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Unfair Inequality and the Demand for Redistribution

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Unfair inequality and the demand for redistribution: Why not all inequality is equal

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Abstract
Political economy research commonly expects a positive relationship between income inequality and the demand for redistribution, which is increasingly attributed to inequality aversion grounded in norms and values. However, people are not averse to a proportion of inequality that fairly results from differences in individual merit. Therefore, this study argues that the effect of inequality crucially depends on the extent to which income fairness is realized. It is primarily unfair inequality, rather than overall inequality, that affects individual redistribution support. The argument is substantiated with an empirical quantification of unfair inequality that measures whether individuals have unequal returns to their labor-related merits. Multilevel models using repeated cross-sections show that this quantification of unfair inequality can explain both within- and between-country variance in redistribution preferences and that it is a better predictor than overall inequality. The results suggest that public opinion cannot be inferred directly from the overall level of inequality.

Keywords: income distribution; political economy; political sociology; public policy; social norms; redistribution

1 Introduction

What is the relationship between income inequality and popular demand for redistribution? The ubiquitous model of Meltzer and Richard (1981) and related rational choice approaches expect a positive relationship because inequality increases the material incentive for the masses to "soak the rich". However, empirical results only offer inconsistent support for this expectation (Dallinger, 2008; Jæger, 2013; Johnston and Newman, 2015; Kenworthy and McCall, 2008; Luebker, 2007), which has led to widespread dissatisfaction with the view that individual rationality is sufficient to explain the political implications of inequality (Dimick *et al.*, 2017). At the same time, aggregate inequality does seem to play a role, with a number of studies finding positive correlations with redistribution preferences (Dallinger, 2008; Jæger, 2013; Johnston and Newman, 2015). In an answer to this puzzle, comparative political economy has rediscovered other-regarding preferences in its theorization. Several contributions argue that inequality does affect the demand for redistribution but only insofar as inequality triggers inequality aversion, which depends on the normative stance of citizens and the specific makeup of inequality (Cavaillé and Trump, 2015; Dimick *et al.*, 2017; Luebker, 2007; Lupu and Pontusson, 2011; Shayo, 2009).

This study contributes to this literature by developing a theory about the circumstances under which inequality affects redistribution preferences and by testing its implications with a novel empirical approach. The argument draws from another literature that focuses on subjective beliefs about inequality. It is a robust finding that individuals actively support a considerable proportion of inequality that can be explained by differences in individual merit (Cappelen *et al.*, 2010; Kuhn, 2011; Lewin-Epstein *et al.*, 2003; Mijs, 2018b). The underlying normative ideal has been referred to as *meritocracy*, *equity*, or *economic fairness* (e.g., Aalberg, 2003, ch. 2; Deutsch, 1975; Konow, 1996). It demands that incomes should be fair, i.e. proportional to individual merit.[1] What is relevant for research on redistribution preferences is that individuals support inequality reduction via redistribution especially when they perceive inequality to be unfair while inequality perceived as fair is less consequential (e.g., Ahrens, 2019; Alesina and La Ferrara, 2005; García-Sánchez *et al.*, 2020).

In line with recent political economy research, I argue that objective inequality affects redistribution support due to normative concerns about inequality. However, it is paramount to take the implications of income fairness research seriously. It is unreasonable to believe that fairness perceptions are separate from objective reality. Some national income distributions should be fairer than others according to an objective standard. Furthermore, individuals should primarily seek to reduce *unfair inequality* via redistribution (i.e. the proportion of inequality that is not warranted by labor merit). *Fair inequality*, on the other hand, should be less consequential because people are less inclined to distort a legitimate income distribution. This is an important point for research on objective inequality because commonly used inequality measures convey no information about the fairness of distributions, and there is no reason to believe that distributive fairness is the same across different populations.

The theoretical expectations are tested empirically with a novel research design. It relies on an empirical quantification of unfair inequality of labor income, applying the measurement approach of Almås *et al.* (2011). The quantification is guided by a fundamental income fairness principle, namely that people with comparable occupation, skills, and effort should receive similar labor income, i.e. non-discrimination. It results in an *unfairness Gini*, which is a variant of the Gini index that solely evaluates whether people receive unequal rewards for their labor-related merits. In contrast to the conventional Gini index commonly used in research, it explicitly considers distributive fairness. The unfairness Gini should therefore capture a form of inequality that spurs redistribution preferences to a better degree than the conventional Gini index.

[1] Please note that fairness ideals are usually more extensive than this short summary may imply. Most importantly, they typically demand equality of opportunity in addition to simple outcome fairness (i.e. proportional merits and rewards). However, this study primarily focuses on outcome fairness.

Unfair inequality as well as different versions of the conventional Gini index measuring overall inequality are estimated for 48 country-years using data from the Luxembourg Income Study (LIS, 2020). In a next step, the effect of these inequality variables on individual demand for redistribution is assessed with multilevel models using repeated cross-sections from the European Social Survey (ESS, 2002-2014). The theoretical expectations are supported. The results show that unfair inequality has a positive relationship with redistribution preferences and that it can explain both within- and between-variance of national redistribution preferences. Furthermore, unfair inequality is a much better predictor of redistribution preferences than overall inequality, which supports the argument that unfair rather than overall inequality affects redistribution support.

This study makes several contributions to the literature. In line with recent political economy scholarship, it firstly underscores that other-regarding preferences drive the relationship between aggregate inequality and redistribution preferences. Secondly, this study reconciles findings from research on objective and subjective income inequality. It takes a novel approach by showing that objectively realized income unfairness is associated with more redistribution support, whereas previous observational work used subjective unfairness evaluations as explanatory variables. Likewise, this study shows that objectively realized inequality matters, which has increasingly been questioned by studies focusing on subjective beliefs (see the review by Janmaat, 2013). Lastly, this study also has an implication for research exploring the socio-political consequences of objective inequality, namely that *not all inequality is equal*. The quantification of unfair inequality and its robust relationship to redistribution preferences suggest that the proportion of inequality that is normatively rejected is not given by a fixed proportion of overall inequality. If possible, it is therefore advisable to consider differences in distributive fairness when exploring the effect of inequality on political preferences and other dependent variables, at least when fairness concerns are influential.

2 Inequality and the demand for redistribution

What is the relationship between objective inequality and the demand for redistribution? Meltzer and Richard's (1981) rational choice approach posits that individual redistribution support negatively depends on the own income relative to the mean income. Under typical lognormal income distributions, this translates into a positive macro association between income inequality and redistribution preferences. In line with the model, a myriad of studies shows that relatively rich people support less redistribution than relatively poor people, thus underscoring the importance of rational motivations (e.g., Rehm, 2009; Schmidt-Catran, 2016). The model's more fine-grained predictions, however, receive little support. Only some studies find a positive association between aggregate inequality and redistribution preferences (Dallinger, 2008; Jæger, 2013; Johnston and Newman, 2015) while others report null findings (Dallinger, 2010; Kenworthy and McCall, 2008; Luebker, 2007; Roller, 1998). Furthermore, the discrepancy in redistribution support between the poor and rich should increase with inequality, but empirical estimates support the opposite pattern, i.e. *less* variance between the rich and poor (Dimick *et al.,* 2017; Finseraas, 2009; Schmidt-Catran, 2016).

In an answer to the shortcomings of rationalist predictions, political economists have rediscovered the role of norms and values. Several contributions continue to theorize a positive impact of objective inequality on redistribution support but expect that inequality aversion drives the relationship. In Dimick *et al.*'s (2017) model, inequality increases redistribution support because people care about the utility of their peers. This other-regarding motivation is allegedly stronger in richer individuals because they assign more utility to social welfare. An empirical analysis confirms this conditional relationship with US data. Luebker (2007) finds a positive cross-country effect of inequality, but only once the differing normative stances prevalent in countries are controlled for. Lupu and Pontusson (2011) argue that rather the *structure* of inequality matters. Specifically, middle-income voters will increasingly emphasize with the poor and support redistributive policies when the income distance between middle- and lower-income earners decreases relative to the distance between upper- and middle-income earners. An empirical analysis confirms this relationship, but it has seen a comprehensive rebuttal in Luebker (2019), who shows that the results were driven by omitted variable bias. Conversely, Cavaillé and Trump (2015) show that inequality *decreased* redistribution support in Great Britain, which they attribute to reduced social affinity with the poor. In the same vein, Shayo's (2009) model implies that the role of inequality is ambiguous; it can lead to both increased and decreased redistribution support, which depends on whether poor people identify with their nation or fellow members of the lower class.

The approach to study the effect of objective inequality on political preferences, especially when normative motivations are theorized, has been critiqued by a literature that rather focuses on subjective beliefs regarding inequality (see Janmaat [2013] for an overview). It questions whether objective inequality and inequality aversion have a consistent relationship (Luebker, 2007), not least because individuals tend to be misinformed about inequality (Engelhardt and Wagener, 2018; Fernández-Albertos and Kuo, 2018; Gimpelson and Treisman, 2018).

One of the most robust findings from studies directly tapping into subjective judgements regarding income inequality is that inequality and inequality aversion are not necessarily related. While people do hold egalitarian views (Dawes *et al.*, 2007; Sachweh, 2012), it is widely accepted among diverse populations that those with higher individual merit, e.g. due to working harder, receive a higher income. To the extent that individuals believe that income differences in their country are warranted by differences in merits rather than circumstances, inequality is considered to be perfectly legitimate (Janmaat, 2013; Lewin-Epstein *et al.*, 2003; Mijs, 2018b, 2019; Sachweh, 2012). The philosophical foundation is a distributive ideal that has been coined *meritocracy*, *equity*, or *economic fairness* by different theorists, which typically includes demands for a proportionality of individual merit and reward as well as equality of opportunity (Aalberg, 2003, ch. 2; Deutsch, 1975; Konow, 1996).

Further research shows that the endorsement of income fairness beliefs, which vary within and between countries, is crucial for individuals' redistribution support. García-Sánchez *et al.* (2020) find that the effect of (perceived) income differences on redistribution support decreases with the endorsement of income fairness beliefs. People who think that actual and ethical wages diverge (Ahrens, 2019; Kuhn, 2010) and those who think that others do not get what they deserve (Benabou and Tirole, 2006) also demand more redistribution. Other studies show that not only outcomes but also processes matter. Those who think that income inequality results from unfair processes, e.g. because only those with a wealthy family can get ahead, demand more redistribution (Ahrens, 2019; Alesina and La Ferrara, 2005; Fong, 2001). Furthermore, experiments show that the association between fairness perceptions and redistribution support is causal. Piff *et al.* (2020) show that people's preference for egalitarian policies increases when they are primed to attribute poverty to situational forces. Lastly, Becker (2020) shows that Americans adjust their redistribution preferences when they are informed about objective inequalities between people with different characteristics ascribed at birth (e.g., gender), which may serve as indicators for economic fairness.

To sum up, researchers in political economy continue to expect (and find) a relationship between objective inequality and redistribution support. This relationship is increasingly attributed to normative considerations. However, research on subjective income inequality questions this practice since *(a)* objective inequality and inequality aversion are not necessarily linked and *(b)* because people are generally misinformed about objective inequality. The following section will outline a theory that reconciles these theoretical approaches and critiques.

3 Theory and hypotheses

This section will advance the theory that, due to citizens' normative concerns, objective inequality affects redistribution preferences. However, it is paramount to take the findings from research on subjective income inequality into account, which shows that the effect of inequality depends on whether inequality is seen as fair or not. Furthermore, fairness perceptions vary considerably between countries, with some countries endorsing much stronger income fairness beliefs than others.[2] While it would be simple to treat these perceptions as separate from reality, I rather expect that individuals in some countries experience more income unfairness than individuals in other countries.

I argue that the effect of inequality on redistribution support depends on the extent to which income fairness is empirically realized. Redistribution support increases with unfair inequality, which cannot be explained by differences in individual merit. Fair inequality that results from individual merit, on the other hand, should be less consequential. Public redistribution is a tool that can be used to equalize the income distribution. People will primarily support use of this tool when they observe that income differences are not deserved because, as Fong (2001, p. 226) notes, "individuals care deeply that other people get what they deserve". The implication is that the relationship between objective inequality and redistribution preferences cannot be inferred from the overall level of inequality alone. Previous research has disregarded this point by using different measures of overall inequality as explanatory variables. For example, the widely used Gini coefficient measures an income distribution's deviation from perfect equality, which does not conform to how popular perceptions of a legitimate income distribution are formed at all. The next section will thus outline an approach to solely measure unfair inequality. Beforehand, however, several theoretical refinements are appropriate.

The argument so far begs question what exactly unfair inequality is. I argue that unfair inequality is inequality that cannot be explained by differences in labor-related merits, i.e. attributes related to occupation, experience, skills, and effort, which I will refer to as occupational attributes. Research reliably shows that occupational attributes are paramount in defining individual deservingness. Cappelen *et al.* (2010) show in an experiment that labor effort and skill legitimize income inequality. Differences in remuneration resulting from differences in productivity (e.g., being able to type more words) are accepted while randomized differences are not. Lewin-Epstein *et al.* (2003) find that differences in individuals' education, skills, and effort on the job warrant unequal reward. Two studies show that individuals in diverse settings support *substantial* income differences between different professions (Kuhn, 2011; Osberg and Smeeding, 2006). Lastly, individuals expect to earn as much their colleagues (Feldman and Turnley, 2004) and employees in the same industry (Verhoogen *et al.*, 2007), which supports the view that occupational attributes define deservingness. The implication is that income differences between people with the same occupational attributes are unfair.

The next question is how individuals form income fairness perceptions. Relying on equity theory (Ahrens, 2019), I argue that people conduct comparisons with and between observable reference groups (c.f. Cruces *et al.*, 2013; Dawtry *et al.*, 2015; Mijs, 2018a). Distributive fairness is judged by comparing people with the similar occupational attributes such as education and profession and inferring whether the rewarded income is similar (Sauer and May, 2017). Income inequality is deemed to be fair when there is a proportionality of inputs (i.e. occupational attributes) and outputs (i.e. income). For example, people will compare themselves to colleagues who work at the same employer and others in the same professions to gauge whether their own income is appropriate. Of course, relevant occupational attributes and incomes are difficult to observe beyond one's immediate social surrounding. Therefore, I expect that the estimated fairness of the own income, where proportionality is most easily assessed, is especially relevant for the formation of overall income fairness perceptions. Insofar as it is possible, however, people also use social comparisons between others to gauge whether the income distribution is fair.

[2] Descriptive statistics on the between-country dispersion of unfairness perceptions are available in the appendix (see Figure A1).

My approach relies on the assumption that people can form a relatively valid estimate of unfair inequality in their society. This is debatable because recent research shows that individuals tend to be misinformed about inequality (Engelhardt and Wagener, 2018; Fernández-Albertos and Kuo, 2018; Gimpelson and Treisman, 2018), presumably because they base their beliefs only on observable subsets of the income distribution (Cruces *et al.,* 2013; Dawtry *et al.,* 2015). I argue that, in the aggregate, individuals assess unfair inequality with less bias than overall inequality. Comprehensive knowledge about all other incomes in society would be required to arrive at an unbiased estimate of both unfair and overall inequality. But since people tend to observe only local subsets of the income distribution, which tend to be much more homogenous than the overall distribution, individual estimates of both fair and overall inequality will be biased in reality (Cruces *et al.,* 2013; Mijs, 2018a). However, there is a fundamental difference between individual estimates of overall and unfair inequality. Most people underestimate overall inequality because their reference groups tend to have similar incomes as themselves. When all overall inequality estimates in a society are summed up, the result will display this downward bias as well. Fairness estimates, on the other hand, do not have this predetermined bias. The homogeneity of observed reference groups allows people to form relatively valid local fairness estimates because perceived income fairness depends on whether people with similar attributes also have similar earnings (e.g., one's colleagues who work the same job, or friends with similar education). Based on how people themselves and others in their observable surrounding are treated, some will have local fairness estimates that are too low, and others will have local fairness estimates that are too high. When averaged across whole societies, the result should be less biased than estimates of overall inequality.

Overall, I argue that people primarily have an aversion to unfair inequality. Individuals' demand for redistribution increases when unfair inequality rises because they do not support inequality that does not reflect individual deservingness. It can be expected that *unfair inequality positively affects redistribution preferences (H1)*. Fair inequality, on the other hand, should be less consequential for redistribution preferences. It is questionable that people support a certain level of merit-based inequality and seek to reduce this inequality at the same time. Fair inequality may influence redistribution preferences if redistribution advances distributive ideals other than economic fairness (e.g., equality). Unfair inequality, however, is clearly more consequential because decreasing it via redistribution most often advances other ideals such as equality in addition to economic fairness. Thus, I expect that *unfair inequality affects redistribution preferences to a stronger degree than overall inequality (H2)*.

4 Measuring unfair inequality

Several empirical approaches to measure realized income (un)fairness in a society have been proposed (e.g., Almås *et al.,* 2011; Devooght, 2008; Krauze and Slomczynski, 1985; Pignataro, 2012). This study applies the approach by Almås *et al.* (2011) because, firstly, it focuses on distributive fairness rather than processual fairness norms such as equality of opportunity (see Pignataro, 2012), which are also consequential but not the theoretical focus of this study. Secondly, the approach by Almås *et al.* allows the researcher to specify individual characteristics that do and do not legitimize inequality rather than having a pre-specified fairness model (e.g., Krauze and Slomczynski, 1985). And thirdly, because the quantification results in a Gini coefficient that solely measures unfair inequality, which implies that empirical results can easily be compared to the conventional Gini coefficient that is frequently used in inequality research.

Almås *et al.*'s (2011) approach to measure unfair inequality requires representative micro datasets that contain information on income and individual characteristics. It involves estimating a hypothetical fair income distribution based on individuals' merits, calculating how much it differs from the actual distribution, and aggregating the results into an unfairness Gini index purged from fair income differentials. A fair distribution is defined as one where everybody has the same returns to their merits. This requires a choice of what individual characteristics are merits, which will be conceived of in broad terms for the purpose of this study. Merits are defined as all attributes related to occupation, skills, experience, and effort. This follows an intentionally minimal fairness principle, namely that individuals in similar employment with similar skills and effort who do similar work should receive similar remuneration, i.e. non-discrimination. The methodology proposed by Almås *et al.* as well as the exact choice of data and variables used in the estimation procedure are presented below.

4.1 The measurement approach of Almås *et al.* (2011)

Incomes vary according to individuals' characteristics. These include *merits* that result in fair inequality and *circumstances* that produce unfair inequality. Estimating unfair inequality proceeds in the following steps. Firstly, the linear regression model given in equation (1) is fitted using log income as the dependent variable and all variables identified as merits and circumstances as independent variables.

$$(1)\ \log y_i = ß_m X_i^m + ß_c X_i^c + \varepsilon_i$$

where y refers to income, X^m to all variables defined as merits, and X^c to all defined as circumstances of individual i. The vector of estimated coefficients $ß_m$ indicates the merits' average market remuneration irrespective of the circumstances' relationship to income, which effectively serve as control variables.

Secondly, equation (2) yields a fair income share for everyone based on the merits' coefficients $ß_m$ and individuals' observed values of the corresponding variables, denoted by lower-case letters.

$$(2)\ \vartheta_i = \frac{\exp\,(ß_m x_i^m)}{\sum_i \exp\,(ß_m x_i^m)}$$

where the numerator of the fraction corresponds to the predicted income of individual i solely based on merit, and the denominator to an aggregation of all predicted merit-based incomes in society. The exponential function is used because of the log-transformation of the dependent variable in the initial regression. The logic of the fair income share ϑ_i is that everyone should receive an income share given by individual merit relative to aggregate merit. A hypothetical fair income y^f is then calculated with equation (3). It multiplies the fair share with the total available income, which is defined as the aggregate income in a country.

$$(3)\ y_i^f = \vartheta_i \sum_i y_i$$

Lastly, the results are aggregated into an *unfairness Gini* index given by equation (4):

$$(4)\ Gini_{unf.} = \frac{1}{2n(n-1)\mu(y)} \sum_i \sum_j |(y_i - y_i^f) - (y_j - y_j^f)|$$

where n refers to the number of individuals, $\mu(y)$ to mean income, and both i and j to individuals (see Almås *et al.*, 2011, pp. 489–490). This unfairness Gini indicates to what extent real incomes deviate from (hypothetical) fair incomes. In contrast, the conventional Gini index indicates to what extent real incomes deviate from perfect equality.

4.2 Empirical application

Unfair inequality is estimated just as proposed by Almås *et al.* (2011) using data from the Luxembourg Income Study (LIS, 2020). The LIS offers a high-quality data infrastructure with harmonized micro datasets on, e.g., the income of the population in Germany in 2012. Each dataset is used to estimate aggregate unfair inequality for a specific country and year, the results of which will be merged to micro-level data from the ESS to assess the impact on redistribution preferences in a subsequent step. The sample selection of country-years depends on mutual data availability in the LIS and ESS data, which will be explained in detail in the ESS data description. Using all available data, unfair inequality can be estimated for 48 country-years from 16 countries.

The regression models (see equation 1 above) are estimated with hourly labor income, gross of taxes, as the dependent variable.[3] Capital income is explicitly disregarded because it is unclear what characteristics legitimize capital income inequality. The samples are restricted to non-retired working age (16-65) individuals in dependent employment with an income above zero, weighted according to the LIS personal weights. Defined as merits are the variables education (dataset-specific categories), profession (10 categories based on ISCO-08), industry (nine categories), sector (public or private), age (five categories: <25, 25-34, 35-44, 45-54, >54), as well as interaction terms between education and profession.[4] All job-related variables refer to the respondents' first job.[5] Defined as circumstances are gender, a children dummy, an interaction of the gender and children dummies, region (dataset-specific categories), the father's education (dataset-specific categories), as well as dummies on the respondents' immigrant background, rural place of living, and permanent employment status. Unfortunately, not all variables are available for each individual regression. Table A1 in the appendix lists which variables are excluded in which country-years. A sensitivity analysis shows that the results are robust to an exclusion of variables that are often not available.[6]

What qualifies the classification of variables as merits or circumstances? As previously stated, the guiding principle is a minimalist conception of income fairness, namely that individuals in similar employment with similar skills and effort who do similar work should receive similar remuneration. Accordingly, merits are defined as all attributes related to occupation, skills, experience, and effort. The merits profession, industry, and sector indicate respondents' *occupation*. Working hours, education, and profession show the *effort* that respondents deliver or have delivered in the past.[7] Lastly, education and age relate to individuals' *skills and experience*. The variables defined as circumstances, on the other hand, are at most loosely related to individuals' occupation, skills, or effort.

4.3 Results

The unfairness Gini measuring unfair inequality is estimated for 48 country-years from 16 countries. In addition, five variants of the conventional Gini index measuring overall inequality are estimated from the same datasets to assess the relative explanatory power of unfair and overall inequality in the empirical analysis. These additional Gini indices measure overall inequality of (1) personal gross labor income among the working-age population in dependent employment (i.e. the same sample used to estimate unfair inequality), (2) personal labor income among the whole population, (3) personal gross total income among the working-age population in dependent employment, (4) personal gross total income

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[3] Incomes crucially depend on working time, and it is necessary to normalize incomes accordingly to make them comparable between individuals. This is achieved by dividing income by annual working time. My framework assumes it to be fair that people who work more receive a larger income. Thus, the normalization according to hours worked is a first consideration of distributive fairness. Hours worked could also be framed as a fair input and used as an independent variable in the income regressions instead. However, it is much cleaner to normalize according to working hours first because otherwise a single coefficient of working hours would have to be estimated for whole workforces.

[4] The preferred specification is not available in some cases because the profession and industry dummies are recorded in rougher or dataset-specific categories. If the 10-category profession specification is not available, I use the three-category specification; and if this is not available, I use the dataset-specific categories. Likewise, I prefer the nine-category industry categorization over the three-category specification over the dataset-specific entry. Lastly, education is used as a continuous variable for the interactions with profession to keep the number of independent variables in check.

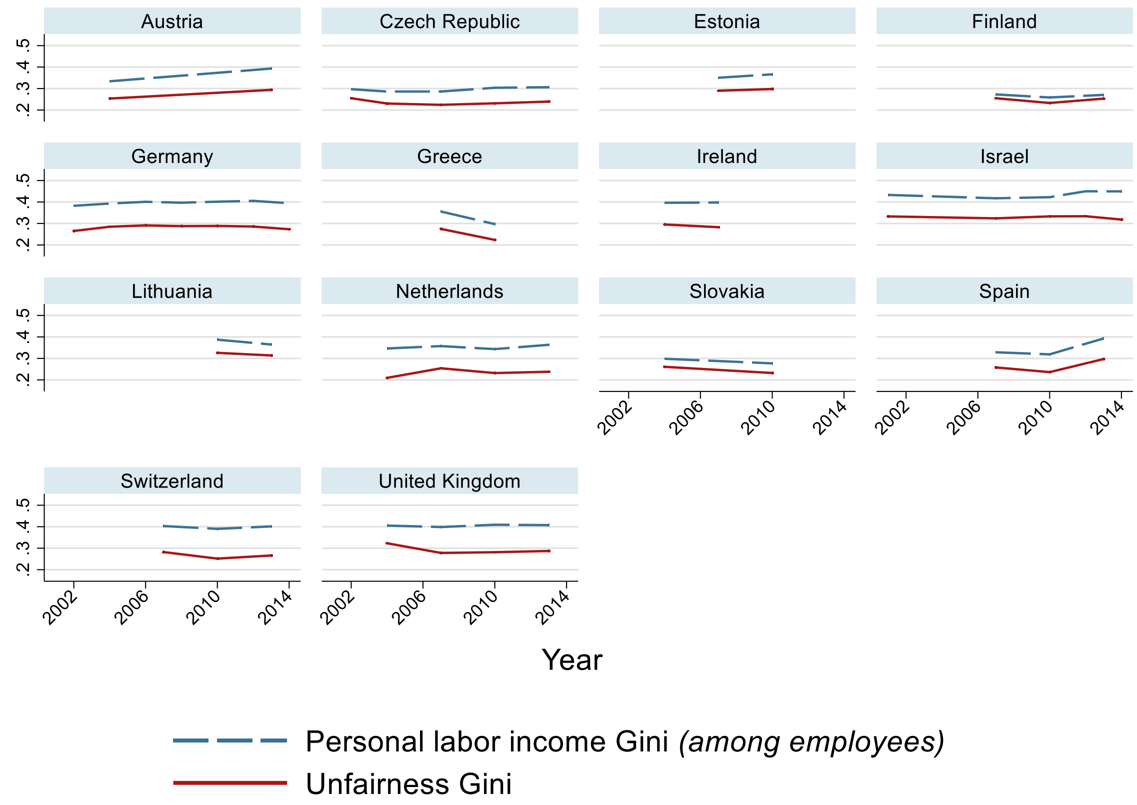
[5] This slightly affects the results because some (but few) individuals also have a second job that is not considered in the income regressions. However, most LIS datasets do not collect information on respondents‘ second job, and including more variables would overload the regressions models.

[6] I re-estimated unfair inequality and excluded the circumstance variables immigrant background, education of father, permanent employment, and rural place of living. The resulting unfairness Gini is highly correlated with the main specification (r=.99). This result is based on data from the countries Germany and Slovakia, which are the only countries that consistently have all four excluded circumstance variables available.

[7] Although working hours is not used as a variable in the income regressions, it is used to normalize the dependent variable, which is a first consideration of distributive fairness.

among the whole population, and (5) household gross total income (equivalized).[8] The full results are available in the appendix.

FIGURE 1: Time series of unfair and overall labor income inequality by country



Note: No time series for Iceland and Luxembourg are shown because only one data-year is available, respectively.

Figure 1 plots estimated unfair inequality. The aim is to show how unfair inequality is distributed among countries and over time. The figure also includes overall inequality (specifically the conventional Gini index of personal labor income among the working-age population in dependent employment; i.e. the same income type and population unfair inequality is estimated from). This allows for a direct comparison of how adjusting the Gini according to distributive fairness affects the results. Figure 1 shows that unfair inequality varies considerably between countries, with the Netherlands having the lowest and Israel the highest values. Furthermore, unfair inequality is consistently lower than overall inequality because a proportion of overall inequality results from individual merit.[9]

[8] People with zero income are excluded from the estimation sample, and LIS personal and household weights are used in each case. Furthermore, household income is equivalized by dividing it by the square root of household members. The aim is to make incomes comparable between households of different size.

[9] It is principally possible that unfair inequality is higher than overall inequality, but this would require that the deviation of actual incomes from perfect equality is smaller than the deviation of actual incomes to fair incomes. This seems like an unlikely scenario because it could only result from grossly unequal returns to labor-related merits and thus labor markets with barely functioning labor pricing.

FIGURE 2: Scatterplot of unfair and overall labor income inequality

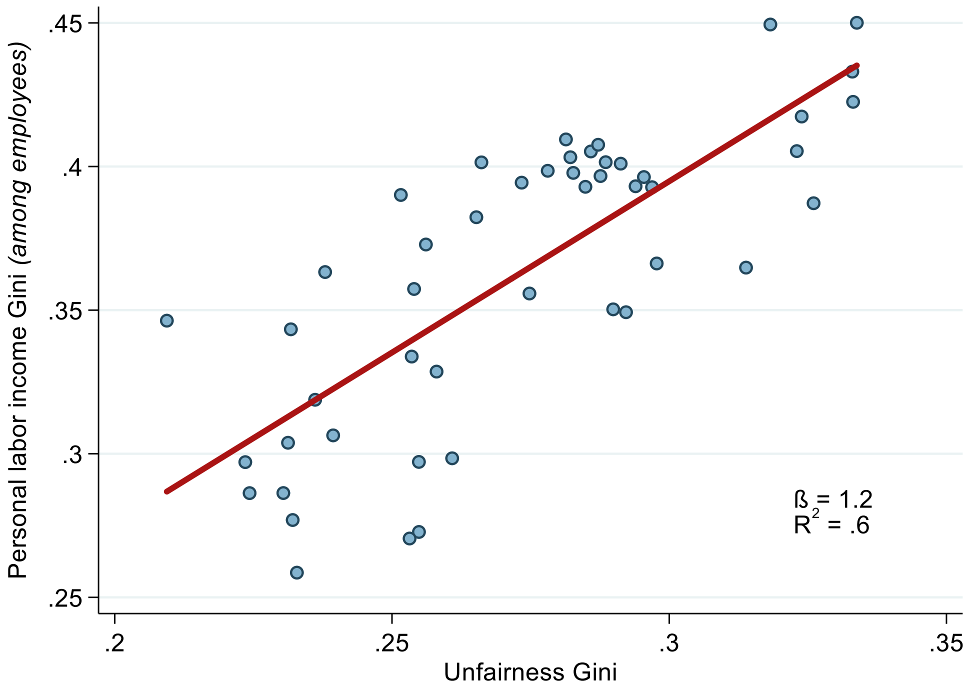


Figure 2 explores the relationship between unfair and overall inequality by depicting a scatterplot with linear fit. It becomes evident that higher overall inequality is associated with higher unfair inequality, but the relationship is not perfect (R^2=.6). As expected, unfair inequality is not given by a fixed proportion of overall inequality. This implies that unfair and overall inequality are related but distinct concepts.

4.4 Is the unfairness Gini a valid measure?

The main empirical analysis, where redistribution preferences are regressed on the unfairness Gini, crucially relies on the assumption that the unfairness Gini is a valid measure of experienced unfairness. This subsection assesses critically whether this assumption is reasonable. It proceeds in two steps. Critiques that can be raised from a theoretical perspective are discussed first; thereafter, the unfairness Gini is validated using empirical data.

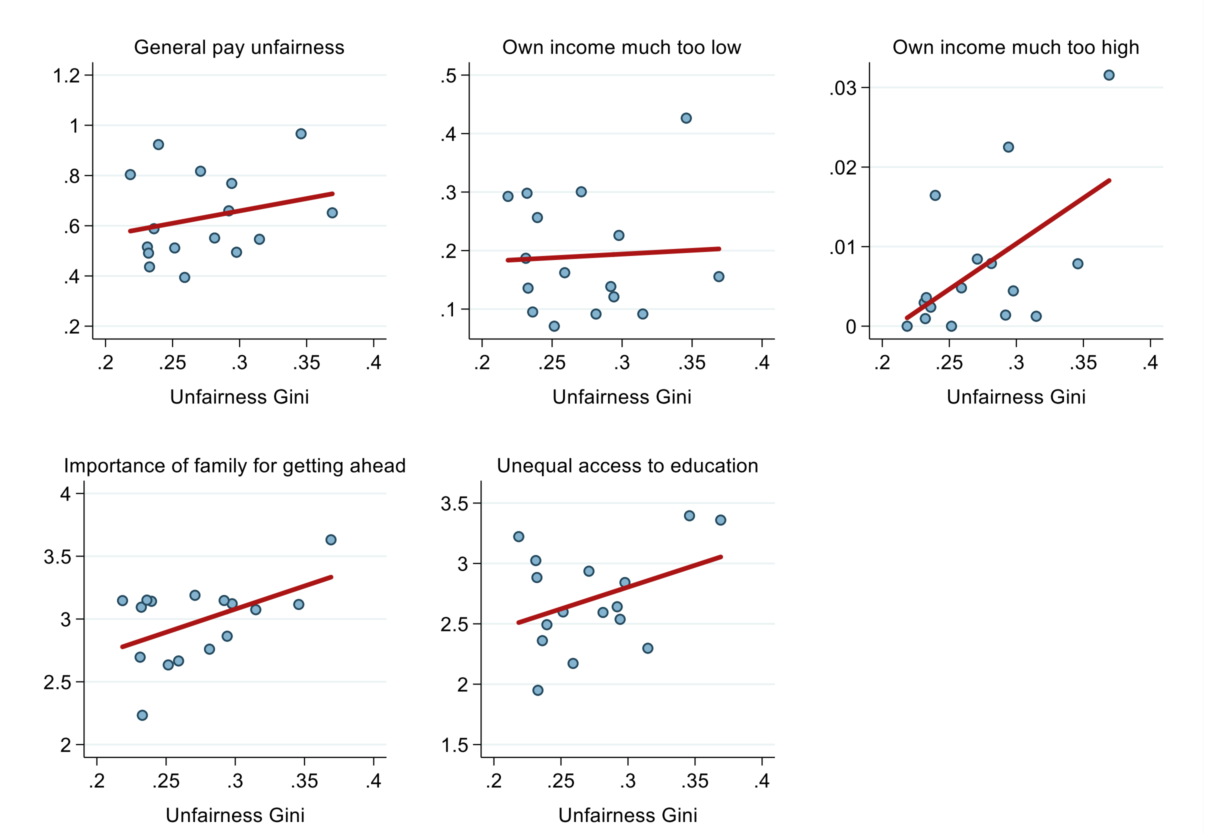
Two critiques can be raised against the quantification of unfair inequality from a theoretical perspective. Firstly, one may question the indicator because it only registers inequality as unfair when people have unequal returns to characteristics defined as merits even though the populace may consider certain returns to be exorbitantly low or high. For example, do people with a university degree really deserve that, on average, they enjoy a sizable income advantage compared to those with non-tertiary education? The proposed unfair inequality measure cannot consider this question. It will only consider inequality as unfair when people with the same occupational attributes (such as a university degree) do not enjoy the same returns to these attributes.

I acknowledge this critique but argue that the unfair inequality measure is nonetheless valid because it assesses the backbone of income fairness, i.e. non-discrimination. There is more to income fairness than non-discrimination, but non-discrimination is fundamental. Returning to the example, people may not always agree that people with a university degree really deserve their high income, but it is likely that all agree that, *ceteris paribus*, degree holders should at least be treated equally in order to satisfy baseline distributional fairness. Furthermore, I expect that the critique has less bite than one may assume. Income fairness is not judged relative to an abstract standard of how much individuals with certain merits ought to earn in absolute terms. Individuals rather adapt their perception of how large income differentials should be to what they observe in reality (Trump, 2018).

The second critique is that the choice of merits and circumstances may seem questionable. Is it sensible to lump labor-related variables together and define them all as legitimizing sources of inequality? Would it not be preferable to arrive at a more fine-grained definition of what labor-related characteristics legitimize inequality, for example by refraining from defining employment in the public vs. the private sector as a merit? I acknowledge that the choice to use all labor-related characteristics as merits is debatable. However, I argue that it is necessary in the context of the macro view that this study takes to follow such a minimalist conceptualization of distributive fairness. The empirical analysis covers 16 countries, and it should be expected that they have different conceptions of income fairness, for example because one country supports seniority-based income advantages more than another. It would be impossible to justify a more sophisticated model that reflects these differences due to the cross-country perspective. However, the proposed minimalist conceptualization of income fairness is a feasible strategy. The fundamental fairness principle that, *at least*, individuals with similar labor-related characteristics should receive a similar income should find broad support in all countries under consideration.

Moving on to the empirical validation of the measure, the goal is to assess whether higher values of the unfairness Gini empirically coincide with increased perceptions of experienced income unfairness. Such an analysis is difficult to implement because data on perceived income unfairness is unavailable in the European Social Survey, which will be used in the main analysis. To offer an empirical validation nonetheless, individual-level data from the 2009 Social Inequality module of the International Social Survey Programme (ISSP) will be used, which contain commonly used unfairness perceptions. Using all available data, sixteen additional datapoints of the unfairness Gini are quantified using LIS data and subsequently merged to the ISSP. Figure 3 plots the relationship between the unfairness Gini and country-level means of five different income unfairness perceptions. Detailed data and variable descriptions are available in Table A2 in the appendix.

FIGURE 3: Empirical validation of the unfairness Gini



Note: The figure plots bivariate relationships between the unfairness Gini and country-level means of different income fairness perceptions. The fairness perceptions are based on the 2009 social inequality module of the ISSP. Data, sample, and variable descriptions are available in the appendix.

Figure 3 reveals that income unfairness according to the unfairness Gini generally coincides with unfairness perceptions on the individual level. In countries with a higher unfairness Gini, people think that ethical and actual labor remuneration diverges more and the proportion of individuals who see their income as much higher than deserved is larger. Likewise, the proportion of people who think that their income is much lower than deserved is also larger, but this relationship is weaker than in the other plots. Furthermore, the unfairness Gini correlates positively with perceptions that circumstances rather than merits determine who flourishes (specifically, the importance of a strong family background and unequal access to education). The results thus suggest that the unfairness Gini indeed taps into individuals' unfairness perceptions. However, it must be stressed that this validation is less perfect than one would prefer because it is only based on 16 countries and uses a different country-year sample than the main analysis.

5 Data and methods for the main analysis

In a next step, the unfair and overall inequality variables are merged to multiple waves of the European Social Survey (2002-2014) to estimate their effect on individual redistribution preferences with multilevel models. The ESS offers high-quality datasets used commonly in redistribution preference research. ESS data rather than other available datasets such as the ISSP are used because the ESS has a vastly superior cross-sectional and longitudinal coverage, which is necessary to reach an acceptable higher-level sample size. The choice of ESS country-waves depends on mutual availability with LIS data, which is assessed in a mutual exclusion process. All country-years with data from both the ESS and LIS that contain all crucial variables are included. Since multilevel models require a sufficient higher-level sample size, it was necessary in some cases to use LIS data from country-years preceding the ESS data by one year (see the appendix, Table A3). This should not influence the results because of the high autocorrelation of labor market fundamentals. The selection process results in a sample of 48 country-years from 16 European countries. Akin to the populations used to estimate unfair inequality, the ESS samples are restricted to working-age individuals (16-65) in dependent employment. The rationale is that it is primarily individuals in dependent employment who *(a)* have the relevant information to gauge income fairness among employees and *(b)* who react to income fairness among employees.

The dependent variable is the demand for redistribution. Individuals indicated their support for the following statement on a five-point scale: "The government should reduce differences in income levels", which I recode onto a scale from zero to one where higher values indicate increased support. This variable is commonly used in studies on redistribution preferences (e.g., Finseraas, 2009; Jæger, 2013; Schmidt-Catran, 2016).

Concerning the individual controls, I firstly use left-right ideology as measured by respondents' self-assessment on an 11-point left-right scale centered around zero. Secondly, I include net household income, which is found to be strongly associated with redistribution preferences (e.g., Alesina and La Ferrara, 2005; Finseraas, 2009; Schmidt-Catran, 2016). Income is inconsistently measured as either absolute or relative categories in the ESS data. I recode the variable to country-specific quintiles following the approach of Schmidt-Catran (2016, p. 127). Furthermore, research shows that individuals support redistribution as a social insurance scheme. Those who expect to lose income in the future tend to increase support while those who expect to gain decrease support (Alesina and La Ferrara, 2005). Following Rehm (2009), I use the occupation-specific unemployment rate[10] to capture the objective unemployment risk. The remaining control variables are the highest level of education, age, a gender dummy, and household size (logged). Lastly, I include ESS-wave dummies indicating from which data wave the data stem (Fairbrother, 2014).

The data have a three-level hierarchical structure with individuals on level one, country-years on level two, and countries on level three. The goal is to assess the impact of a country-year-level variable, i.e. unfair inequality, on individual redistribution preferences. Thus, I employ multilevel models with random intercepts for both country-years and countries, treating the dependent variable as continuous. Multilevel models allow the researcher to *(a)* regress micro-level variables on macro-level variables and *(b)* to analyze hierarchical data without invalidating hypothesis tests (Hox, 2010). The advantage of the model is that the impact of macro-level variables can be assessed while controlling for individual characteristics.

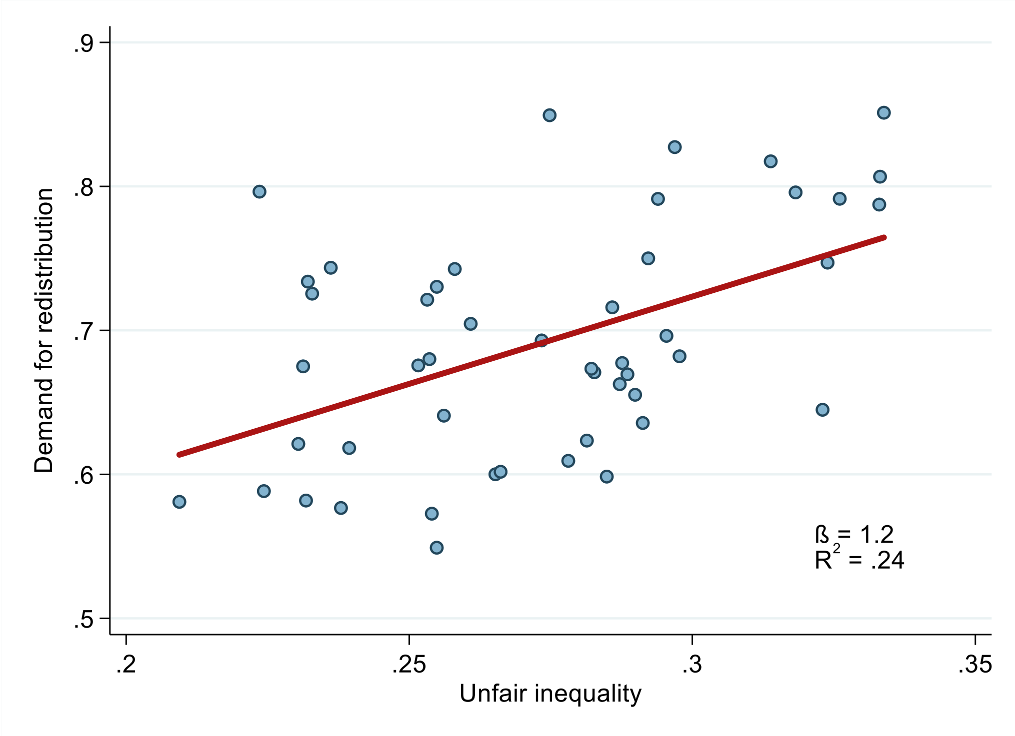
6 Results

This section reports the results from several multilevel models. The analysis is conducted in three steps. A first set of regressions considers the relationship between unfair inequality and redistribution support. A second set of regressions subsequently compares the explanatory power of unfair inequality with the explanatory power of several measures of overall inequality, each based on a different definition of income type and baseline population. The third step analyzes the cross-sectional and longitudinal variance of unfair inequality separately. All regression models use a common sample of 31,309 individuals. Unless stated otherwise, the data are weighted according to the post-stratification weight of the ESS,[11] and the standard errors are derived from the observed information matrix (i.e. model-based standard errors).

[10] Occupation-specific unemployment is estimated separately for each country-wave from the ESS data. It is based on the 1-digit ISCO-08 classification of occupations.

[11] Post-stratification weights aim to remove both sample error and non-response bias.

FIGURE 4: Scatterplot of unfair inequality and mean redistribution support



6.1 Relationship between unfair inequality and demand for redistribution

Figure 4 plots the bivariate relationship between unfair inequality and mean redistribution support on the country-year level. The results indicate a positive relationship. Unfair inequality explains 24% of the variance in redistribution support on the country-year level, which is considerable given that preference formation is complicated and there should be multiple other factors driving variance.

The results of a first set of regressions are displayed in Table 1. All four models assess the relationship between unfair inequality and the demand for redistribution. Model 1 only contains unfair inequality. Model 2, the main specification, then introduces all control variables. In both cases, unfair inequality has a positive and highly significant coefficient, which supports Hypothesis 1. The coefficient from Model 2 indicates that the demand for redistribution increases by 0.06 across its zero-to-one range when unfair inequality increases by two standard deviations.[12] This is roughly the same as the difference in redistribution support between the first and fourth income quintile. Therefore, the effect of unfair inequality is not only significant in a statistical but also in a substantive sense.

Unfortunately, the country-level sample size is smaller than one would prefer (*N*=16), which in the worst case is associated with a high type I error rate due to deflated standard errors (Maas and Hox, 2004; Stegmueller, 2013). Deflated standard errors are not necessarily an issue because the estimates rely on 48 country-years of unfair inequality, which is above the recommended higher-level sample size. There is, however, remarkable intra-country correlation of unfair inequality and it should thus be excluded that my inferences are biased by deflated standard errors. Model 3 thus uses robust standard errors clustered by countries, which prevent error deflation but are inefficient when the number of clusters is low (Maas and Hox, 2004); and Model 4 uses standard errors corrected for denominator degrees of freedom, which have recently been shown to deal with biased standard errors (see Elff *et al.*, 2020). The results of Models 3 and 4 show that unfair inequality retains its positive and highly significant coefficient.

[12] Unfair inequality has a standard deviation of 0.032.

TABLE 1: The effect of unfair inequality on redistribution preferences

	(1)	(2)	(3)	(4)
Unfair inequality	0.94***	1.02***	1.02***	0.95***
	(0.32)	(0.27)	(0.18)	(0.29)
Left-right		-0.02***	-0.02***	-0.02***
		(0.00)	(0.00)	(0.00)
Gender (ref.: female)		-0.03***	-0.03***	-0.03***
		(0.00)	(0.00)	(0.00)
Age		0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)
Occupational risk		0.52***	0.52***	0.52***
		(0.06)	(0.15)	(0.06)
Education				
Below secondary		ref.	ref.	ref.
Lower secondary		-0.00	-0.00	-0.00
		(0.01)	(0.01)	(0.01)
Upper secondary		-0.01	-0.01	-0.00
		(0.01)	(0.01)	(0.01)
Post-secondary		-0.02**	-0.02*	-0.02*
		(0.01)	(0.01)	(0.01)
Tertiary		-0.05***	-0.05***	-0.04***
		(0.01)	(0.01)	(0.01)
Income				
1st income quintile		ref.	ref.	ref.
2nd income quintile		-0.01**	-0.01***	-0.02***
		(0.01)	(0.00)	(0.01)
3rd income quintile		-0.03***	-0.03***	-0.04***
		(0.01)	(0.01)	(0.01)
4th income quintile		-0.05***	-0.05***	-0.06***
		(0.01)	(0.01)	(0.01)
5th income quintile		-0.10***	-0.10***	-0.11***
		(0.01)	(0.01)	(0.01)
Household size (log)		0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)
Constant	0.44***	0.37***	0.37***	0.39***
	(0.09)	(0.08)	(0.05)	(0.09)
Model	RI-ML	RI-ML	RI-ML	RI-ML
Year fixed effects	No	Yes	Yes	Yes
Standard errors	OIM	OIM	Robust	DF-adjust
Weighted	Yes	Yes	Yes	No
Observations	31,309	31,309	31,309	31,309
Number of countries	16	16	16	16
Number of country-years	48	48	48	48

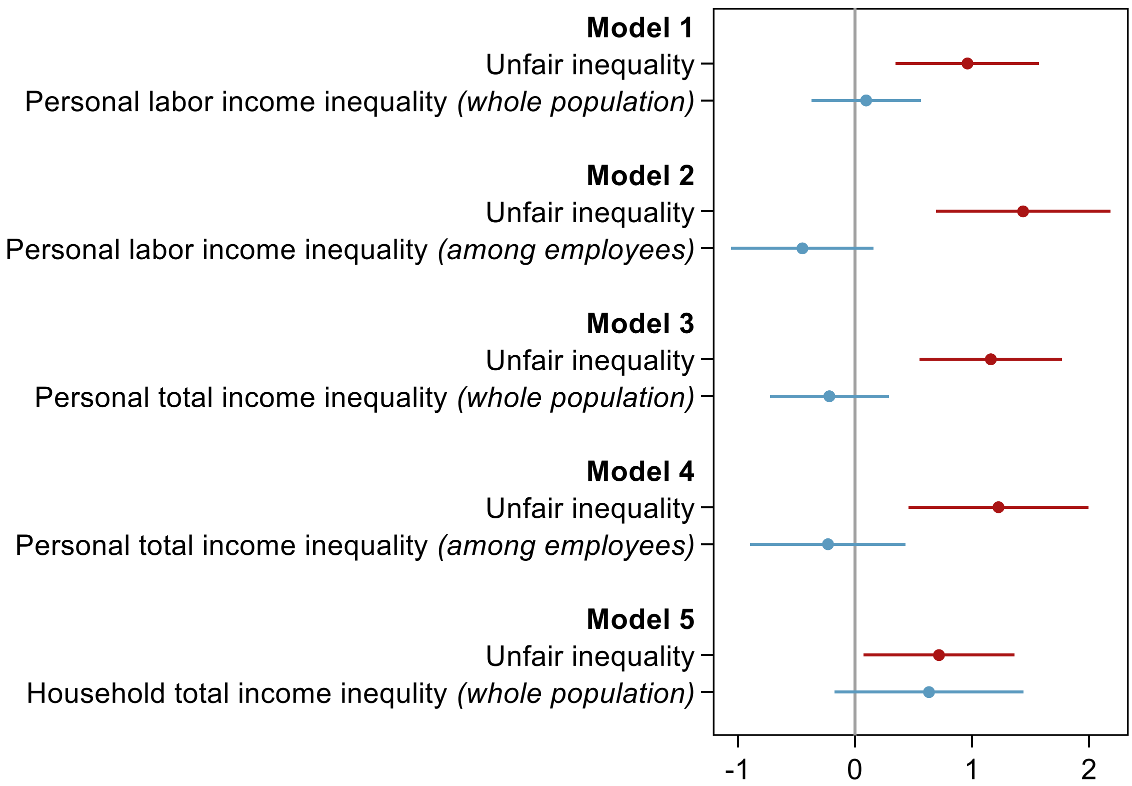
Note: Standard errors in parentheses. * p<.1 ** p<.05 *** p<.01. *RI-ML* refers to a random intercept multilevel model. *OIM* refers to standard errors derived from the observed information matrix, *Robust* to robust standard errors clustered by countries, and *DF-adjust* to degrees-of-freedom adjusted standard errors following the approach of Elff *et al.* (2020).

The results are corroborated by additional robustness checks based on the main specification (i.e. Model 2 from Table 1). Full regression results are available in Table A5 of the appendix. A first robustness check drops the control variable *left-right ideology* because of possible endogeneity with redistribution preferences. Secondly, a model with random slopes for all variables is estimated because the effect of the control variables and unfair inequality may vary considerably across countries. Thirdly, the regression is re-estimated without the post-stratification weights. All robustness estimates still yield a positive and highly significant coefficient for unfair inequality. Lastly, it is checked whether the results depend on the inclusion of certain countries in the sample. The main specification is re-estimated 16 times, dropping one of the included countries each time.[13] The resulting coefficients remain stable (varying between 0.9 and 1.1) and are each significant at a $p<0.01$ level. Overall, there is thus strong support for Hypothesis 1. The demand for redistribution is higher when there is stronger unfair inequality.

6.2 Comparison with simple inequality measures

The second set of regressions assesses Hypothesis 2, which states that unfair inequality affects redistribution preferences to a stronger degree than overall inequality. This is achieved by evaluating the relative explanatory power of the unfairness Gini and common variants of the Gini index that measure overall inequality, i.e. the deviation of realized incomes from perfect equality. Unfair inequality is checked against five measures of overall inequality based on the following income types and populations: (1) personal gross labor income among the whole population, (2) personal gross labor income among the working-age population in dependent employment (i.e. the same population used to estimate unfair inequality), (3) personal gross total income among the whole population, (4) personal gross total income among the working-age population in dependent employment, and (5) household gross total income (equivalized).

FIGURE 5: Relative explanatory power of different Gini variants



Note: The figure plots coefficients of regressions using the demand for redistribution as the dependent variable. The grey bars represent 95% confidence intervals. All models also include the full set of control variables. See the online appendix for full results.

Figure 5 depicts the results of several multilevel regressions that each include unfair inequality in addition to one of the five measures of overall inequality (as well as all control variables). The results show that it does not matter whether unfair inequality is entered into a common model with overall inequality

[13] The full results are available upon request.

of labor income or total income; whether overall inequality on the personal or household level is considered; and whether the population among which overall inequality is measured is restricted to the same population used to estimate unfair inequality or not. In every model, unfair inequality retains is positive and significant coefficient even though overall inequality measures are included in the same model. Furthermore, all overall inequality measures are insignificant and mostly have negligible effect sizes that are vastly smaller than the effect size of unfair inequality. However, there is one exception, namely overall inequality of total household income. Unfair inequality retains its positive and significant coefficient while overall inequality of household income has a smaller and insignificant coefficient when both are entered in the same model. But strictly speaking, the two coefficients are indistinguishable in size due to their overlapping confidence intervals.

The inconsistent results may emerge from the differing applicability of income fairness norms to personal and household income inequality (remember that only Model 5 compared the effect of unfair inequality to a measure of *household* income inequality). The fairness principle of input-output-proportionality is directly applicable to personal income. For example, it is widely supported that those who work more receive a higher personal income. I expect that, for this reason, unfair inequality consistently trumps naïve measures of overall inequality when the personal income level is considered. In contrast, income fairness is more obscure when it comes to household income inequality since it should generally be accepted that incomes are shared within households. To return to the example, consider that our hardworking person has a spouse who is not in the labor force. While it is considered as fair that this spouse has no *personal* income, it will also be accepted that the spouse bears the fruits of their partner's efforts. Fairness norms therefore follow different logics regarding personal and household income, and a quantification of unfair inequality appropriately applied to household income would be better suited for a comparison to overall household inequality.

Overall, the results offer support for Hypothesis 2, which expected that unfair inequality is more influential for redistribution preferences that overall inequality. There are some caveats regarding the comparison to household income inequality, but it remains difficult to compare the implications of unfair inequality of personal income to those of overall inequality of household income. Furthermore, the results further strengthen Hypothesis 1, which simply expected that unfair inequality is positively related to redistribution preferences.

6.3 Disaggregation into longitudinal and cross-sectional variance

The previous sections established that there is a relationship between unfair inequality and redistribution preferences that is independent from overall inequality. This section analyzes to what extent the relationship results from cross-sectional or longitudinal variance of unfair inequality. Distinguishing between longitudinal and cross-sectional variance is possible because the estimation sample consists of repeated cross-sections, at least for most countries.[14] Unfair inequality and the demand for redistribution thus vary *within* and *between* countries. Fairbrother (2014) proposes a method to analyze cross-sectional- and longitudinal variance separately. It is implemented by generating two variants of the unfair inequality variable: Between-variance is captured by a variable measuring country-specific means of unfair inequality; and within-variance is captured by intra-country deviations from country-specific means, which is akin to the approach commonly used to implement unit fixed effects in panel models.[15]

[14] There are, e.g., biannual data between 2002 and 2012 for Germany.

[15] More formally, between-variance is assessed with the following variable: $X_c^{BE} = \bar{X}_c$, whereas the subscript *c* denotes countries; and within-variance with: $X_{ct}^{WE} = X_{ct} - \bar{X}_c$, where *t* denotes time.

TABLE 2: Within- and between decomposition of unfair inequality (selected results)

	(1)	(2)	(3)	(4)	(5)
Unfair inequality (within)	0.83**	0.97***	0.97***	0.88**	0.83***
	(0.38)	(0.32)	(0.25)	(0.35)	(0.27)
Unfair inequality (between)	1.21**	1.16**	1.16**	1.14*	
	(0.61)	(0.52)	(0.49)	(0.54)	
All controls included	No	Yes	Yes	Yes	Yes
Model	RI-ML	RI-ML	RI-ML	RI-ML	FE
Year fixed effects	No	Yes	Yes	Yes	Yes
Standard errors	OIM	OIM	Robust	DF-adjust	Robust
Weighted	Yes	Yes	Yes	No	No

Note: All models analyze a sample of 31,309 observations from 48 country-years. Standard errors in parentheses. * p<.1 ** p<.05 *** p<.01. *RI-ML* refers to a random intercept multilevel model and *FE* to a fixed effects panel model. *OIM* refers to standard errors derived from the observed information matrix, *Robust* to robust standard errors clustered by countries, and *DF-adjust* to degrees-of-freedom adjusted standard errors following the approach of Elff *et al.* (2020). Full regression results are available in Table A6 in the online appendix.

Table 2 reports selected results of several regression models analyzing cross-sectional and temporal variance separately. Only the estimated coefficients of the within- and between-variants of unfair inequality are shown while the full results are available in the appendix. Model 1 only contains the unfair inequality variables and Model 2, the main specification, additionally includes all control variables. As expected, both the within- and the between-variants of unfair inequality are positive and significant, which offers further support for Hypothesis 1. The effect sizes from Model 2 indicate that the demand for redistribution increases by 0.025 across its zero-to-one range when the within-variant of unfair inequality increases by two standard deviations and by 0.065 when the between-variant increases by two standard deviations.[16] The between-variant thus has a fairly strong effect (again comparable to the difference in redistribution support between the first and fourth income quintiles) and the within-variant a moderate effect, which is roughly comparable to the difference between the first and third income quintiles.

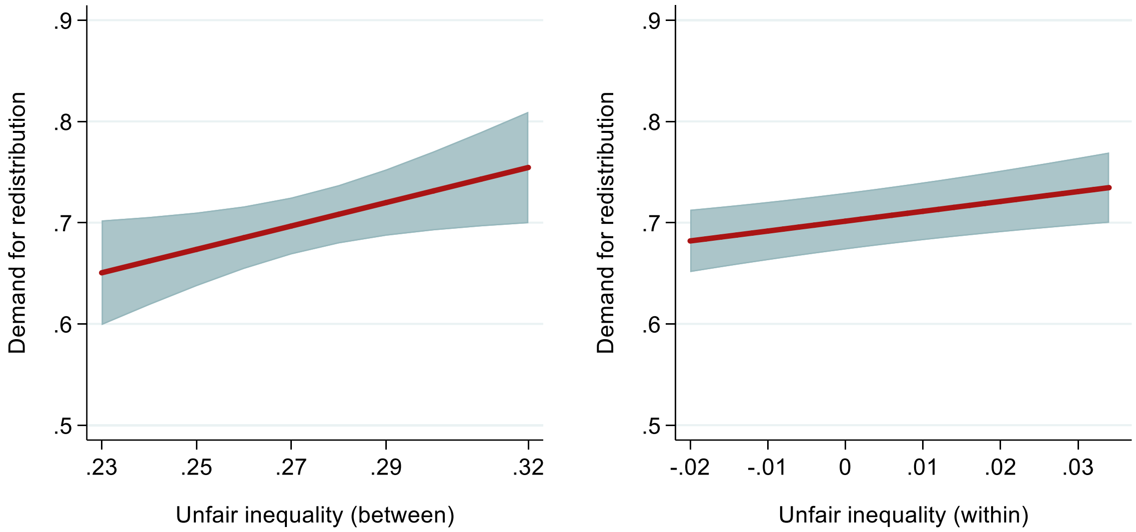
Models 3 and 4 re-assess the results using cluster-robust and degrees-of-freedom adjusted standard errors (see above). Both the within- as well as the between-variant of unfair inequality remain to be positive and significant. Lastly, Model 5 uses a standard fixed effects panel specification that relies solely on intra-country variance of unfair inequality.[17] Again, the results remain unchanged, which supports the validity of the strict exogeneity assumption required for the initial random intercept specifications (uncorrelated independent variables and errors) since fixed effects models do not make this assumption. The estimated coefficient of unfair inequality is therefore not biased by country-specific time-invariant confounders.

The results are corroborated with additional robustness checks (available in Table A5 in the appendix). Again, the robustness checks drop the control variable *left-right ideology*, repeat the estimations with unweighted data, and estimate random slopes for all variables, all of which leave the results unchanged. Furthermore, the main specification (Model 2 in Table 2) is re-estimated 16 times, dropping one of the included countries each time.[18] The results regarding the within-variant of unfair inequality remain stable with coefficients that vary between 0.8 and 1.1 and p-values that consistently stay below 0.05. The between-variant also keeps a fairly stable coefficient (0.9-1.4), but p-values drop below 0.1 in three cases, with a maximum p-value of 0.13. This does not come as a major surprise because, after all, results regarding the between-variant rely on only sixteen unique observations; and besides that, the opposite result also holds: p-values decrease in several cases and reach the $p<0.01$ threshold in two of them. Overall, there is strong and consistent evidence for a within-association between unfair inequality

[16] The within-variant has a standard deviation of 0.01 and the between-variant of 0.03.
[17] Serially correlated errors are dealt with via cluster-robust standard errors.
[18] Again, the full results are available upon request.

and the demand for redistribution; most likely owing to the low sample size, there is also less strong evidence for a between-association. These results offer further support for Hypothesis 1. They imply that both *(a)* countries with higher unfair inequality have stronger redistribution preferences and *(b)* that countries that increase their unfair inequality over time develop stronger redistribution preferences. It is a particularly strong result that the estimated coefficients of both unfair inequality variables have very similar coefficient sizes in all specifications.

FIGURE 6: Between- and within- effects of unfair inequality



Note: The marginal effects are calculated from Model 2 in Table 2. The areas represent 95% confidence intervals.

Figure 6 plots predicted redistribution preferences by observed values of the between- and within-variant of unfair inequality. Resulting values of redistribution support increase from 0.67 to 0.73 (within-variant) and from 0.65 to 0.76 (between-variant) across the whole range of observed values.[19] I conclude that unfair inequality is substantially consequential for individuals' demand for redistribution.

7 Discussion and conclusion

I argued that the effect of objective income inequality depends on its unfairness, i.e. whether income differences cannot be explained by differences in labor-related merits. It is primarily unfair inequality that affects the demand for redistribution rather than overall inequality. The results of the quantitative analysis line up with this expectation. An empirical quantification of unfair inequality is associated positively with redistribution preferences. Countries with higher unfair inequality have stronger redistribution preferences (although this result is associated with a degree of uncertainty), and countries where unfair inequality rises over time display rising redistribution preferences. Secondly, unfair inequality has superior predictive power compared to overall inequality.

How does this study compare to related research in political economy? In the tradition of the discipline, I argue that objective inequality increases redistribution support. However, the present study stands in obvious contrast with classical rational choice approaches (e.g., Jæger, 2013; Johnston and

[19] The range of predicted redistribution support values is larger for the between-variant even though the between- and within-variants have similar coefficients similar because there is a wider range of empirically observed values of the between-variant.

Newman, 2015; Schmidt-Catran, 2016). Like some of these studies, I find a positive impact of inequality, but my approach differs in its theoretical foundation, which focuses on fairness norms, and its customized inequality indicator, which aims to measure unfair rather than overall inequality. My approach is similar to Schmidt-Catran (2016), who also uses repeated cross-sections to assess the impact of between- and within-variance of inequality on redistribution support. Schmidt-Catran only finds a within-effect of overall inequality, whereas unfair inequality can explain between-variance as well. This discrepancy may merely result from different country-year samples, but I expect that it reflects the importance of addressing income fairness in theory and inequality measurement.

Furthermore, the present study is closely related to recent scholarship that also expects an impact of objective inequality due to other-regarding preferences (Cavaillé and Trump, 2015; Dimick *et al.*, 2017; Luebker, 2007; Lupu and Pontusson, 2011; Shayo, 2009). My approach is most similar to Dimick *et al.* (2017) and Luebker (2007), who also find that aggregate inequality increases redistribution support, at least once differences in distributive justice concerns across or within countries are accounted for. It contrasts most with studies that introduce the possibility that inequality may also *negatively* affect inequality aversion and redistribution support due to detrimental effects on social affinity (Cavaillé and Trump, 2015; Shayo, 2009) and people's ability to appreciate structural income differences (Mijs, 2019). A direct comparison is difficult because of varying inequality measures and country-year samples, but my empirical results suggest the opposite, namely that (unfair) inequality rather exerts a positive influence.

Overall, the present study underscores that objective inequality matters for individuals' redistribution support, and that people are driven by normative concerns about this inequality. Countries have more or less fair income distributions, and it is not always the case that more inequality means more unfairness and thus a stronger taste for redistribution. Whether people are averse to inequality crucially depends on the empirical realization of distributive fairness. At the same time, this study is not without limitations. It was shown that the quantified unfairness Gini is positively associated with redistribution preferences, but it remains an assumption that this relationship can indeed be explained by people's fairness perceptions. It is required that *(a)* the unfairness Gini is a valid measure of how unfairly people are treated, *(b)* people's unfairness perceptions are triggered by this conception of unfairness, and *(c)* that, in the aggregate, people's unfairness perceptions are not fundamentally biased in the same way their beliefs regarding overall inequality are biased. Supportive theoretical arguments and empirical evidence have been presented to substantiate these claims, but they remain assumptions nonetheless.

Future research should be conscious about what part of inequality is accepted by the public and what part of inequality is not. It will be fruitful to assess how other quantifications of realized income fairness relate to policy preferences, for example by using another fairness model specification for a different version of Almås *et al.*'s (2011) unfairness Gini. Furthermore, there are various quantifications of realized equality of opportunity (see Pignataro, 2012). As public opinion research shows (e.g., Alesina and La Ferrara, 2005; Fong, 2001), this is an influential fairness ideal that had to be disregarded in this study.

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Appendix

Table A1: Missing variables in the LIS income regressions

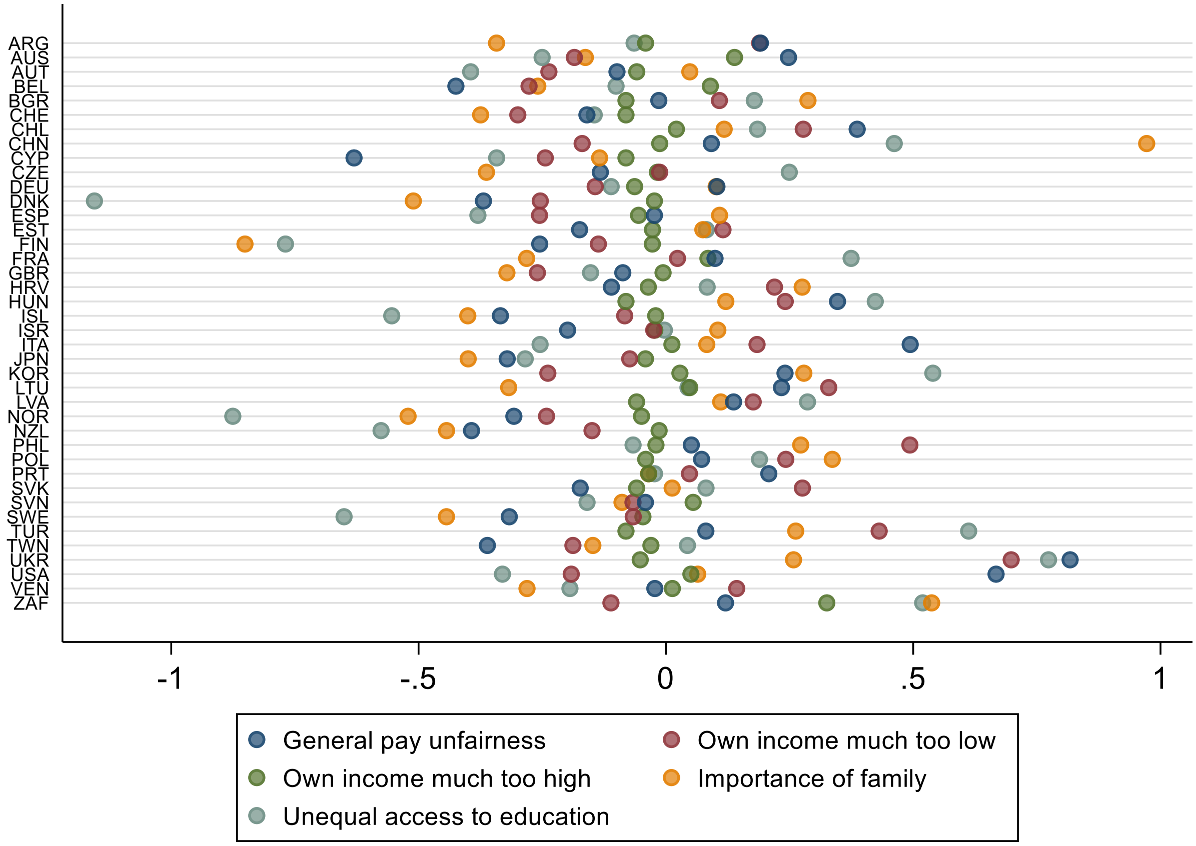
Country	Missing variables
Austria	Education father
Czech Republic	Education father, permanent employment dummy (only 2002)
Estonia	Education father (only 2007)
Finland	Immigrant dummy, education father
Germany	
Greece	Education father (only 2007)
Iceland	Region, education father
Ireland	Education father
Israel	Education father, permanent employment dummy
Lithuania	Immigrant dummy, education father
Luxembourg	Region, education father, rural place of living dummy
Netherlands	Region, education father, rural place of living dummy
Slovakia	
Spain	Education father (only 2007 & 2013)
Switzerland	Education father (only 2007 & 2013)
United Kingdom	Immigrant dummy, education father, permanent employment dummy (only 2004, 2007 & 2010), rural place of living dummy

Table A2: Data and variable description of empirical validation of the unfairness Gini

Data	2009 Social Inequality module of the International Social Survey Programme
Included countries (LIS data year in parentheses)	The following country-level sample resulted from a mutual exclusion process. Only countries are included which are represented in the ISSP data and for which the unfairness Gini could be estimated from a LIS dataset with temporal proximity to the ISSP data. The temporal match between the ISSP and LIS is unfortunately inferior to the match between ESS and LIS. Australia (2008), Austria (2007), Chile (2009), Czech Republic (2010), Estonia (2010), Finland (2010), Germany (2009), Hungary (2009), Iceland (2010), Italy (2008), Russia (2010), Slovakia (2010), South Africa (2008), Spain (2010), Switzerland (2010), United Kingdom (2010)

Sample	Working age population (18-65) in dependent employment
Var. 1: General pay unfairness	Summary measure. Respondents were asked to estimate what individuals in five professions actually earn and indicate what they should earn (the professions are unskilled workers, shop assistants, doctors in general practice, cabinet ministers, and chairmen of large corporations). In a first step, the magnitude of divergence between actual and ethical earnings is calculated for each profession. The value one indicates perfect congruence between actual and ethical earnings, whereas values above one show that actual earnings diverge from ethical earnings. A value of two, for example, shows that respondents think that a certain profession earns twice as much or half as much as it should. This divergence is averaged over all five professions. The variable is subsequently logged to deal with outliers and a heavily skewed distribution.
Var. 2: Own income is much too low	The proportion of respondents who answered “much less than just” to the following question: “Is your pay just? We are not asking about how much you would like to earn – but what you feel is just given your skills and effort”:
Var. 3: Own income is much too high	The proportion of respondents who answered “much more than just” to the following question: “Is your pay just? We are not asking about how much you would like to earn – but what you feel is just given your skills and effort”:
Var. 4: Importance of family for getting ahead	Unweighted average of responses to the following two questions. “To begin we have some questions about opportunities for getting ahead. Please tick one box for each of these to show how important you think it is for getting ahead in life.” “How important is coming from a wealthy family?” “How important is having well-educated parents?” Scale: 1-5
Var. 5: Unequal access to education	Unweighted average of responses to the following two questions. “To what extent do you agree or disagree with the following statements?” “In <R's country> only students from the best secondary schools have a good chance to obtain a university education.” “In <R's country> only the rich can afford the costs of attending university.” Scale: 1-5

Figure A1: Mean support of income unfairness perceptions across countries



Note: Figure 3 relies on the data and variables introduced in Table A2, whereas all countries available in the ISSP are included. To make the between-country variable comparable between countries, all variables are standardized across the whole dataset so that their mean equals zero and their standard deviation one.

Table A3: LIS and ESS datasets in use

Country	ESS 1	ESS 2	ESS 3	ESS 4	ESS 5	ESS 6	ESS 7
Austria		2004					2013
Czech Republic	2002	2004		2007	2010		2013
Estonia				2007	2010		
Finland				2007	2010		2013
Germany	2002	2004	2006	2008	2010	2012	2014
Greece				2007	2010		
Iceland		2004					
Ireland		2004		2007			
Israel	2001			2007	2010	2012	2014
Lithuania					2010		2013
Luxembourg		2004					
Netherlands		2004		2007	2010		2013
Slovakia		2004			2010		
Spain				2007	2010		2013
Switzerland				2007	2010		2013
United Kingdom		2004		2007	2010		2013

Note: The table displays which country-years of the unfairness Gini measure calculated from the LIS data are merged to which waves of the ESS data. The years in the cells indicate the data year from the LIS data. The ESS data refer to the following years: 2002 (ESS1), 2004 (ESS2), 2006 (ESS3), 2008 (ESS4), 2010 (ESS5), 2012 (ESS6), 2014 (ESS7). There are principally more datasets with mutual availability in the LIS and ESS, but in the remaining cases there were essential missing data in either LIS or ESS.

Table A4: Gini estimation results

Country	Year	Unfairness Gini	Personal labor income Gini (employee population)	Personal labor income Gini (whole population)	Personal total income Gini (employee population)	Personal total income Gini (whole population)	Household total income Gini (whole population)
AT	2004	0.2535626	0.384912	0.333839	0.382042	0.327691	0.318779
AT	2013	0.2939379	0.460317	0.393134	0.434938	0.36651	0.345628
CZ	2002	0.2548572	0.345051	0.297168	0.377822	0.276643	0.310341
CZ	2004	0.2304106	0.345511	0.286322	0.373841	0.269849	0.32144
CZ	2007	0.2243231	0.347601	0.286294	0.360067	0.269458	0.310123
CZ	2010	0.2312565	0.351019	0.303832	0.360266	0.287116	0.304068
CZ	2013	0.2393968	0.359877	0.3064	0.36019	0.294341	0.304639
EE	2007	0.2899007	0.522524	0.350278	0.451809	0.340014	0.366781
EE	2010	0.2977447	0.425344	0.366248	0.430095	0.351316	0.364659
FI	2007	0.2548706	0.430381	0.272776	0.396947	0.257545	0.330539
FI	2010	0.2328548	0.43575	0.258602	0.397698	0.246925	0.326078
FI	2013	0.2531793	0.438779	0.270492	0.392896	0.257552	0.325328

DE	2002	0.2652219	0.438528	0.382348	0.437221	0.367381	0.350805
DE	2004	0.2848896	0.445857	0.392944	0.43695	0.375152	0.355128
DE	2006	0.2912536	0.453217	0.401001	0.445822	0.38677	0.363362
DE	2008	0.2876091	0.448802	0.396694	0.441861	0.386094	0.363389
DE	2010	0.288545	0.45045	0.401516	0.439098	0.387574	0.35545
DE	2012	0.285867	0.449821	0.405254	0.438024	0.391026	0.358772
DE	2014	0.2733872	0.443336	0.394382	0.431486	0.380987	0.361616
GR	2007	0.2748025	0.445644	0.35579	0.434173	0.358334	0.374284
GR	2010	0.2235503	0.379271	0.297086	0.390024	0.298783	0.358092
IS	2004	0.2922138	0.42026	0.349285	0.39998	0.344604	0.306648
IE	2004	0.2954362	0.446623	0.39634	0.577649	0.370014	0.394469
IE	2007	0.2827006	0.462097	0.39779	0.568775	0.36894	0.373469
IL	2001	0.333025	0.442621	0.433035	0.442621	0.433035	0.421933
IL	2007	0.3238923	0.465922	0.417404	0.465922	0.417404	0.421403
IL	2010	0.3331662	0.474438	0.422516	0.474438	0.422516	0.437565
IL	2012	0.3338394	0.466593	0.450049	0.466593	0.450049	0.414343
IL	2014	0.3182458	0.46234	0.449443	0.46234	0.449443	0.404958
LT	2010	0.3260387	0.420645	0.387226	0.415025	0.374851	0.369248
LT	2013	0.3138558	0.441739	0.364808	0.437499	0.353142	0.389549
LU	2004	0.2561179	0.404068	0.372857	0.405345	0.367042	0.318625
NL	2004	0.2094011	0.444983	0.346339	0.426272	0.334101	0.325817
NL	2007	0.2539908	0.458033	0.357373	0.429937	0.342027	0.335707
NL	2010	0.2317674	0.446714	0.343328	0.41743	0.327791	0.320989
NL	2013	0.2379448	0.46513	0.363261	0.43532	0.349857	0.332952
SK	2004	0.2608595	0.32472	0.298421	0.35589	0.285325	0.318073
SK	2010	0.2320941	0.343685	0.276927	0.352092	0.267485	0.296377
ES	2007	0.258044	0.386857	0.328606	0.38475	0.320264	0.337691
ES	2010	0.2361435	0.373244	0.3188	0.389181	0.308636	0.351232
ES	2013	0.2969099	0.480747	0.392805	0.440284	0.373236	0.376915
CH	2007	0.2821779	0.447688	0.403235	0.434194	0.39116	0.3208
CH	2010	0.2516013	0.441719	0.390101	0.42099	0.374574	0.310442
CH	2013	0.2661356	0.446883	0.401452	0.424294	0.386262	0.311458
UK	2004	0.3230144	0.43904	0.405371	0.474585	0.399342	0.388095
UK	2007	0.2780944	0.430897	0.398523	0.484025	0.374722	0.384999
UK	2010	0.2813751	0.440507	0.409445	0.48042	0.382728	0.380897
UK	2013	0.2871877	0.435165	0.407576	0.456474	0.380169	0.375181

Table A5: Further robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Unfairness Gini	1.04***		0.95***		1.12***	
	(0.27)		(0.27)		(0.34)	
Unfairness Gini (within)		1.02***		0.87***		1.28**
		(0.32)		(0.31)		(0.54)
Unfairness Gini (between)		1.10**		1.13**		0.96**
		(0.51)		(0.51)		(0.43)
Left-right			-0.02***	-0.02***	-0.02***	-0.02***
			(0.00)	(0.00)	(0.00)	(0.00)
Gender (ref.: female)	-0.04***	-0.04***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Occupational risk	0.55***	0.55***	0.52***	0.52***	0.64***	0.64***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)
Education						
Below secondary	ref.	ref.	ref.	ref.	ref.	ref.
Lower secondary	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Upper secondary	-0.01	-0.01	-0.00	-0.00	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post-secondary	-0.02*	-0.02*	-0.02*	-0.02*	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tertiary	-0.04***	-0.04***	-0.04***	-0.04***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income						
1st income quintile	ref.	ref.	ref.	ref.	ref.	ref.
2nd income quintile	-0.01**	-0.01**	-0.02***	-0.02***	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3rd income quintile	-0.03***	-0.03***	-0.04***	-0.04***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
4th income quintile	-0.05***	-0.05***	-0.06***	-0.06***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5th income quintile	-0.11***	-0.11***	-0.11***	-0.11***	-0.10***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size (log)	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.37***	0.35**	0.40***	0.34**	0.34***	0.39***
	(0.08)	(0.14)	(0.08)	(0.14)	(0.10)	(0.12)
Model	RI-ML	RI-ML	RI-ML	RI-ML	RS-ML	RS-ML
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	OIM	OIM	OIM	OIM	OIM	OIM
Weighted	Yes	Yes	No	No	Yes	Yes
Observations	31,309	31,309	31,309	31,309	31,309	31,309
Number of countries	16	16	16	16	16	16
Number of country-years	48	48	48	48	48	48

Note: Standard errors in parentheses. * p<.1 ** p<.05 *** p<.01. RI-ML refers to a random intercept multilevel model and RI-MS to a random slope multilevel model (random intercepts are also included here). OIM refers to standard errors derived from the observed information matrix

Table A6: Relative effect of other Gini measures

	(1)	(2)	(3)	(4)	(5)
Unfairness Gini	0.96***	1.43***	1.16***	1.22***	0.72**
	(0.31)	(0.38)	(0.31)	(0.39)	(0.33)
Personal labor income Gini (full sample)	0.09				
	(0.24)				
Personal labor income Gini (employee sample)		-0.45			
		(0.31)			
Personal total income Gini (full sample)			-0.22		
			(0.26)		
Personal total income Gini (employee sample)				-0.23	
				(0.34)	
Household total income Gini (full sample)					0.63
					(0.41)
Left-right	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gender (ref.: female)	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Occupational risk	0.52***	0.52***	0.52***	0.52***	0.52***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Education					
Below secondary	ref.	ref.	ref.	ref.	ref.
Lower secondary	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Upper secondary	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post-secondary	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tertiary	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income					
1st income quintile	ref.	ref.	ref.	ref.	ref.
2nd income quintile	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3rd income quintile	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
4th income quintile	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5th income quintile	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size (log)	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.35***	0.41***	0.42***	0.39***	0.24**
	(0.10)	(0.09)	(0.10)	(0.09)	(0.12)
Model	RI-ML	RI-ML	RI-ML	RI-ML	RI-ML
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Standard errors	OIM	OIM	OIM	OIM	OIM
Weighted	Yes	Yes	Yes	Yes	Yes
Observations	31,309	31,309	31,309	31,309	31,309
Number of countries	16	16	16	16	16
Number of country-years	48	48	48	48	48

Note: Standard errors in parentheses. * p<.1 ** p<.05 *** p<.01. RI-ML refers to a random intercept multilevel model. OIM refers to standard errors derived from the observed information matrix.

Table A7: Within- and between decomposition of unfair inequality

	(1)	(2)	(3)	(4)	(5)
Unfairness Gini (within)	0.83**	0.97***	0.97***	0.88**	0.83***
	(0.38)	(0.32)	(0.25)	(0.35)	(0.27)
Unfairness Gini (between)	1.21**	1.16**	1.16**	1.14*	
	(0.61)	(0.52)	(0.49)	(0.54)	
Left-right		-0.02***	-0.02***	-0.02***	-0.02***
		(0.00)	(0.00)	(0.00)	(0.00)
Gender (ref.: female)		-0.03***	-0.03***	-0.03***	-0.03***
		(0.00)	(0.00)	(0.00)	(0.00)
Age		0.00***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)
Occupational risk		0.52***	0.52***	0.52***	0.53***
		(0.06)	(0.15)	(0.06)	(0.18)
Education					
Below secondary		ref.	ref.	ref.	ref.
Lower secondary		-0.00	-0.00	-0.00	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)
Upper secondary		-0.01	-0.01	-0.00	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)
Post-secondary		-0.02**	-0.02*	-0.02*	-0.02
		(0.01)	(0.01)	(0.01)	(0.01)
Tertiary		-0.05***	-0.05***	-0.04***	-0.05***
		(0.01)	(0.01)	(0.01)	(0.01)
Income					
1st income quintile		ref.	ref.	ref.	ref.
2nd income quintile		-0.01**	-0.01***	-0.02***	-0.02***
		(0.01)	(0.00)	(0.01)	(0.00)
3rd income quintile		-0.03***	-0.03***	-0.04***	-0.03***
		(0.01)	(0.01)	(0.01)	(0.01)
4th income quintile		-0.05***	-0.05***	-0.06***	-0.05***
		(0.01)	(0.01)	(0.01)	(0.01)
5th income quintile		-0.10***	-0.10***	-0.11***	-0.10***
		(0.01)	(0.01)	(0.01)	(0.01)
Household size (log)		0.01***	0.01***	0.01***	
		(0.00)	(0.00)	(0.00)	
Constant	0.37**	0.33**	0.33**	0.34**	0.65***
	(0.17)	(0.14)	(0.14)	(0.15)	(0.03)
Model	RI-ML	RI-ML	RI-ML	RI-ML	FE
Year fixed effects	No	Yes	Yes	Yes	Yes
Standard errors	OIM	OIM	Robust	DF-adjust	Robust
Weighted	Yes	Yes	Yes	No	No
Observations	31,309	31,309	31,309	31,309	31,309
Number of countries	16	16	16	16	16
Number of country-years	48	48	48	48	48

Note: Standard errors in parentheses. * p<.1 ** p<.05 *** p<.01. RI-ML refers to a random intercept multilevel model and FE to a fixed effects panel model. OIM refers to standard errors derived from the observed information matrix, Robust to robust standard errors clustered by countries, and DF-adjust to degrees-of-freedom adjusted standard errors following the approach of Elff *et al.* (2020).
information matrix