indicator and provides high-quality data. We analyze rounds six to eleven (2012–2022) of the ESS for 24 European countries. We restrict our analysis to this period to facilitate data comparison and avoid the influence of breaks in the data series, since rounds one to five of ESS either used a different scale to measure income—which are not commensurable with the last rounds—or only included data on the ISCO-88 rather than ISCO-08. Concerning the range of countries, seeking to maximize generability but maintaining countries with similar economic and political configurations, we include in the analysis all 23 EU member states included in ESS plus the UK.[3] This amounts to a consolidated dataset of 24 countries, 108 country-years and 78,230 individuals with full information on every SES indicator. In addition, we restrict our analysis to the working age population (25–65 years) to avoid the distortion produced by young people who are still studying or do not have a permanent job and by retirees, who do not face risk of unemployment or skill specificity.[4]

Our main dependent variable is support for redistribution, measured as the agreement with the statement "The government should take measures to reduce differences in income levels". Possible answers are "agree strongly", "agree", "neither agree nor disagree", "disagree", and "disagree strongly". For ease of interpretation, we reverse the order of responses to assess agreement. Several prior studies use this variable to capture the support for redistribution (e.g. Finseraas 2009; Rueda 2018). Yet in supplementary analyses discussed below, we present results regarding four other outcomes.

Our main explanatory variables are the conceptualizations of SES: income, social class, skill specificity, risk of unemployment and routine task intensity. To measure income we use two different approaches. First, we measure income as a categorical variable by employing the decile of the individual's household according to net income, using nine dummy variables for deciles 2 through 10—with decile 1 (the richest decile) as the reference category. Secondly, we use an alternative measure of income as a linear estimate of actual equivalized income. For each respondent the actual household income is calculated as the mid-point interval of the decile to which the household belongs, with the lower and upper bounds of each decile taken from ESS fieldwork documents. Moreover, to account for differences in household

[2] Mccall et al. (2011) is an exception.

[3] This includes Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Spain, Slovakia, Slovenia, Sweden and UK.

[4] For categories based on ISCO-08, such as ESEC, we also excluded individuals for which information is only available at one-digit ISCO level and workers from group 0 (the military).

size, we use an equivalized measure of income by dividing household income by the square root of household size. Finally, to account for differences in income between countries, individual incomes are standardized within country-year. The first operationalization allows us to capture potentially non-linear effects of income groups. The second approach, in contrast, takes into account the absolute distance between individuals. These two variables are termed *deciles* and *income*.

The *skill specificity* of respondents' occupations is measured following Iversen and Soskice (2001) and Cusack et al. (2006). Absolute skill specificity for a particular branch of occupations (two digits ISCO-08) measures the share of ISCO-08 codes (four digits) within this branch over its share of the labor force. Thus, a higher absolute skill specificity indicates that more detailed occupations are needed to describe the skills of fewer workers in the labour force. Relative skill specificity is then obtained by dividing the absolute skill specificity by the skill level.[5] The risk of unemployment (*risks*), following Rehm (2009), is measured as the unemployment rate of individual's occupation (ISCO-08 level 1). The unemployment rates by occupation and the share of the labor force by ISCO-08 group were obtained from the EU labour force surveys (Eurostat 2021). To measure routine task intensity (*RTI*), we follow Goos et al. (2014) and use the *Dictionary of Occupational Titles* (DOT) for occupation definitions.[6] RTI is the difference between the log of the index of routine intensity of each occupation and the log of the sum of the indices of manual and abstract characteristics for this occupation. This measure is constant across countries and time, and it is available at two digits ISCO-88. Therefore, we translated our ISCO-08 codes into ICO-88 codes and then assign the RTI of each ISCO-88 two digits.[7]

We capture the role of social class through two different schemas: The ESeC (Rose and Harrison 2010) and the classification proposed by Oesch (2006). The ESeC schema includes nine classes: "large employers and higher managers and professionals", "lower managers and professionals, and higher supervisors", "intermediate occupations", "small employers and self-employed (without agriculture)", "small employers and self-employed (agriculture)", "lower supervisors and technicians", "lower sales and service workers", "lower technical workers" and "routine workers". The Oesch (2006) schema includes 12 classes: "technical experts", "technicians", "skilled manual workers", "low-skilled manual workers", "higher-grade managers and administrators", "lower-grade managers and administrators", "skilled clerks", "unskilled clerks", "socio-cultural professionals", "socio-cultural semi-professionals", "skilled service workers" and "low-skilled service workers". All models include control variables for gender (dichotomous), education (3 categories: lower second-

[5] According to Iversen and Soskice (2001), the skill level can be measured by either the skill level according to ISCO-08 classification or individual education level, which produces two different measures of relative skill specificity. Following Cusack et al. (2006), we use a composite indicator of skill specificity as the average of the two proposed measures of skill specificity.

[6] As noted by Thewissen and Rueda (2019), this amounts to using US data for European occupations but no better alternative is yet available and previous works on European occupations still rely on US data (e.g. Goos et al. 2014).

[7] RTI is not available for six groups at the two-digit ISCO-88 level and, therefore, workers from these groups have not been included in the analysis.

ary or less; upper secondary and post-secondary; and college), age (25–34; 35–44; 45–54; and 55–65 years old) and survey year. Appendix B includes detailed definitions and operationalizations of all variables. Table 1 provides descriptive statistics of the dependent and independent variables.

Concerning our analytical strategy, we estimate eight OLS regression models. The first model is called the *No SES* model as it is the baseline, it only includes the control variables (excluding any SES conceptualization): gender, age group (25–34 years, 35–44 years, 45–54 years and 55–65 years), education level (lower secondary or less, upper secondary and university) and dummies for country and year of the survey. The following successive models 2–8 add successively variables corresponding to each of the seven SES conceptualizations: *income, income deciles, ESEC, Oesch*, *risk* of unemployment, *skill specificity* and *RTI*. For each of the 2–8 models we include one conceptualization at a time (excluding the other six) in order to compare the predictive power of that model with the remaining models. And, since we pool several countries and years in our regressions, each model includes dummy variables for country and year.

After estimating the OLS models, we evaluate the predictive power of each conceptualization, by comparing the goodness of fit of each model using four criteria: the R^2, the adjusted R^2, the AIC and the BIC as defined by Claeskens and Hjort (2008). While the R^2 measures the proportion of the variance in the dependent variable explained by the variables in the equation, the adjusted R^2 captures a combination of explanatory power and parsimony by penalizing the explained variance by the number of parameters in the equation (Hooghe et al. 2007). Similarly, the Bayesian approach (BIC and AIC measures) combines the explanatory power and parsimony to select the model that minimizes its deviance with respect to the data using the smallest number of parameters. Concerning the differences between the two information criteria, BIC penalizes more than AIC the inclusion of additional parameters, rewarding parsimony; and simulation studies conclude that BIC is superior to AIC at identifying the correct model (Raffalovich et al. 2008). Concerning the treatment of missing values, since some fitting measures (especially BIC values) might be seriously affected by differences in sample sizes, we estimate every model using listwise deletion and keeping the same sample for each model, i.e. the sample with complete information that results from excluding cases with any missing information for any of the control variables and conceptualizations.

Results

We conduct the empirical analysis in four stages. First, we explore the association between each of the SES conceptualizations and redistribution preferences. Second, we compare the predictive power of seven conceptualizations of SES. Third, given the preeminence of income in our results, we report a series of sensitivity analyses to assess the stability of the main patterns found in the analysis. Finally, we consider whether using four alternative dependent variables might have an impact on our findings.

SES and redistribution preferences

We begin by reviewing the distribution of the dependent variable and describing its association with each of the SES conceptualizations. As is well-known, Europeans are generally supportive of redistribution. In our sample, 73.8% of respondents agree or strongly agree with the idea that government should reduce income differences. More importantly, there is a negative and substantial association between the seven conceptualizations of SES and the dependent variable. Focusing on income the support for redistribution on the five points scale goes from 3.5 for those who are two standard deviations above the average income of the country to 3.9 for those on the average and 4.1 for those who are two standard deviations below the average income of the country. Regarding the effect of ESeC class schema, the support for redistribution of high managers/professionals and routine workers is 3.5 and 4.0, respectively. Similar patterns are visible regarding the Oesch class schema and the risk of unemployment. Differences between workers at the highest and the lowest scores of skill specificity and at the highest and the lowest scores of RTI are smaller than the ones reported for income, class schemas and risk of unemployment.

We now compare a baseline model without SES with each of the operationalizations. In Fig. 1 we report the values of R^2, adjusted R^2, BIC and AIC obtained after each OLS model (raw values are also reported on Table 2 in the Appendix). Based on Fig. 1, the pattern is clear: the baseline model without SES performs generally worse than the other models in terms of explanatory power and parsimony. The adjusted R^2 for the baseline model is lower than for income operationalizations, class schemas and risks of unemployment, but as good as the adjusted *R*2 for models based on RTI scores and skills specificity. This is consistent with the previously outlined finding that SES is a relevant predictor of preferences for redistribution in most European countries. Having said that, the explanatory power of socio-economic status regarding preferences for redistribution is limited. According to the R^2 values, models including any conceptualization of income plus controls for socio-demographic attributes account for about 10% of the variation in preferences for redistribution. This means, despite the prevalence of the socio-economic status as the main predictor in the literature, there are still other important and unaccounted factors.

Comparing the predictive power of the seven SES conceptualizations

It is now possible to assess the explanatory power of the baseline model without SES with models after including each operationalization successively. Figure 1 includes the R^2, adjusted R^2, BIC and AIC and suggests two clear patterns. First, there are substantial differences in explanatory power across models. Second and more importantly, the models based on income – measured by either income deciles or linear income – outperform the other alternatives, with income deciles being the predictor that conveys the most explanatory power. Especifically regarding the R^2, income deciles generate the highest R^2 and adjusted R^2 of all conceptualizations. After the income variables, the next operationalization in explanatory power according to the R^2 is Oesch class schema, closely followed by the ESeC class schema. Skill specificity and RTI scores have the lowest explanatory power with the risk of unemployment

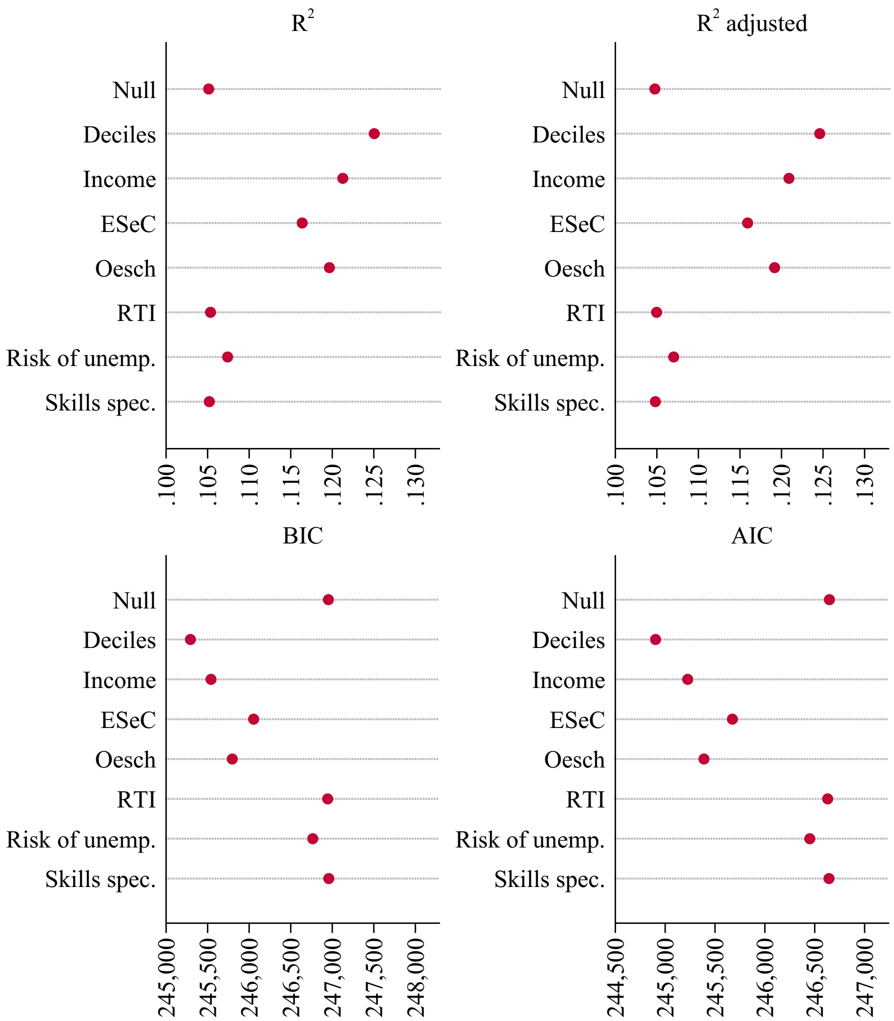

Fig. 1 Goodness of fit statistics of OLS models predicting support for redistribution in European countries, 2012–2022. The dependent variable is support for redistribution. Each model includes oneof the SES indicator and its interaction with country plus controls for gender, age and education and dummies for country and year

somewhere in between. Therefore, if we only focus on predictive power, income (either linear or deciles) is the best predictor of preferences for redistribution.

We now turn to our two measures of predictive power that explicitly combines explanatory power and parsimony: BIC and AIC. Even though BIC penalizes more heavily the inclusion of additional parameters into the model, in Figure 1 income measured by deciles is still the best predictor of preferences for redistribution in terms of predictive power and parsimony, followed by linear income. As in the case for R^2, income is followed by Oesch and ESeC class schemas and risk of unemployment. Interestingly, the BIC values of the models including skill specificity and RTI scores are indistinguishable from the null model (not including any operationalization). The pattern is equivalent if we use AIC values, although in this case RTI scores produces a better fit than the null model.

Hence, all in all, our findings indicate that income deciles is the best predictor of preferences for redistribution among the seven operationalizations of SES, followed by linear income and the class schemas, while skill specificity and RTI scores are the worst predictors with the risk of unemployment somewhere in between. As previously argued, income is highly visible in public discourse and Europeans are more likely to classify people in terms of income rather than in terms of some more abstract conceptualizations. Moreover, while unemployment constitutes one of the most important concerns for individuals in the labor force, neither skill specificity nor the risk of unemployment are better predictors of preferences for redistribution. These findings suggest that, individual preferences for redistribution are motivated by income aspirations rather than by insurance concerns, since risks of unemployment and particularly skill specificity perform worse than income and class schemas. We return to this issue in the Discussion.

Sensitivity analyses

The results reported so far could still be driven by (a) certain age or gender group; (b) the econometric specification of the models; (c) the control for education level; (d) the handling of missing values; and (e) the measure of income. We may thus wonder: is the preponderance of income uniform across groups in other divides (e.g. gender or age)? To answer this, we conduct a series of robustness checks in which we estimate regression models for specific groups of the population and then compute goodness of fit statistics. First, patterns for both men and women are very similar (Tables 3 and 4): income deciles outperforms other operationalizations. Regarding age, the patterns by age group (25–44 and 45–65 years old) (Tables 5 and 6) are also equivalent.

Moreover, are the results equivalent using alternative modeling strategies? Additional robustness tests indicate that our findings are not driven by model specification. Binary logistic for a dichotomized dependent variable (agree and strongly agree against the other categories) (Table 7) and ordered logistic models (Table 8) for the original dependent variable (without dichotomization) produce similar findings in terms of explanatory power. Moreover, all conceptualizations of SES are systematically related to education levels. We may, therefore, wonder what is the impact of excluding education as a control variable? After excluding the education variable (Table 9), income deciles is still the best model. Furthermore, other control variables (except year of the survey to account for period effects), such as gender or age may absorb some of the effect of SES. We, therefore, re-estimate all the models removing all the control variables and compute goodness of fit statistics (Table 10). After removing the individual control variables, the income based model is still the preferred model.

Since several of these conceptualizations generate non-negligible proportions of missing values and this may affect the results, we thus also utilize data imputation in order to use as much information as possible (Tables 11 and 12) to generate 10 imputed datasets. We then estimate our models and compute goodness of fit on each imputed dataset. Estimates align with our previous findings in the sense that the income decile is the preferred model in all the imputed datasets. Income deciles produce the highest R^2 in the ten imputations as well as the lowest BIC.

Readers may wonder whether the effect of income changes through time. Even though our data cover a limited time period, we divide our sample into two periods (2012–2016 and 2018–2022) and replicate the analysis of the two periods. Results indicate that the pattern remains almost unchanged from one period to the next (Tables 13 and 14).

Alternative dependent variables

To what extent is the effect of income on individual preferences confined to the selected outcome: support for redistribution? We use four alternative dependent variables to explore the predictive power of the SES conceptualizations on attitudes towards a different set of public policies. The first revolves around preferences for government responsibility in the protection of dependent social groups. We specifically compute an index of government responsibility with two variables measuring agreement on a 10 point scale with the responsibility of government to: (a) 'ensure a reasonable standard of living for the old', and (b) 'ensure a reasonable standard of living for the unemployed'.[8] Results are reported in Fig. 2 and are in line with findings concerning preferences for redistribution (also Table 15). Also in this case, income deciles is the preferred model in terms of explanatory power and parsimony (except in the case of BIC, where linear income produces a lower value).

We analyze two additional variables included in ESS round eight. The first one measures the degree of agreement with the statement "For a society to be fair, differences in people's standard of living should be small" (*fair society*) and the second one measures the degree of agreement with the statement "Large differences in people's incomes are acceptable to properly reward differences in talents and efforts" (*rewards*). According to the R^2 and the AIC values income deciles is the best predictor of the outcome *fair society* (Fig. 3, Table 16), both in terms of explanatory power and parsimony. The pattern is quite similar in the case of the outcome *rewards* (Fig. 4, Table 17). However, according to the R^2 Oesch class schema conveys an explanatory power similar to any operationalization of linear income, although Oesch class schema performs worse than income deciles.

Finally, we test the explanatory power of the seven conceptualizations in the case of ideology (left-right). According to the R^2, income measured by deciles is the best predictor, closely followed by Oesch class schema and linear income, while according to the BIC values both measures of income outperform Oesch class schema (Fig. 5, Table 18). Even though left-right ideology encompasses preferences in many different dimensions, income decile provides the best the best SES predictor of ideology. We can conclude that the income dimension—and especially the income deciles operationalization—has the highest predictive power and that this highest predictive power is certainly not restricted to redistribution preferences.

[8] Information for these two variables is only included in ESS round eight and is available for 18 countries. To compute the index we use Principal Component Analysis (PCA) and keep the first component, which explains 92.5% of the variance.

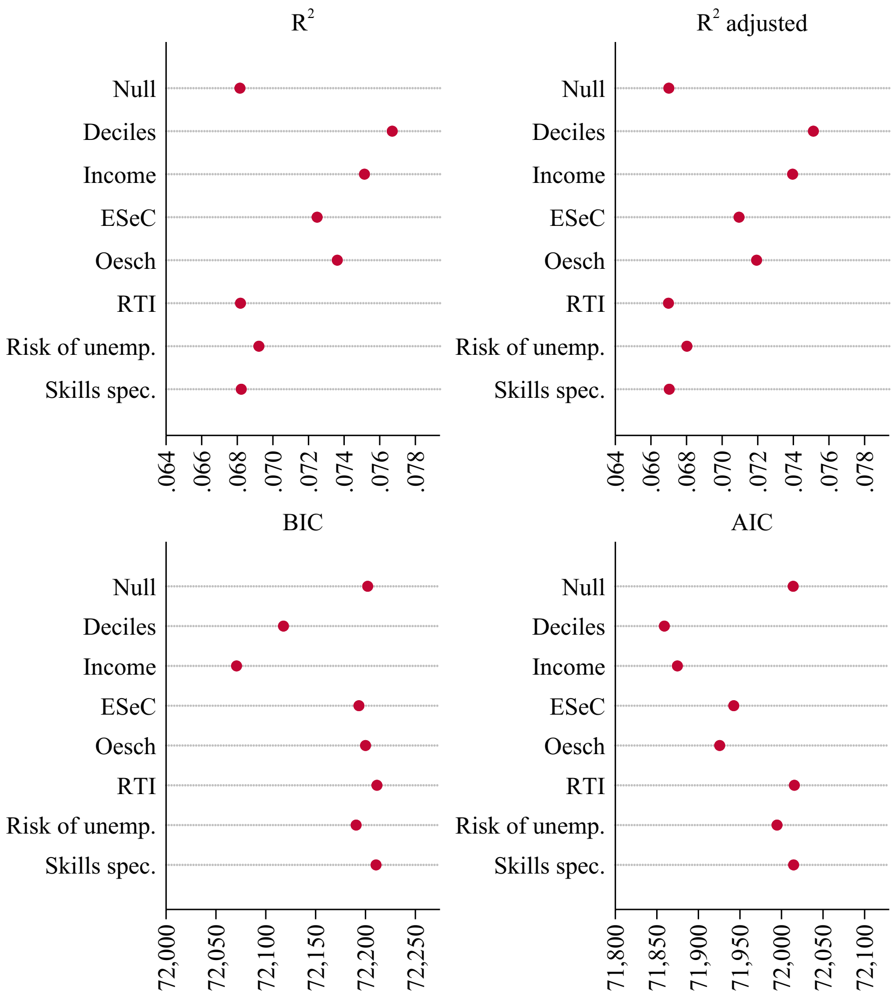

Fig. 2 Goodness of fit statistics of OLS models predicting support for government responsibility for the old and unemployed, 2012–2022. *Note*: The dependent variable is support for government responsibility for the old and unemployed. Each model includes one of the SES indicator and its interaction with country plus controls for gender, age and education and dummies for country and year.

Discussion

In recent decades many social scientists have explored divides concerning redistribution preferences in order to identify macro-level conditions and socio-political coalitions that may facilitate welfare reforms. Following this interest, many publications in economics, political science and sociology have examined the role of SES on redistribution preferences and have consistently shown that objective socio-economic location predicts support for state-driven inequality reduction. However, this body of work is rather fragmented due to the plethora of available operationalizations of SES and the disciplinary insularity of debates. This manuscript takes up the task of comparing and contrasting the

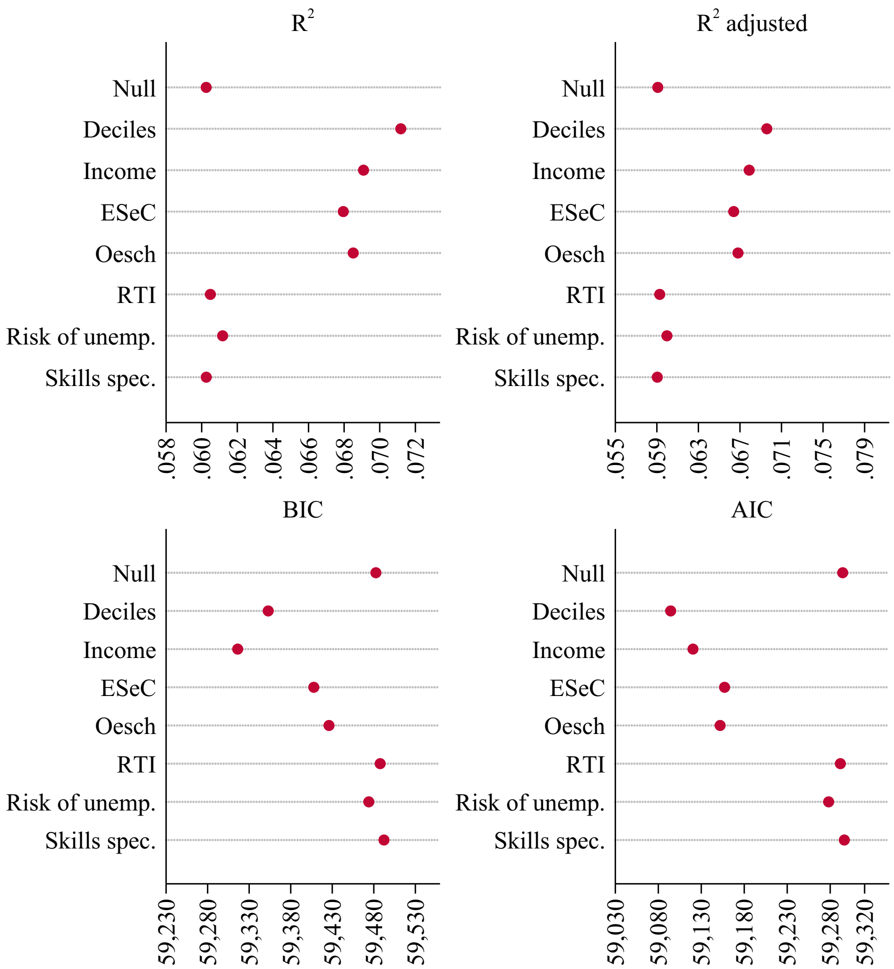

Fig. 3 Goodness of fit statistics of OLS models predicting support for the statement that fair societies need small income differences, 2012–2022. *Note*: The dependent variable is support for the statement that for a society to be fair, differences in people's standard of living should be small. Each model includes one of the SES indicator and its interaction with country plus controls for gender, age and education and dummies for country and year

predictive validity of seven operationalizations of SES that have been the focus of scholarly attention: linear income, categorical income deciles, the ESeC and Oesch schemas, and indices of skills specificity, unemployment risks, and routine task intensity. The analysis considers 23 EU countries plus the UK in 2012–2022 and to contrast the conceptualizations, we jointly consider the explanatory power and parsimony of the models using different goodness of fit measures. The analysis yields two main findings.

First and foremost, income-based operationalizations clearly prevail over all other five approaches. Operationalizations of income are better predictors of preferences for redistribution in terms of both explanatory power and parsimony. Second, of the two income-based conceptualizations considered—one with linear income and an alternative with a multicategorical variable for income deciles -, the measure of income deciles

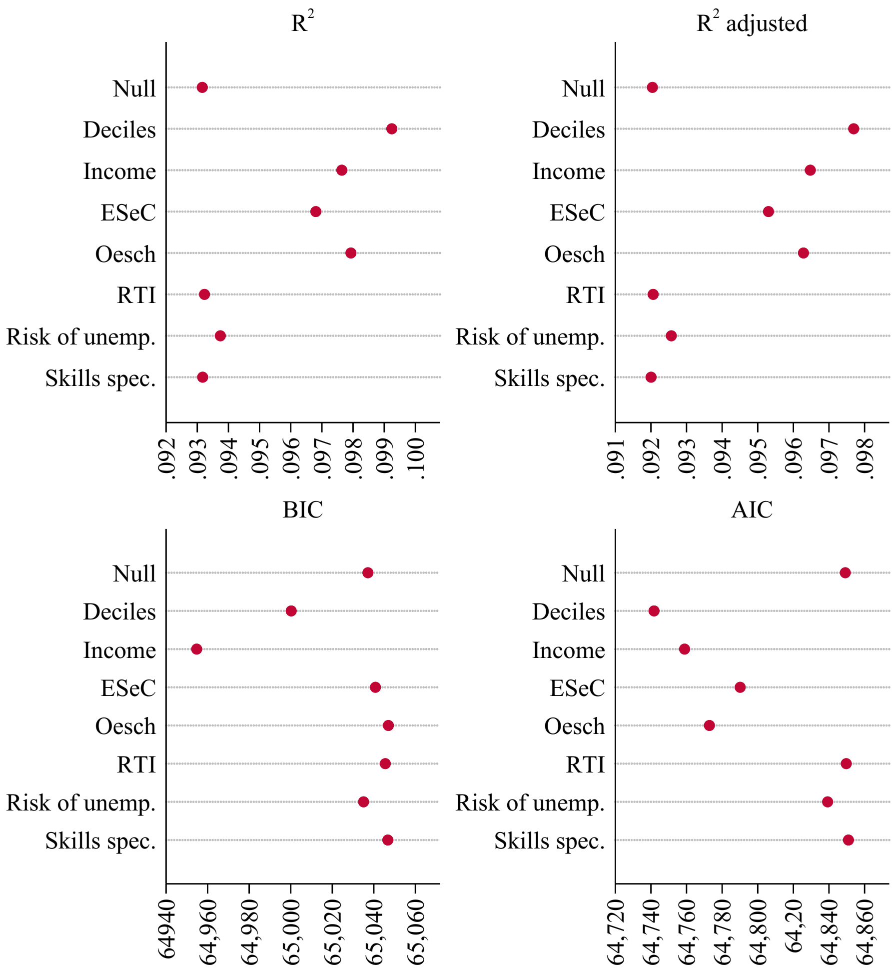

Fig. 4 Goodness of fit statistics of OLS models predicting support for the statement that income inequalities are necessary to reward talents and effort, 2012–2022. *Note*: The dependent variable is support for the statement that large differences in people's incomes are acceptable to properly reward differences in talents and efforts. Each model includes one of the SES indicator and its interaction with country plus controls for gender, age and education and dummies for country and year

stands out. Fitness statistics are generally better for the two income operationalizations than for those associated with large class schemas and indexes capturing occupational characteristics, but they become quite similar once income is operationalized in linear or categorical terms. Also importantly, similar results are obtained using alternative regression strategies, other transformations of the outcome, multiple imputation, replicating the analysis for each gender and major age groups and without controlling for individual education. This study demonstrates that income, moreover, is not only the best predictor of redistribution attitudes; it is also the best predictor of perceptions of government responsibility to protect dependent groups and left-right ideology.

These results have important implications for the burgeoning literatures on attitudes towards redistribution and social policy. Most directly, for scholars interested either in

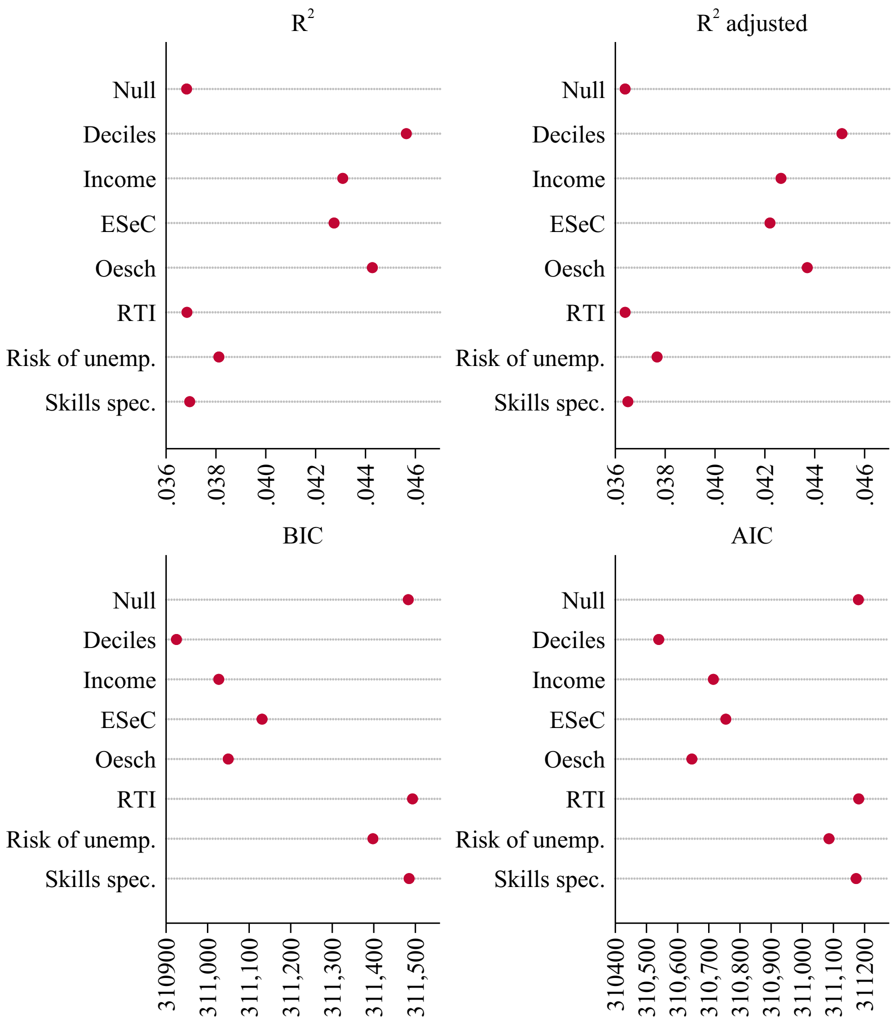

Fig. 5 Goodness of fit statistics of OLS models predicting left-right ideology, 2012–2022. *Note*: The dependent variable is the left-right index. Each model includes one of the SES indicatorand its interaction with country plus controls for gender, age and education and dummies for country and year

(a) examining country-level factors shaping SES effects or (b) simply seeking to control for the SES dimension, the linear version of income offers a comprehensive and efficient solution. Since this operationalization has the desirable property of capturing the largest amount of information at the lowest level of impact on parsimony, scholars interested in either of the two questions can feel confident that effects of SES-as-linear-income captures well the influence of socio-economic location. The findings have important substantive implications for how we understand preferences for redistribution. Preferences are primarily driven by relative income position rather than by insurance concerns related to labor market risks or occupational characteristics. In other words, individuals seem to anchor their attitudes towards redistribution in their relative income standing within society, reflecting the salience of visible income inequalities over more abstract socio-economic risks. This reinforces the self-interest model of redistributive preferences but in a more straightforward way than many complex theories imply: what matters most for shaping attitudes is where individuals are themselves in the income distribution. At the same time, the study also shows that SES explains only part of the variation in redistributive preferences, pointing to the need to further examine the role of cultural values, political identities, and other-regarding considerations.

The findings have also some policy implications. Since income position emerges as the strongest predictor of redistributive preferences, policymakers aiming to build support for redistribution should formulate discourses that focus visible income inequalities rather than focusing on occupational or labor market risks. At the same time, because socio-economic status accounts for only a modest share of variation in redistributive preferences, policymakers cannot rely solely on material interests to mobilize support. Framing redistribution in ways that appeal to broader values such as fairness, solidarity, and social cohesion may be essential to build durable political coalitions around expansionary welfare reforms.

Like every other one, this study certainly has limitations. The analysis does not consider a fully comprehensive range of factors predicting redistribution preferences. Personality traits, social values, and other-regardingness beliefs, for instance, also shape these preferences (Fehr et al. 2024; Heide-Jørgensen et al. 2023; Kulin and Svallfors 2013), but were not included in the analysis, either due to data limitations in the European Social Survey or to minimize the risk of reversed causality. However, we do not have strong reasons to believe that any of these factors are highly correlated with any indicator of SES. Moreover, as the above analysis focuses on individual-level dynamics, it does not consider macro-level conditions affecting the higher predictive power of income either. The study cannot determine if similar patterns are observable for other high-income countries (e.g. Japan, North America or South Korea) or low- or middle-income countries.

Future work could fruitfully explore two key unresolved questions. First, given that linear income is clearly the most reliable operationalization of SES in terms of predictive power, more methodological research is also needed regarding the operationalization of this aspect. Future work could, furthermore, explore if income has a greater predictive power of attitudes if measured at individual or household level, by employing the best survey-design strategies. Second, more research is clearly needed regarding the political, psychological and social mechanisms linking income levels and policy attitude formation. Such analyses could, thus, help reveal general psychological and social mechanisms of attitude formation. Until that work is conducted, this study advances the literature by showing that income represents a more effective predictor of redistribution attitudes than the ESeC and Oesch schemas and indexes of specific skills, unemployment risks and routine task intensity.

Appendix A

See Tables 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Redistribution Preference	78,230	3.794	1.237	0	1
Control variables					
Female	78,915	0.527	0.499	0	1
Age					
25–34 years	78,915	0.202	0.401	0	1
35–44 years	78,915	0.242	0.428	0	1
45–54 years	78,915	0.263	0.440	0	1
55–65 years	78,915	0.293	0.455	0	1
Education					
Lower secondary or less	78,915	0.182	0.386	0	1
Upper secondary	78,915	0.536	0.499	0	1
University	78,915	0.282	0.450	0	1
Conceptualizations					
Household income (Z-scores)	78,915	0.018	0.997	−2.412	8.021
Risk of unemployment	78,915	0.059	0.055	0.000	0.383
Skill specificity	78,915	4.014	3.440	0.902	49.295
RTI	78,915	−0.097	0.981	−1.465	2.410
Household income (deciles)					
1st decile	78,915	0.075	0.263	0	1
2nd decile	78,915	0.084	0.278	0	1
3rd decile	78,915	0.094	0.291	0	1
4th decile	78,915	0.101	0.301	0	1
5th decile	78,915	0.106	0.308	0	1
6th decile	78,915	0.110	0.313	0	1
7th decile	78,915	0.117	0.321	0	1
8th decile	78,915	0.115	0.319	0	1
9th decile	78,915	0.099	0.299	0	1
10th decile	78,915	0.099	0.298	0	1
ESeC					
Higher managers & profs	78,915	0.199	0.397	0	1
Lower managers & profs	78,915	0.191	0.393	0	1
Intermediate occupations	78,915	0.075	0.263	0	1
Small employers (no agricult.)	78,915	0.060	0.237	0	1
Small employers (agriculture)	78,915	0.012	0.108	0	1
Lower superv. and technicians	78,915	0.077	0.266	0	1
Lower sales and service	78,915	0.146	0.353	0	1
Lower technical workers	78,915	0.107	0.309	0	1
Routine workers	78,915	0.138	0.345	0	1
Kitschelt-Rehm					
Technical experts	78,915	0.040	0.196	0	1
Technicians	78,915	0.046	0.209	0	1
Skilled manual workers	78,915	0.162	0.369	0	1
Low-skilled manual workers	78,915	0.092	0.288	0	1
Higher-grade managers	78,915	0.099	0.299	0	1
Lower-grade managers	78,915	0.089	0.284	0	1
Skilled clerks	78,915	0.092	0.289	0	1
Unskilled clerks	78,915	0.014	0.117	0	1

Table 1 (continued)

Variable	Obs	Mean	Std. Dev	Min	Max
Socio-cultural professionals	78,915	0.053	0.223	0	1
Socio-cultural semi-prof	78,915	0.090	0.287	0	1
Skilled service workers	78,915	0.118	0.322	0	1
Low-skilled service workers	78,915	0.106	0.308	0	1

Table 2 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	246,581.6	246,647.6	246,953.4	246,986.4	0.105	0.105	78,230	33
Income	245,157.8	245,225.8	245,540.9	245,574.9	0.121	0.121	78,230	34
Deciles	244,819.7	244,903.7	245,292.9	245,334.9	0.125	0.125	78,230	42
ESeC	245,592.0	245,674.0	246,054.0	246,095.0	0.116	0.116	78,230	41
Risks	246,382.1	246,450.1	246,765.2	246,799.2	0.107	0.107	78,230	34
Skills	246,575.2	246,643.2	246,958.3	246,992.3	0.105	0.105	78,230	34
Oesch	245,301.0	245,389.0	245,796.8	245,840.8	0.120	0.119	78,230	44
RTI	246,562.2	246,630.2	246,945.3	246,979.3	0.105	0.105	78,230	34

Preferences for redistribution

Table 3 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	119,972.4	120,036.4	120,309.1	120,341.1	0.111	0.111	37,056	32
Income	119,202.8	119,268.8	119,549.9	119,582.9	0.130	0.129	37,056	33
Deciles	119,018.5	119,100.5	119,449.8	119,490.8	0.134	0.133	37,056	41
ESeC	119,395.5	119,475.5	119,816.3	119,856.3	0.125	0.124	37,056	40
Risks	119,842.8	119,908.8	120,190.0	120,223.0	0.114	0.114	37,056	33
Skills	119,968.3	120,034.3	120,315.5	120,348.5	0.111	0.111	37,056	33
Oesch	119,171.0	119,257.0	119,623.3	119,666.3	0.130	0.129	37,056	43
RTI	119,956.4	120,022.4	120,303.5	120,336.5	0.112	0.111	37,056	33

Preferences for redistribution. Men

Table 4 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	126,163.9	126,227.9	126,503.9	126,535.9	0.093	0.093	41,174	32
Income	125,521.3	125,587.3	125,871.9	125,904.9	0.108	0.107	41,174	33
Deciles	125,361.9	125,443.9	125,797.6	125,838.6	0.111	0.110	41,174	41
ESeC	125,751.0	125,831.0	126,176.1	126,216.1	0.103	0.102	41,174	40
Risks	126,088.6	126,154.6	126,439.3	126,472.3	0.095	0.094	41,174	33
Skills	126,161.5	126,227.5	126,512.1	126,545.1	0.094	0.093	41,174	33
Oesch	125,646.8	125,732.8	126,103.7	126,146.7	0.105	0.104	41,174	43
RTI	126,154.9	126,220.9	126,505.6	126,538.6	0.094	0.093	41,174	33

Preferences for redistribution. Women

Table 5 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	110,071.0	110,133.0	110,395.1	110,426.1	0.105	0.104	34,697	31
Income	109,462.9	109,526.9	109,797.5	109,829.5	0.121	0.120	34,697	32
Deciles	109,339.1	109,419.1	109,757.3	109,797.3	0.124	0.123	34,697	40
ESeC	109,672.9	109,750.9	110,080.7	110,119.7	0.115	0.114	34,697	39
Risks	109,996.4	110,060.4	110,331.0	110,363.0	0.107	0.106	34,697	32
Skills	110,070.6	110,134.6	110,405.1	110,437.1	0.105	0.104	34,697	32
Oesch	109,552.8	109,636.8	109,991.9	110,033.9	0.118	0.117	34,697	42
RTI	110,058.6	110,122.6	110,393.1	110,425.1	0.105	0.105	34,697	32

Preferences for redistribution. 25–44 years old

Table 6 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	136,347.9	136,409.9	136,679.0	136,710.0	0.105	0.104	43,533	31
Income	135,527.3	135,591.3	135,869.1	135,901.1	0.121	0.121	43,533	32
Deciles	135,320.9	135,400.9	135,748.1	135,788.1	0.125	0.125	43,533	40
ESeC	135,740.9	135,818.9	136,157.5	136,196.5	0.117	0.116	43,533	39
Risks	136,227.1	136,291.1	136,568.9	136,600.9	0.107	0.106	43,533	32
Skills	136,340.2	136,404.2	136,682.0	136,714.0	0.105	0.104	43,533	32
Oesch	135,575.8	135,659.8	136,024.4	136,066.4	0.120	0.119	43,533	42
RTI	136,341.1	136,405.1	136,682.9	136,714.9	0.105	0.104	43,533	32

Preferences for redistribution. 45–65 years old

Table 7 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	N	k
Baseline	82,888.1	82,954.1	83,259.9	83,292.9	78,230	33
Income	81,834.7	81,902.7	82,217.8	82,251.8	78,230	34
Deciles	81,663.0	81,747.0	82,136.2	82,178.2	78,230	42
ESeC	82,068.6	82,150.6	82,530.5	82,571.5	78,230	41
Risks	82,628.3	82,696.3	83,011.4	83,045.4	78,230	34
Skills	82,875.2	82,943.2	83,258.3	83,292.3	78,230	34
Oesch	81,940.1	82,028.1	82,435.9	82,479.9	78,230	44
RTI	82,871.3	82,939.3	83,254.4	83,288.4	78,230	34

Preferences for redistribution. Logit models

Table 8 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	N	k
Baseline	188,218.4	188,284.4	188,590.3	188,623.3	78,230	33
Income	186,867.9	186,935.9	187,251.0	187,285.0	78,230	34
Deciles	186,590.4	186,674.4	187,063.6	187,105.6	78,230	42
ESeC	187,309.8	187,391.8	187,771.7	187,812.7	78,230	41
Risks	188,001.1	188,069.1	188,384.2	188,418.2	78,230	34
Skills	188,208.0	188,276.0	188,591.1	188,625.1	78,230	34
Oesch	187,092.8	187,180.8	187,588.5	187,632.5	78,230	44
RTI	188,200.7	188,268.7	188,583.8	188,617.8	78,230	34

Preferences for redistribution. Ordered logit models

Table 9 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	247,647.7	247,709.7	247,997.0	248,028.0	0.093	0.093	78,230	31
Income	245,455.0	245,519.0	245,815.6	245,847.6	0.118	0.118	78,230	32
Deciles	245,096.2	245,176.2	245,546.9	245,586.9	0.122	0.122	78,230	40
ESeC	245,743.5	245,821.5	246,183.0	246,222.0	0.115	0.114	78,230	39
Risks	247,011.0	247,075.0	247,371.5	247,403.5	0.100	0.100	78,230	32
Skills	247,528.9	247,592.9	247,889.4	247,921.4	0.094	0.094	78,230	32
Oesch	245,480.7	245,564.7	245,954.0	245,996.0	0.118	0.117	78,230	42
RTI	247,477.3	247,541.3	247,837.9	247,869.9	0.095	0.094	78,230	32

Preferences for redistribution. No control for education

Table 10 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	248,245.8	248,299.8	248,550.1	248,577.1	0.086	0.086	78,230	27
Income	245,962.4	246,018.4	246,277.9	246,305.9	0.112	0.112	78,230	28
Deciles	245,459.7	245,531.7	245,865.4	245,901.4	0.118	0.117	78,230	36
ESeC	246,265.6	246,335.6	246,660.0	246,695.0	0.109	0.108	78,230	35
Risks	247,576.1	247,632.1	247,891.6	247,919.6	0.094	0.093	78,230	28
Skills	248,156.0	248,212.0	248,471.4	248,499.4	0.087	0.087	78,230	28
Oesch	245,932.9	246,008.9	246,361.1	246,399.1	0.113	0.112	78,230	38
RTI	248,029.8	248,085.8	248,345.3	248,373.3	0.088	0.088	78,230	28

Preferences for redistribution. No controls

Table 11 Goodness of fit measures

	Imputation	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	1	407,026.7	407,096.7	407,438.7	407,473.7	0.094	0.093	129,458	35
Income	1	404,932.3	405,004.3	405,356.1	405,392.1	0.108	0.108	129,458	36
Deciles	1	333,829.8	333,917.8	334,339.3	334,383.3	0.112	0.112	106,691	44
ESeC	1	405,645.3	405,731.3	406,151.5	406,194.5	0.103	0.103	129,458	43
Risks	1	406,403.1	406,475.1	406,826.8	406,862.8	0.098	0.098	129,458	36
Skills	1	407,020.6	407,092.6	407,444.4	407,480.4	0.094	0.093	129,458	36
Oesch	1	385,833.4	385,925.4	386,372.6	386,418.6	0.107	0.107	123,104	46
RTI	1	406,997.7	407,069.7	407,421.5	407,457.5	0.094	0.094	129,458	36
Baseline	2	407,023.6	407,093.6	407,435.6	407,470.6	0.094	0.093	129,458	35
Income	2	404,907.3	404,979.3	405,331.0	405,367.0	0.108	0.108	129,458	36
Deciles	2	333,830.3	333,918.3	334,339.7	334,383.7	0.112	0.112	106,691	44
ESeC	2	405,656.5	405,742.5	406,162.7	406,205.7	0.103	0.103	129,458	43
Risks	2	406,400.7	406,472.7	406,824.4	406,860.4	0.098	0.098	129,458	36
Skills	2	407,017.9	407,089.9	407,441.7	407,477.7	0.094	0.093	129,458	36
Oesch	2	385,834.2	385,926.2	386,373.3	386,419.3	0.107	0.107	123,104	46
RTI	2	406,993.7	407,065.7	407,417.5	407,453.5	0.094	0.094	129,458	36
Baseline	3	407,028.3	407,098.3	407,440.3	407,475.3	0.094	0.093	129,458	35
Income	3	404,999.1	405,071.1	405,422.8	405,458.8	0.108	0.107	129,458	36
Deciles	3	333,830.8	333,918.8	334,340.2	334,384.2	0.112	0.112	106,691	44
ESeC	3	405,631.2	405,717.2	406,137.4	406,180.4	0.103	0.103	129,458	43
Risks	3	406,338.3	406,410.3	406,762.1	406,798.1	0.098	0.098	129,458	36
Skills	3	407,021.7	407,093.7	407,445.5	407,481.5	0.094	0.093	129,458	36
Oesch	3	385,833.9	385,925.9	386,373.1	386,419.1	0.107	0.107	123,104	46
RTI	3	406,995.4	407,067.4	407,419.2	407,455.2	0.094	0.094	129,458	36
Baseline	4	407,018.9	407,088.9	407,430.9	407,465.9	0.094	0.093	129,458	35
Income	4	404,972.8	405,044.8	405,396.6	405,432.6	0.108	0.108	129,458	36
Deciles	4	333,827.4	333,915.4	334,336.8	334,380.8	0.112	0.112	106,691	44
ESeC	4	405,650.1	405,736.1	406,156.2	406,199.2	0.103	0.103	129,458	43
Risks	4	406,416.5	406,488.5	406,840.3	406,876.3	0.098	0.098	129,458	36
Skills	4	407,013.4	407,085.4	407,437.2	407,473.2	0.094	0.093	129,458	36
Oesch	4	385,833.9	385,925.9	386,373.1	386,419.1	0.107	0.107	123,104	46
RTI	4	406,992.0	407,064.0	407,415.7	407,451.7	0.094	0.094	129,458	36
Baseline	5	407,031.2	407,101.2	407,443.2	407,478.2	0.094	0.093	129,458	35
Income	5	404,991.8	405,063.8	405,415.5	405,451.5	0.108	0.108	129,458	36
Deciles	5	333,831.8	333,919.8	334,341.2	334,385.2	0.112	0.112	106,691	44
ESeC	5	405,651.1	405,737.1	406,157.3	406,200.3	0.103	0.103	129,458	43
Risks	5	406,410.9	406,482.9	406,834.6	406,870.6	0.098	0.098	129,458	36
Skills	5	407,024.5	407,096.5	407,448.2	407,484.2	0.094	0.093	129,458	36
Oesch	5	385,835.4	385,927.4	386,374.6	386,420.6	0.107	0.107	123,104	46
RTI	5	407,004.0	407,076.0	407,427.7	407,463.7	0.094	0.094	129,458	36

Preferences for redistribution. Imputed datasets

Table 12 Goodness of fit measures

	Imputation	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	6	407,016.8	407,086.8	407,428.8	407,463.8	0.094	0.093	129,458	35
Income	6	404,900.0	404,972.0	405,323.8	405,359.8	0.108	0.108	129,458	36
Deciles	6	333,829.8	333,917.8	334,339.2	334,383.2	0.112	0.112	106,691	44
ESeC	6	405,676.1	405,762.1	406,182.2	406,225.2	0.103	0.103	129,458	43
Risks	6	406,416.5	406,488.5	406,840.2	406,876.2	0.098	0.098	129,458	36
Skills	6	407,013.8	407,085.8	407,437.6	407,473.6	0.094	0.093	129,458	36
Oesch	6	385,831.5	385,923.5	386,370.7	386,416.7	0.107	0.107	123,104	46
RTI	6	406,989.6	407,061.6	407,413.4	407,449.4	0.094	0.094	129,458	36
Baseline	7	407,024.2	407,094.2	407,436.1	407,471.1	0.094	0.093	129,458	35
Income	7	404,873.7	404,945.7	405,297.5	405,333.5	0.109	0.108	129,458	36
Deciles	7	333,830.9	333,918.9	334,340.3	334,384.3	0.112	0.112	106,691	44
ESeC	7	405,660.0	405,746.0	406,166.1	406,209.1	0.103	0.103	129,458	43
Risks	7	406,421.1	406,493.1	406,844.9	406,880.9	0.098	0.098	129,458	36
Skills	7	407,019.5	407,091.5	407,443.3	407,479.3	0.094	0.093	129,458	36
Oesch	7	385,833.2	385,925.2	386,372.4	386,418.4	0.107	0.107	123,104	46
RTI	7	406,991.2	407,063.2	407,415.0	407,451.0	0.094	0.094	129,458	36
Baseline	8	407,017.4	407,087.4	407,429.3	407,464.3	0.094	0.093	129,458	35
Income	8	404,952.0	405,024.0	405,375.7	405,411.7	0.108	0.108	129,458	36
Deciles	8	333,826.5	333,914.5	334,336.0	334,380.0	0.112	0.112	106,691	44
ESeC	8	405,660.0	405,746.0	406,166.1	406,209.1	0.103	0.103	129,458	43
Risks	8	406,366.5	406,438.5	406,790.3	406,826.3	0.098	0.098	129,458	36
Skills	8	407,012.3	407,084.3	407,436.1	407,472.1	0.094	0.093	129,458	36
Oesch	8	385,831.8	385,923.8	386,370.9	386,416.9	0.107	0.107	123,104	46
RTI	8	406,990.7	407,062.7	407,414.5	407,450.5	0.094	0.094	129,458	36
Baseline	9	407,018.9	407,088.9	407,430.8	407,465.8	0.094	0.093	129,458	35
Income	9	405,068.1	405,140.1	405,491.9	405,527.9	0.107	0.107	129,458	36
Deciles	9	333,831.3	333,919.3	334,340.7	334,384.7	0.112	0.112	106,691	44
ESeC	9	405,646.8	405,732.8	406,152.9	406,195.9	0.103	0.103	129,458	43
Risks	9	406,355.4	406,427.4	406,779.2	406,815.2	0.098	0.098	129,458	36
Skills	9	407,015.1	407,087.1	407,438.9	407,474.9	0.094	0.093	129,458	36
Oesch	9	385,832.3	385,924.3	386,371.5	386,417.5	0.107	0.107	123,104	46
RTI	9	406,990.9	407,062.9	407,414.6	407,450.6	0.094	0.094	129,458	36
Baseline	10	407,030.0	407,100.0	407,442.0	407,477.0	0.094	0.093	129,458	35
Income	10	404,983.2	405,055.2	405,407.0	405,443.0	0.108	0.108	129,458	36
Deciles	10	333,834.8	333,922.8	334,344.2	334,388.2	0.112	0.112	106,691	44
ESeC	10	405,630.4	405,716.4	406,136.6	406,179.6	0.103	0.103	129,458	43
Risks	10	406,379.2	406,451.2	406,802.9	406,838.9	0.098	0.098	129,458	36
Skills	10	407,025.3	407,097.3	407,449.1	407,485.1	0.094	0.093	129,458	36
Oesch	10	385,837.1	385,929.1	386,376.2	386,422.2	0.107	0.107	123,104	46
RTI	10	407,001.9	407,073.9	407,425.6	407,461.6	0.094	0.094	129,458	36

Preferences for redistribution. Imputed datasets

Table 13 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	180,826.5	180,886.5	181,155.2	181,185.2	0.108	0.108	57,166	30
Income	179,759.3	179,821.3	180,098.9	180,129.9	0.125	0.124	57,166	31
Deciles	179,543.6	179,621.6	179,970.8	180,009.8	0.128	0.128	57,166	39
ESeC	180,071.2	180,147.2	180,487.4	180,525.4	0.120	0.119	57,166	38
Risks	180,701.7	180,763.7	181,041.3	181,072.3	0.110	0.110	57,166	31
Skills	180,821.4	180,883.4	181,161.0	181,192.0	0.108	0.108	57,166	31
Oesch	179,811.8	179,893.8	180,260.8	180,301.8	0.124	0.123	57,166	41
RTI	180,799.2	180,861.2	181,138.8	181,169.8	0.109	0.108	57,166	31

Preferences for redistribution. 2012–2016

Table 14 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	65,456.0	65,516.0	65,754.7	65,784.7	0.108	0.107	21,064	30
Income	65,096.3	65,158.3	65,405.0	65,436.0	0.123	0.122	21,064	31
Deciles	64,960.5	65,038.5	65,348.8	65,387.8	0.129	0.127	21,064	39
ESeC	65,214.8	65,290.8	65,593.1	65,631.1	0.118	0.117	21,064	38
Risks	65,430.6	65,492.6	65,739.2	65,770.2	0.109	0.108	21,064	31
Skills	65,454.9	65,516.9	65,763.5	65,794.5	0.108	0.107	21,064	31
Oesch	65,182.2	65,264.2	65,590.4	65,631.4	0.119	0.118	21,064	41
RTI	65,456.0	65,518.0	65,764.6	65,795.6	0.108	0.107	21,064	31

Preferences for redistribution. 2018–2022

Table 15 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	71,966.1	72,014.1	72,202.2	72,226.2	0.068	0.067	18,768	24
Income	71,824.7	71,874.7	72,070.7	72,095.7	0.075	0.074	18,768	25
Deciles	71,793.0	71,859.0	72,117.7	72,150.7	0.077	0.075	18,768	33
ESeC	71,878.6	71,942.6	72,193.4	72,225.4	0.072	0.071	18,768	32
Risks	71,944.6	71,994.6	72,190.6	72,215.6	0.069	0.068	18,768	25
Skills	71,964.6	72,014.6	72,210.6	72,235.6	0.068	0.067	18,768	25
Oesch	71,855.6	71,925.6	72,200.0	72,235.0	0.074	0.072	18,768	35
RTI	71,965.5	72,015.5	72,211.5	72,236.5	0.068	0.067	18,768	25

Government responsibility

Table 16 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	59,246.5	59,294.5	59,482.5	59,506.5	0.060	0.059	18,641	24
Income	59,070.4	59,120.4	59,316.2	59,341.2	0.069	0.068	18,641	25
Deciles	59,028.4	59,094.4	59,352.9	59,385.9	0.071	0.070	18,641	33
ESeC	59,093.1	59,157.1	59,407.8	59,439.8	0.068	0.066	18,641	32
Risks	59,228.2	59,278.2	59,474.0	59,499.0	0.061	0.060	18,641	25
Skills	59,246.5	59,296.5	59,492.3	59,517.3	0.060	0.059	18,641	25
Oesch	59,081.9	59,151.9	59,426.1	59,461.1	0.069	0.067	18,641	35
RTI	59,241.9	59,291.9	59,487.7	59,512.7	0.060	0.059	18,641	25

Fair society

Table 17 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	64,801.2	64,849.2	65,037.2	65,061.2	0.093	0.092	18,637	24
Income	64,708.9	64,758.9	64,954.7	64,979.7	0.098	0.096	18,637	25
Deciles	64,675.8	64,741.8	65,000.2	65,033.2	0.099	0.098	18,637	33
ESeC	64,726.1	64,790.1	65,040.8	65,072.8	0.097	0.095	18,637	32
Risks	64,789.2	64,839.2	65,035.1	65,060.1	0.094	0.093	18,637	25
Skills	64,800.9	64,850.9	65,046.8	65,071.8	0.093	0.092	18,637	25
Oesch	64,702.9	64,772.9	65,047.0	65,082.0	0.098	0.096	18,637	35
RTI	64,799.7	64,849.7	65,045.5	65,070.5	0.093	0.092	18,637	25

Large differences

Table 18 Goodness of fit measures

	Deviance	AIC	BIC	CAIC	R2	R2adj	N	k
Baseline	311,114.1	311,180.1	311,483.0	311,516.0	0.037	0.036	71,652	33
Income	310,646.7	310,714.7	311,026.8	311,060.8	0.043	0.043	71,652	34
Deciles	310,455.4	310,539.4	310,924.9	310,966.9	0.046	0.045	71,652	42
ESeC	310,672.7	310,754.7	311,131.1	311,172.1	0.043	0.042	71,652	41
Risks	311,017.8	311,085.8	311,397.9	311,431.9	0.038	0.038	71,652	34
Skills	311,104.9	311,172.9	311,485.0	311,519.0	0.037	0.037	71,652	34
Oesch	310,557.7	310,645.7	311,049.6	311,093.6	0.044	0.044	71,652	44
RTI	311,113.1	311,181.1	311,493.2	311,527.2	0.037	0.036	71,652	34

Ideology

Appendix B

Variables and definitions

Dependent variable

The government should take measures to reduce differences in income levels

1. Agree + agree strongly

0. Disagree + disagree strongly + neither agree nor disagree

SES operationalizations

Income decile

1. First decile

...

10. Tenth decile

Linear income. The log of per capita equivalized net income.

$$\ln \frac{(y_{up} - y_{lo})/2}{\sqrt{h}}$$

where y_{up} is the upper bound of the income decile of the household, y_{lo} is the lower bound of the income decile of the household and h is household size.

Skill specificity: The absolute skill specificity is defined as the ratio of the share of occupations within the ISCO-08 occupational group over the share of labor force in this occupational group. Relative skill specificity is defined as the absolute skill specificity divided by the skill level. Skill level can be measured by a) the ISCO measure of skill level for each particlar occupational group or b) the individual educational level. This gives raise to two measures of skill specificity: s_1 and s_2.

$$as_j = \frac{OC4_j/OCT}{l_j/pa}$$

where as_j is absolute skill specificity for the j two digits ISCO-08 occupational group, $OC4_j$ is the number of occupations at four digits ISCO-08 within the j occupational group, *OCT* is the total number of occupations in ISCO-08, l_j is the working population in the j occupational group and pa is the total active population.

$$s_1 = \frac{as_j}{sk_{ij}}, s_2 = \frac{as_j}{ed_i}$$

where sk_{ij} is the the ISCO-08 skill level for individual i in ISCO-08 group j and ed_i is the educational level of individual i. Our measure of skill specificity is the average of s_1 and s_2.

Risk of unemployment. Unemployment rate at one digit ISCO-08 using data from EU Labor Force Survey.

RTI. We use RTI scores from http://www.lisdatacenter.org/resources/other-databases/, prepared by Mahutga et al. (2018), where RTI is measured as the difference between the log of routine and the sum of the log of abstract and the log of manual.

ESeC.

1. Large employers, higher grade professional, administrative and managerial occupations
2. Lower grade professional, administrative and managerial occupations and higher grade technician and supervisory occupations
3. Intermediate occupations
4. Small employer and self employed occupations
5. Self employed occupations
6. Lower supervisory and lower technician occupations

7. Lower services, sales and clerical occupations
8. Lower technical occupations
9. Routine occupations

Oesch.

1. Higher grade managers
2. Technical experts
3. Socio-cultural professionals
4. Associate managers
5. Technicians
6. Socio-cultural semi-professionals
7. Skilled office
8. Skilled crafts
9. Skilled service
10. Unskilled routine
11. Routine operatives/agriculture
12. Routine service

Funding This research has been funded by the European Commission (Directorate-General XII, Science, Research, and Development), Project Social Classes in The Digital Age (DIGCLASS).

Data Availability Replication files for this article can be accessed at https://doi.org/10.6084/m9.figshare.31703836

Declarations

Conflict of interest No potential conflict of interest was reported by the authors.

References

Barone, Carlo, Florian R Hertel and Oscar Smallenbroek. 2021. What we think when we speak about stratification. *SocArXiv. January* 7.

Beramendi, Pablo, and Philipp Rehm. 2016. Who gives, who gains? Progressivity and preferences. *Comparative Political Studies* 49(4): 529–563.

Bonnet, Julien, Emanuel Ciani, Gianluca Grimalda, Fabrice Murtin and David Pipke. 2024. What explains preferences for redistribution?: Evidence from an international survey. Technical Report 32 OECD Papers on Well-being and Inequalities Paris: .

Brady, David, and Amie Bostic. 2015. Paradoxes of social policy: Welfare transfers, relative poverty, and redistribution preferences. *American Sociological Review* 80(2): 268–298.

Brady, David, Marco Giesselmann, Ulrich Kohler, and Anke Radenacker. 2018. How to measure and proxy permanent income: Evidence from Germany and the US. *The Journal of Economic Inequality* 16(3): 321–345.

Busemeyer, Marius R and Alexander HJ Sahm. 2021. Social investment, redistribution or basic income? Exploring the association between automation risk and welfare state attitudes in Europe. *Journal of Social Policy* pp. 1–20.

Carriero, Renzo. 2021. Social Position and Support for the Welfare State in Western European Countries. A Test of Oesch's Class Schema and a Comparison with ESEC. *Polis* 36(1):41–68.

Claeskens, Gerda, and Nils Lid Hjort. 2008. *Model selection and model averaging*. Cambridge: Cambridge University Press.

Cusack, Thomas, Torben Iversen, and Philipp Rehm. 2006. Risks at work: The demand and supply sides of government redistribution. *Oxford review of economic policy* 22(3): 365–389.

Dimick, Matthew, David Rueda, and Daniel Stegmueller. 2018. Models of other-regarding preferences, inequality, and redistribution. *Annual Review of Political Science* 21:441–460.
Doherty, Daniel, Alan S. Gerber, and Donald P. Green. 2006. Personal income and attitudes toward redistribution: A study of lottery winners. *Political Psychology* 27(3): 441–458.
Eurostat. 2021. European Union-Labor Force Survey.
Evans, Geoffrey and Noah Carl. 2017. Class and politics. In *The Sage Handbook of Political Sociology*, ed. William Outhwaite and Stephen P. Turner. Sage pp. 107–124.
Fehr, Ernst, Thomas Epper and Julien Senn. 2024. Social preferences and redistributive politics. *Review of Economics and Statistics* pp. 1–45.
Fernández, Juan J., and Antonio M. Jaime-Castillo. 2018. The institutional foundation of social class differences in pro-redistribution attitudes: A cross-national analysis, 1985–2010. *Social Forces* 96(3): 1009–1038.
Finseraas, Henning. 2009. Income inequality and demand for redistribution: A multilevel analysis of European public opinion. *Scandinavian Political Studies* 32(1): 94–119.
Fiske, Susan T, Amy JC Cuddy, Peter Glick and Jun Xu. 2018. A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. In *Social cognition*. Routledge pp. 162–214.
Goldthorpe, John H. 2000. *On sociology*, vol. 1. Redwood City: Stanford University Press.
Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104(8): 2509–26.
Guillaud, Elvire. 2013. Preferences for redistribution: An empirical analysis over 33 countries. *The Journal of Economic Inequality* 11(1): 57–78.
Heide-Jørgensen, Tobias, Peter Thisted Dinesen, and Kim Mannemar Sønderskov. 2023. Personality and roots of welfare state support: How openness to experience moderates the influence of self-interest and ideology on redistributive preferences. *Political Behavior* 45(4): 1467–1489.
Hooghe, Liesbet, Jing Jing Huo, and Gary Marks. 2007. Does occupation shape attitudes on Europe? Benchmarking validity and parsimony. *Acta Politica* 42:329–351.
Horwitz, Suzanne R., Kristin Shutts, and Kristina R. Olson. 2014. Social class differences produce social group preferences. *Developmental Science* 17(6): 991–1002.
Iversen, Torben, and David Soskice. 2001. An asset theory of social policy preferences. *American Political Science Review* 95(4): 875–893.
Kevins, Anthony, Alexander Horn, Carsten Jensen, and Kees Van Kersbergen. 2019. The illusion of class in welfare state politics? *Journal of Social Policy* 48(1): 21–41.
Kitschelt, Herbert, et al. 1994. *The transformation of European social democracy*. Cambridge: Cambridge University Press.
Kitschelt, Herbert, and Philipp Rehm. 2014. Occupations as a site of political preference formation. *Comparative Political Studies* 47(12): 1670–1706.
Kriesi, Hanspeter, Edgar Grande, Romain Lachat, Martin Dolezal, Simon Bornschier, and Timotheos Frey. 2008. *West European politics in the age of globalization*. Cambridge: Cambridge University Press.
Kulin, Joakim, and Stefan Svallfors. 2013. Class, values, and attitudes towards redistribution: A European comparison. *European Sociological Review* 29(2): 155–167.
Kumlin, Staffan. 2007. The welfare state: Values, policy preferences, and performance evaluations. In *The Oxford handbook of political behavior*, ed. J. Russell. Oxford: Oxford University Press.
Lindh, Arvid, and Leslie McCall. 2020. Class position and political opinion in rich democracies. *Annual Review of Sociology* 46:419–441.
Lipset, Seymour Martin. 1960. *Political man: The social bases of politics*. Baltimore: Johns Hopkins University Press.
Mahutga, Matthew C., Michaela Curran, and Anthony Roberts. 2018. Job tasks and the comparative structure of income and employment: Routine task intensity and offshorability for the LIS. *International Journal of Comparative Sociology* 59(2): 81–109.
Manza, Jeff and Ned Crowley. 2018. Class divisions and political attitudes in the 21st century. In *The Handbook of Attitudes*, ed. Dolores Albarracín and Blair T. Johnson. Routledge pp. 367–397.
McCall, Leslie and Jeff Manza. 2011. Class differences in social and political attitudes in the United States. In *The Oxford handbook of American public opinion and the media*, ed. Lawrence R. Jacobs George, C. Edwards III and Robert Y. Shapiro. Oxford: Oxford University Press.
Meltzer, Allan H., and Scott F. Richard. 1981. A rational theory of the size of government. *Journal of Political Economy* 89(5): 914–927.

Oesch, Daniel. 2006. *Redrawing the class map: Stratification and institutions in Britain, Germany, Sweden and Switzerland*. Berlin: Springer.
Paskov, Marii, and David Weisstanner. 2022. Cross-class embeddedness through family ties and support for income redistribution. *European Sociological Review* 38(2): 286–303.
Persson, Torsten, and Guido Tabellini. 2000. *Political economics. Explaining economic policy*. Cambridge: MIT Press.
Raffalovich, Lawrence E., Glenn D. Deane, David Armstrong, and Hui-Shien. Tsao. 2008. Model selection procedures in social research: Monte-Carlo simulation results. *Journal of Applied Statistics* 35(10): 1093–1114.
Rehm, Philipp. 2009. Risks and redistribution: An individual-level analysis. *Comparative Political Studies* 42(7): 855–881.
Rehm, Philipp. 2011. Social policy by popular demand. *World Politics* 63(2): 271–299.
Rehm, Philipp. 2016. *Risk inequality and welfare states: Social policy preferences, development, and dynamics*. Cambridge: Cambridge University Press.
Roberts, Kevin W.S. 1977. Voting over income tax schedules. *Journal of Public Economics* 8.
Rose, David and Eric Harrison. 2010. *Social class in Europe: An introduction to the European Socio-economic Classification*. Routledge.
Rueda, David. 2018. Food comes first, then morals: Redistribution preferences, parochial altruism, and immigration in Western Europe. *The Journal of Politics* 80(1): 225–239.
Schraff, Dominik. 2018. Labor market disadvantage and political alienation: A longitudinal perspective on the heterogeneous risk in temporary employment. *Acta Politica* 53:48–67.
Shahbazian, Roujman, and Erik Bihagen. 2022. Does your class give more than a hint of your lifetime earnings? Assessing indicators for lifetime earnings over the life course for Sweden. *European Sociological Review* 38(4): 527–542.
Steele, Liza G., Joseph Nathan Cohen, and Joseph R. van der Naald. 2022. Wealth, income, and preferences for redistribution: Evidence from 30 countries. *Social Science Research* 108:102746.
Stubager, Rune, James Tilley, Geoffrey Evans, Joshua Robison, and Gitte Sommer Harrits. 2018. In the eye of the beholder: What determines how people sort others into social classes? *Social Science Research* 76:132–143.
Thewissen, Stefan, and David Rueda. 2019. Automation and the welfare state: Technological change as a determinant of redistribution preferences. *Comparative Political Studies* 52(2): 171–208.
Van den Berg, Job C., and Hilde Coffé. 2012. Educational and class cleavages in voting behaviour in Belgium: The effect of income, EGP class and education on party choice in Flanders and Wallonia. *Acta Politica* 47:151–180.
Van Drunen, Yaël., Bram Spruyt, and Filip Van Droogenbroeck. 2021. The salience of perceived societal conflict in Europe: A 27 country study on the development of a measure for generalized conflict thinking. *Social Indicators Research* 158(2): 595–635.
Vlandas, Tim. 2021. The political economy of individual-level support for the basic income in Europe. *Journal of European Social Policy* 31(1): 62–77.
Walter, Stefanie. 2017. Globalization and the demand-side of politics: How globalization shapes labor market risk perceptions and policy preferences. *Political Science Research and Methods* 5(1): 55–80.
Weeden, Kim A., and David B. Grusky. 2012. The three worlds of inequality. *American Journal of Sociology* 117(6): 1723–1785.
Wright, Eirk O. 1985. *Classes*. Verso.