Measuring Unfair Inequality: Reconciling Equality of Opportunity and Freedom from Poverty

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Abstract

Empirical evidence on distributional preferences shows that people do not judge inequality as problematic per se but that they take the underlying sources of income differences into account. In contrast to this evidence, current measures of inequality do not adequately reflect these normative preferences. In this paper we address this shortcoming by developing a new measure of unfair inequality that reconciles two widely-held fairness principles: equality of opportunity and freedom from poverty. We provide two empirical applications of our measure. First, we analyze the development of inequality in the US from 1969 to 2014 from a normative perspective. Second, we conduct a corresponding international comparison between the US and 31 European countries in 2010. Our results document increasing unfairness in the US over time. This trend is driven by a strong decrease in social mobility that puts the "land of opportunity" among the most unfair countries in 2010.

JEL-Codes: D31; D63; I32
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1 INTRODUCTION

Rising income inequality in many countries around the world has led to intense debates – both in academia and in the public. Calls for more redistribution are often countered by pointing out that outcome inequalities are i) necessary to incentivize individuals and ii) may reflect the just deserts of people in a market economy. However, standard measures of inequality are inappropriate to inform the fairness debate because they neither correspond to standard principles of distributive justice nor to the distributional preferences upheld by the larger public. In this paper, we propose a new measure of (unfair) inequality that reconciles two widely-held normative principles, namely equality of opportunity and freedom from poverty, into a joint indicator. Bringing this new measure to the data, we provide important insights about the fairness of inequality, both over time (in the US) and across countries (in 2010).

Following the seminal work by Piketty and Saez (2003), the literature has documented a continued increase of income inequality since the beginning of the 1980s in many Western societies.[1] This evidence has strongly influenced public discourse. For example, the Occupy Wall Street movement's slogan – "*We are the 99%*" – directly follows from research on the income share of the top 1%. Among other interest groups, this movement has fiercely advocated for more redistribution. To the contrary, free-market pundits emphasize that through trickle-down effects everybody benefits from growth among the job creators at the top. As a consequence, more redistribution would dis-incentivize those individuals and lead to lower welfare for everybody in the long-run. While the equity-efficiency trade-off dominates public discourse on inequality, an explicit discussion of what we understand by an equitable distribution of income is mostly absent. To the contrary, the implicit assumption in much of public discourse as well as in the recent economics literature seems to be that less inequality by necessity implies a more equitable distribution. However, it is highly questionable whether our conception of equity is adequately represented by

[1]See, among others, Atkinson and Piketty (2007), Leigh (2007), Roine and Waldenström (2015), Guvenen and Kaplan (2017), and Piketty et al. (2018).

an inequality measure that invokes perfect equality as the normative benchmark. For instance, is it really the case that everybody receiving the same income (i.e. a Gini coefficient of 0) represents the most equitable distribution when people exert different levels of effort?

In contrast, most theories of distributive justice argue that we should not be concerned by outcome inequality per se, but that we should rather focus on the sources and structure of inequality. To do so, these theories differentiate between fair (justifiable) and unfair (unjustifiable) sources of inequality. Unfair inequality shall be eliminated completely while fair inequalities ought to persist.[2] For example, according to responsibility-sensitive egalitarian theories of justice, outcome inequalities are unfair if they are rooted in factors beyond individual control. These factors could not have been influenced by individual choice and therefore people should not be held responsible for the (dis-)advantages that follow from them.[3] In line with this reasoning, individuals are more willing to accept income differences which are due to effort and preferences rather than exogenous circumstances (Fong 2001; Cappelen et al. 2007; Alesina and Giuliano 2011; Alesina et al. 2018).[4] Yet, in spite of its wide acceptance, invoking the notion of individual responsibility alone is insufficient to define fairness (e.g. Konow 2003; Konow and Schwettmann 2016). For example, when an outcome is such that it brings deep deprivation to an individual, questions of how it came about seem secondary to the moral imperative of addressing the extremity of the outcome, be it hunger, homelessness, violence or insecurity (Bourguignon et al. 2006).[5] Hence, while outcome differences based on exogenous circumstances imply vi-

[2] In the social choice literature these two intuitions are formally represented by *compensation* and *reward* principles (Fleurbaey 2008; Fleurbaey and Maniquet 2011).

[3] A non-comprehensive list of works emphasizing this distinction includes Rawls (1971), Sen (1980), Dworkin (1981a, 1981b), Arneson (1989), Cohen (1989), Roemer (1993, 1998), and Lippert-Rasmussen (2001, 2011).

[4] Moreover, the literature branches on intergenerational mobility (see, e.g., Solon 1992; Björklund and Jäntti 1997; Black and Devereux 2011; Corak 2013; Chetty et al. 2014a; Chetty et al. 2014b), the gender pay gap (see, e.g., Blau and Kahn 2017; Kleven et al. 2018) and also on racial disparities (see, e.g., Lang and Lehmann 2012; Kreisman and Rangel 2015) are concerned with inequalities that are in each case rooted in one specific factor beyond individual control. The volume of academic research on these topics is a further indication that circumstance-based inequalities are of foremost public interest.

[5] To illustrate this point, Kanbur and Wagstaff (2016) suggest the following thought experiment: Imagine yourself serving on a soup line. The indigents move forwards and you hand out hot soup. But

olations of fairness, the reverse statement does not hold true. To the contrary, in addition to the responsibility criterion there are many reasons why a given outcome distribution could be considered unfair – one of them being that not everybody has enough to make ends meet.

In this paper, we propose the first family of measures for unfair inequality that incorporate the principles of equality of opportunity (EOp) and freedom from poverty (FfP) in a co-equal fashion. In line with the previous discussion, we therefore take seriously the idea that equity is not represented by the absence of any inequality in outcomes, but that it requires life success to be orthogonal to exogenous circumstances (EOp) *and* that everybody should have enough to make ends meet (FfP).

To do so, we build on the norm-based approach towards inequality measurement (Cowell 1985; Magdalou and Nock 2011). In a first step, we construct a fair income distribution that complies with both the principles of EOp and FfP as the benchmark.[6] In a second step, we measure unfair inequality as the divergence between this norm distribution and the observed income distribution. We show that our proposed measure is easily interpretable and exhibits desirable properties identified in the measurement literature. It furthermore nests standard measures of both equality of opportunity and poverty.

Our paper makes two main contributions. First, we develop the first measure of unfair inequality that reconciles EOp and FfP in a co-equal fashion. Both EOp and FfP have a vast theoretical and empirical literature. Yet, characterizations of unfairness that have relied on separate application of either principle have been criticized concerning their theoretical scope as well as their policy implications (Kanbur and Wagstaff 2016). Moreover, previous attempts to reconcile the two principles are scant and subject to important drawbacks. For example, existing works give priority to either EOp or FfP,

in one case a new piece of information is given to you. You are told that the outcome of the person in front of you was not due to circumstances but a lack of effort. Would you withdraw your soup holding hand because her outcome is morally justifiable according to the responsibility criterion? If not, clearly some other principle is cutting across the power of the responsibility-sensitive egalitarian argument.

[6] Note that standard measures of inequality, such as the Gini index, can also be understood as norm-based measures, in which the norm vector requires perfect equality. The explicit construction of a norm distribution lays bare the normative assumptions that underpin the respective inequality measure.

while treating the second principle as a mere weighting factor (Brunori et al. 2013). We address these shortcomings by treating EOp and FfP as co-equal principles conveying different grounds for compensation. That is, we develop an inequality measure that detects unfairness emanating from unequal opportunities or poverty even if one of the two guiding principles is satisfied.

Second, our measure yields important insights for the inequality debate and the design of appropriate policy responses. We provide two empirical applications of our measure. First, we analyze the development of inequality in the US over the time period 1969-2014 from a normative perspective. Our results show that the US trend in unfair inequality has mirrored the marked increase of total inequality since the beginning of the 1980s. However, beginning with the 1990s unfair inequality follows a steeper growth curve than total inequality. We illustrate that this trend is mainly driven by a less equal distribution of opportunities across people that face different circumstances beyond their individual control. Second, we provide a corresponding international comparison between the US and 31 European countries in 2010. We find that unfairness in the US shows a remarkably different structure than in societies with comparable levels of unfairness in Europe. Our evidence suggests that inequality in the most unfair European societies is largely driven by poverty increases that followed the financial crisis of 2008. To the contrary, unfairness in the US is driven by marked decreases in social mobility. Finally, we acknowledge that the exact definition of the categories "fair" and "unfair" is a normative choice and hence open to debate. We therefore provide extensive sensitivity analyses in which we probe our baseline results against alternative normative assumptions.

The remainder of this paper is organized as follows. In section 2 we clarify the underlying normative principles of EOp and FfP. In section 3 we develop our measure of unfair inequality. Section 4 provides the two empirical applications describing unfair inequality in the US over time and in an international comparison. Sensitivity analyses with respect to alternative normative assumptions are provided in section 5. Lastly, section 6 concludes.

2 NORMATIVE PRINCIPLES

Equality of Opportunity. Equality of opportunity (EOp) is a popular concept of fairness that is used to evaluate distributions of various outcomes, including health, education or income. Following the seminal contributions by Van de gaer (1993), Fleurbaey (1995), and Roemer (1993, 1998), a vivid theoretical and empirical literature evolved that weaves the idea of personal responsibility into inequality research.[7] Opportunity egalitarians deem inequalities ethically acceptable to the extent that they are rooted in factors of individual responsibility. To the contrary, they condemn inequalities that follow from factors beyond individual control. Prominent examples of the latter are, for example, the biological sex, race, or the socioeconomic status of parents. If individual responsibility factors were the sole determinants of the observed outcome distribution, the EOp ideal would be realized to its full extent.

To operationalize the opportunity-egalitarian idea, the literature draws on the concepts of *circumstances* and *efforts*, where circumstances are those outcome determinants for which individuals shall not be held responsible. On the contrary, efforts belong to the realm of personal responsibility. To the extent that the former rather than the latter are stronger (weaker) determinants of the empirical outcome distribution, a society is considered less (more) fair than otherwise. Measures of EOp are underpinned by two fundamental ideas. First, people should be compensated for unequal circumstances. A prominent formulation of this idea is the principle of *ex-ante compensation* which postulates that opportunity sets ought to be equalized across people with differential circumstances. The principle is *ex-ante* because opportunity sets are evaluated prospectively without regard to the individual level of effort exertion. Second, people should be appropriately rewarded for their efforts. While there are again different formulations of this idea, one prominent version is the principle of *utilitarian reward*. Utilitarian reward states that effort should be rewarded in a way that maximizes the aggregate outcome of people

[7] See Roemer and Trannoy (2016), Ferreira and Peragine (2016), and Ramos and Van de gaer (2016) for recent overviews.

with the same circumstances. It entails that outcome differences between individuals with the same circumstances are a matter of indifference. *Ex-ante utilitarian* measures of EOp therefore boil down to measures of between-group inequality where groups are defined by their respective circumstance characteristics.[8] The precise cut between circumstances and efforts is normatively contentious. For example, some argue in favor of including genetic endowments into the set of circumstances (Lefranc et al. 2009) while others deny that outcomes flowing from advantageous natural endowments are less praiseworthy than outcomes flowing from effort (Miller 1996). Similarly, it is widely debated whether the correlation between effort levels and circumstances constitutes a ground for compensation or not. While some argue in favor of holding people responsible for their preferences regardless of how they are formed (Barry 2005), others allocate such correlation to the circumstances that demand compensation (Roemer 1998). In our baseline empirical application in section 4, we draw on commonly accepted circumstance characteristics and allocate the correlation between circumstances and efforts to the unfair determinants of inequality. However, we provide sensitivity analyses for different responsibility cuts in section 5.

Beyond theoretical reasoning, there is compelling empirical evidence that people indeed disapprove of inequalities that are rooted in factors beyond individual control. Alesina et al. (2018) use information treatments to show that policy preferences with respect to taxation and spending on opportunity-equalizing policies are robustly correlated with perceptions of social mobility. The lower social mobility within a society, the more people are willing to remedy existing inequalities by appropriate policy interventions. Faravelli (2007) demonstrates that perceptions of justice tend to more equal distributions when income differences originate from contextual factors that could not have been influenced by individuals. The works of Cappelen et al. (2007) and Krawczyk (2010) confirm that people uphold the equal-opportunity ideal even if it adversely affects their own material interests.

[8] For a comprehensive discussion of different compensation and reward principles see the works of Fleurbaey and Peragine (2013) and Ramos and Van de gaer (2016).

Freedom from Poverty. Poverty is an important focal point in public debates about the appropriate distribution of material resources. In the philosophical literature the focus on the least advantaged has been defended by reference to sufficientarian conceptions of justice (Frankfurt 1987) and arguments that consider material deprivation as a violation of the undeniable rights we have in virtue of being humans (Fleurbaey 2007).[9] Akin to the literature on EOp, the normative concern for deprivation operates on a principle of compensation: Deprived people are entitled to be compensated so as to attain the material conditions to live a life of reasonable comfort.

While there is wide-spread appreciation for the multidimensionality of poverty (Aaberge and Brandolini 2015), much of the empirical poverty literature focuses on the income dimension only. In general, poverty measurement follows a two-step process. First, set a threshold that partitions the population into its deprived and non-deprived fractions. All else equal, the more lenient the definition of the deprivation threshold, the larger the group to which compensation is owed. Second, choose a function to aggregate the gaps between observed incomes and the deprivation threshold for those whose income falls below the threshold. In analogy to the cut between circumstances and effort, the appropriate setting of the poverty line is a widely debated issue in the literature (among others Foster 1998; Decerf 2017). In our baseline empirical application in section 4, we draw on an internationally comparable absolute poverty threshold but provide sensitivity analyses for this choice in section 5.

The concern for poverty alleviation is strongly reflected in the distributional preferences of the general public. The evidence summarized in Konow (2003) and Konow and Schwettmann (2016) indicates that fairness preferences are sensitive to individual needs and reflect a concern for everybody having enough to make ends meet. Cappelen et al. (2013b) use an international dictator game to show that transfers increase if the recipient comes from a poorer country, while Fisman et al. (2018) show that inequality

[9] Some object that freedom from poverty does not belong to the theoretical realm of fairness or even justice *although* it is morally objectionable. Such moral objections could be raised from a humanitarian or human rights perspective. In this paper we use the term “unfair” in a colloquial sense to indicate that a distribution of some good is unfair if it raises moral objection.

aversion goes hand in hand with a preference for increasing the incomes of the worst-off in society.

Reconciling EOp and FfP. In this work we treat EOp and FfP as co-equal principles conveying different grounds for compensation. Our approach is philosophically inspired by the recognition that both EOp and FfP are individually insufficient to characterize what a fair distribution of resources requires (Anderson 1999; Vita 2007). These theoretical insights are bolstered by empirical evidence that distributional preferences are sensitive to i) ex-ante inequalities that are determined by exogenous circumstances and ii) ex-post inequalities that are insensitive to responsibility considerations. For example, the experiments of Cappelen et al. (2013a) show that people largely endorse an ex-ante equal-opportunity ethic, however, they also correct for ex-post inequalities that are the result of luck. Andreoni et al. (2019) suggest that social preferences are a mix of ex-ante and ex-post considerations where the latter gain in importance once the outcome is observed. Consistent with these findings Gaertner and Schwettmann (2007) show that people tend to compensate extreme outcomes irrespective of whether they are the result of individual responsibility factors or not. In Figure S.5 we furthermore show survey evidence on public support for four principles of justice in 18 European countries that are part of our empirical application. A consistent pattern emerges: People are not perfect outcome egalitarians. Instead, they most strongly endorse a distribution of income that is sensitive to individual need (FfP) and rewards individual effort but not family background characteristics (EOp).

In spite of this evidence, previous attempts to reconcile the (ex-ante) EOp principle with the (ex-post) FfP principle are scant. First, Brunori et al. (2013) propose an "opportunity-sensitive poverty measure" according to which identical incomes below the poverty line receive less weight the more advantageous the circumstances of the poor individuals that are compared. However, since EOp serves as a mere weighting factor in the evaluation of incomes below the deprivation threshold, their measure does not detect any unfairness in societies that are free from poverty but that are characterized by severe violations of EOp. The measure is therefore informative if one aims to prioritize poor individuals based on the responsibility criterion. However, it does not allow to quantify the overall level of fairness in an observed income distribution. Second, Ferreira and Peragine (2016) suggest the construction of "opportunity-deprivation profiles" where members of circumstance types are considered opportunity-deprived if their average outcome falls below a pre-specified deprivation threshold. Effectively, this amounts to applying standard poverty measures to circumstance types instead of individuals. As a consequence the measure is informative for the identification of particularly opportunity deprived types. However, just as the "opportunity-sensitive poverty measure" it does not allow to quantify the overall level of fairness in an observed income distribution.

3 MEASURING UNFAIR INEQUALITY

In this section we describe how we construct measures of unfair inequality that – in contrast to previous work – treat EOp and FfP as co-equal principles conveying different grounds for compensation.

3.1 Notation

Consider the society $\mathcal{N} = \{1, 2, .., N\}$ and an associated vector of non-negative incomes $Y^e = (y_1^e, y_2^e, ..., y_N^e)$. Y^e corresponds to the empirical income distribution. Let us furthermore define a minimum income threshold y_{min} that is required to make ends meet. Based on Y^e and y_{min} we can partition the population into a poor and a non-poor fraction:

$$\mathcal{P} = \{i \in \mathcal{N} \mid y_i^e \leq y_{\text{min}}\}, \tag{1}$$

$$\mathcal{R} = \{i \in \mathcal{N} \mid y_i^e > y_{\text{min}}\}. \tag{2}$$

Individual incomes at all levels are the result of two sets of factors: First, a set of *circumstances* beyond individual control $\Omega \subseteq \mathbb{R}^C$. Second, a set of individual *efforts* $\Theta \subseteq \mathbb{R}^E$. We define the vector $\omega_i \in \Omega$ as a comprehensive description of the circumstances with which $i \in \mathcal{N}$ is endowed. Analogously we define the vector $\theta_i \in \Theta$ as a comprehensive description of the efforts that are exerted by $i \in \mathcal{N}$. Based on the realizations of circumstances we can partition the population into T circumstance *types* that are defined as follows:

$$\mathcal{T}(\omega) = \{i \in \mathcal{N} : \omega_i = \omega\}. \tag{3}$$

Similarly, we can partition the population into S effort *tranches* that are defined as follows:

$$\mathcal{S}(\theta) = \{i \in \mathcal{N} : \theta_i = \theta\}. \tag{4}$$

For any subgroup $\mathcal{X} \subseteq \mathcal{N}$ of individuals, we denote by $N_{\mathcal{X}} = \text{card}(\mathcal{X})$ the number of individuals in this subgroup and by $\mu^e_{\mathcal{X}} = \frac{1}{N_{\mathcal{X}}} \sum_{i \in \mathcal{X}} y^e_i$ their average income. For ease of notation, we let hereafter $N = N_{\mathcal{N}}$ and $\mu^e = \mu^e_{\mathcal{N}}$.

Next to the empirical income distribution Y^e, consider a norm (or reference) income distribution $Y^r = (y^r_1, y^r_2, ..., y^r_N)$ that describes the fair distribution of incomes. It is the normatively desirable income distribution for which the society should strive in absence of incentive constraints and behavioral responses to redistribution. While Y^e is given in the data, Y^r must be constructed based on explicit normative principles.[10] Before outlining the construction of a Y^r that is consistent with the normative intuitions of EOp and FfP in section 3.3, we will now describe how to aggregate the differences between Y^e and Y^r into a scalar measure of inequality.

3.2 Measuring Divergence

Endowed with both Y^e and Y^r one must decide how to aggregate the discrepancies between both vectors into a scalar measure of unfair inequality. Prominent divergence measures include the works by Cowell (1985), Magdalou and Nock (2011), and Almås et al. (2011), each of which generalizes standard measures of inequality. While Cowell

[10]Note that standard measures of inequality such as the Gini coefficient adhere to the norm of outcome egalitarianism, i.e. this norm distribution is the perfect equality distribution where $y^r_i = \mu^e,\ \forall\ i \in \mathcal{N}$.

(1985) and Magdalou and Nock (2011) provide generalizations of the entropy class of inequality measures, Almås et al. (2011) generalize the Gini index. The key difference to standard measures of inequality is that these generalized measures do not decrease (increase) with progressive (regressive) transfers from rich (poor) to poor (rich) but rather with transfers that reduce (increase) the distance between the empirical and the reference distribution. Note that this requirement is equivalent to the standard Pigou-Dalton principle of transfers if and only if the reference distribution is equivalent to the sample mean μ^e. Otherwise, transfers from poor to rich can be desirable if the income of the poor exceeds its reference value, while the income of the rich falls short of it.

In our baseline, we use the measures proposed by Magdalou and Nock (2011) yielding the following aggregator for the divergence between Y^e and Y^r:[11]

$$D(Y^e||Y^r) = \sum_{i \in \mathcal{N}} \left[\phi(y_i^e) - \phi(y_i^r) - (y_i^e - y_i^r)\phi'(y_i^r)\right], \tag{5}$$

where

$$\phi(z) = \begin{cases} -\ln z, & \text{if } \alpha = 0, \\ z \ln z, & \text{if } \alpha = 1, \\ \frac{1}{\alpha(\alpha-1)} z^{\alpha}, & \text{otherwise.} \end{cases} \tag{6}$$

As in the family of generalized entropy measures, α is indicative of different value judgments: The higher α, the more weight is attached to positive divergences of empirical income y_i^e from its respective norm income y_i^r. The lower α, the more weight is attached to shortfalls from y_i^r. In the baseline we choose $\alpha = 0$. This choice is guided by the fact that the MN-measure with $\alpha = 0$ nests the mean log deviation (MLD) if we set $y_i^r = \mu^e$, $\forall\ i \in \mathcal{N}$. As such we ensure close proximity to the empirical literature on EOp, in which the use of the MLD is prevalent (among others Ferreira and Gignoux 2011; Hufe et al. 2017). Furthermore, attaching a higher weight to shortfalls from y_i^r is consistent

[11] We abbreviate this class with *MN* in the following. The MN-family of divergence measures is characterized by the properties of *scale invariance*, the *principle of population*, and *subgroup decomposability*. These properties carry directly over to our measures of unfair inequality. Robustness checks using the measures of Cowell (1985) and Almås et al. (2011) are provided in section 5.4.

with recent experimental evidence showing a preference for overcompensating the undeserving instead of failing to compensate the deserving (Cappelen et al. 2018).[12] Thus, our baseline measure of unfair inequality aggregates divergences between Y^e and Y^r as follows:

$$D(Y^e||Y^r) = \frac{1}{N}\sum_{i\in\mathcal{N}}\left[\ln\frac{y_i^r}{y_i^e} - \frac{y_i^r - y_i^e}{y_i^r}\right].^{13} \tag{7}$$

We will now turn to the construction of a norm vector Y^r that accords with the principles of EOp and FfP.

3.3 Baseline Measure

Norm Vector. Let $\mathcal{D} \subseteq \mathbb{R}_+^N$ be the set containing all possible income distributions d. In the following we will define subsets of eligible distributions $\mathcal{D}^h \in \mathcal{D}$ that are consistent with the normative intuitions embodied in the principles of EOp and FfP.

First, since we are concerned with the fair distribution of available resources in a given society, we follow the inequality measurement literature and rule out creatio ex nihilo:

$$\mathcal{D}^1 = \left\{ d \in \mathcal{D} \,\middle|\, \sum_{i\in\mathcal{N}} y_i^r = \sum_{i\in\mathcal{N}} y_i^e \right\}. \tag{8}$$

Thus, $\mathcal{D}^1$ is the subset of distributions in which the total amount of available resources match their empirical counterpart. By fixing the total amount of resources we let the distribution of these resources be the only margin of difference between the observed and the benchmark situation.[14] This assumption is standard in the literature on inequality measurement but highlights an important difference to the quest for optimal tax design. The latter is concerned with trading off equity and efficiency concerns. In such a framework, restriction (8) would rule out behavioral responses to taxation and only makes sense

[12] Robustness checks using alternative specifications of α are provided in section 5.4.

[13] Note that we can scale the measure by $1/N$ to satisfy the *principle of population* without further adjustment since we will constrain the mean of Y^r to match the mean of Y^e (Magdalou and Nock 2011).

[14] Cappelen and Tungodden (2017) call restriction $\mathcal{D}^1$ the “no-waste-condition”.

in a first-best setting.[15]

Second, we characterize the EOp principle by reference to the principle of ex-ante compensation (Fleurbaey and Peragine 2013; Ramos and Van de gaer 2016) which states that the expected income of an individual should not be correlated to her circumstance type. Hence, we are infinitely inequality averse with respect to inequalities *between* circumstance types and the ideal of an equal-opportunity society is realized if there is equality across average type incomes $\mu^e_{\mathcal{T}(\omega)}$. $\mathcal{D}^2$ is the subset of distributions for which this criterion is satisfied:

$$\mathcal{D}^2 = \left\{ d \in \mathcal{D} \;\middle|\; \mu^r_{\mathcal{T}(\omega)} = \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{T}(\omega)} y^r_i = \frac{1}{N} \sum_{j \in \mathcal{N}} y^e_j = \mu^e, \; \forall\, \omega \in \Omega \right\}. \tag{9}$$

Note that in this specification we implicitly treat the correlation between Ω and Θ as morally objectionable. This assumption is in line with the normative account of Roemer (1998). However, we provide sensitivity checks to this assumption in section 5.

Third, we maintain that people have a claim for a minimum level of resources y_{min} even if their outcomes can be ascribed to factors within their realm of control. Opportunity equalization alone does not achieve this objective. Next to compensating circumstances Ω, opportunity-egalitarians want to preserve income differences due to effort exertion. Consistent with this idea, we impose that within types $\mathcal{T}(\omega)$ efforts should be respected by distributing incomes proportionally to empirical incomes y^e_i:

$$\frac{y^r_i}{y^r_j} = \frac{y^e_i}{y^e_j}, \; \forall\, i, j \in \mathcal{T}(\omega), \; \forall\, \omega \in \Omega.^{16} \tag{10}$$

However, while such ex-post proportionality within $\mathcal{T}(\omega)$ maintains relative differences

[15] The efficiency costs of reaching the norm distribution are never part of inequality measurement. Accounting for efficiency costs, however, could be part of further analysis. Assuming the joint minimization of EOp and FfP to be a goal of public policy, our framework could be integrated into models of fair taxation (Fleurbaey and Maniquet 2006; Weinzierl 2014; Ooghe and Peichl 2015; Saez and Stantcheva 2016) in which the planner seeks to realize a specific notion of fairness while taking behavioral responses to taxation into account. See also Fleurbaey and Maniquet (2018) for a recent overview on the integration of fairness principles into the standard Mirrleesian optimal tax framework.

[16] This condition is a relative version of the "equal-transfer-for-equal-[circumstance]" condition laid out in Bossert and Fleurbaey (1995).

in effort exertion, it may keep (push) some $i \in \mathcal{P}$ ($i \in \mathcal{R}$) below y_{min}. To realize FfP we therefore want to identify those who are poor due to a lack of effort exertion instead of exogenous circumstances and compensate them so that they are able to make ends meet. In line with this insight we define a partition according to which people are labeled (non-)poor after considering their counterfactual gains from opportunity equalization while holding them responsible for their individual efforts θ_i:

$$\mathcal{P}(\omega) = \left\{ i \in \mathcal{T}(\omega) \;\middle|\; y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \leq y_{\text{min}} \right\},\ \forall\ \omega \in \Omega, \tag{11}$$

$$\mathcal{R}(\omega) = \left\{ i \in \mathcal{T}(\omega) \;\middle|\; y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} > y_{\text{min}} \right\},\ \forall\ \omega \in \Omega. \tag{12}$$

Based on the definition of $\mathcal{P}(\omega)$ and $\mathcal{R}(\omega)$, we formulate the FfP requirement:

$$\mathcal{D}^3 = \left\{ d \in \mathcal{D} \;\middle|\; y_i^r = y_{\text{min}},\ \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega \right\}. \tag{13}$$

The FfP requirement can be broken down into two parts: $y_i^r = \frac{1}{N_{\mathcal{P}(\omega)}} \sum_{j \in \mathcal{P}(\omega)} y_j^r = \mu^r_{\mathcal{P}(\omega)}$ and $\mu^r_{\mathcal{P}(\omega)} = y_{\text{min}}$. The first component states infinite inequality aversion with respect to income differences among the poor – they all have an *equal* claim to a certain level of resources. The second component states infinite inequality aversion with respect to the average shortfall of the poor population from the poverty line. Within an equal-opportunity society, they all have an equal claim to nothing less (but also nothing more) than exactly the *minimum subsistence level* y_{min}.

Fourth, combining the proportionality requirement (10) with the FfP condition (13), there is zero inequality aversion with respect to the share of income that exceeds the poverty line. Hence, $\mathcal{D}^4$ denotes the subset of distributions in which within-type inequality of excess income above the poverty line remains unaltered in comparison to the counterfactual equal-opportunity income distribution:

$$\mathcal{D}^4 = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y_i^r - y_{\text{min}}}{y_j^r - y_{\text{min}}} = \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\text{min}}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\text{min}}},\ \forall\ i, j \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega \right\}. \tag{14}$$

The intersection $\cap_{h=1}^{4}\mathcal{D}^h$ characterizes our baseline norm distribution which is summarized in Proposition 1:

Proposition 1. *Suppose $\mu^e > y_{min}$. Then, the intersection $\cap_{h=1}^{4}\mathcal{D}^h$ yields a singleton which defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega, \\ y_{min} + \underbrace{(y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{min})}_{=\tilde{y}_i} \underbrace{\frac{(\mu^e - y_{min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)}\frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{min})}}_{=\delta_{\mathcal{T}(\omega)}}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega. \end{cases} \tag{15}$$

Conversely, if $\mu \leq y_{min}$, then $\cap_{h=1}^{4}\mathcal{D}^h = \emptyset$. The proof for this proposition is given in Appendix A.

Individuals in $\mathcal{P}(\omega)$ receive a norm income of $y_{\min}$. This prescription directly follows from the FfP requirement specified in (13): Those who are poor due to factors other than exogenous circumstances are owed compensation to make ends meet but nothing more.

Norm incomes for individuals in $\mathcal{R}(\omega)$ are determined by the individual share of (counterfactual) income above the poverty threshold, $\tilde{y}_i \in (0, \infty)$, and a type-specific scaling factor, $\delta_{\mathcal{T}(\omega)} \in (0, \infty)$. First, conditional on the individual circumstance type, y_i^r increases with $\tilde{y}_i$. This relation follows from the proportionality condition in (14): In absence of additional normative grounds for income inequality aversion, relative income differences among people with similar circumstance characteristics that are able to make ends meet need to be preserved. Second, the type-specific scaling factor $\delta_{\mathcal{T}(\omega)}$ increases with the total amount of resources that are available relative to the poverty line $(\mu^e - y_{\min})$. This relation follows from the constant resource requirement specified in (8) and from fixing incomes of the poor population $\mathcal{P}(\omega)$ at the minimum threshold $y_{\min}$ (13): The higher the total amount of available resources, the smaller the share of resources that needs to be given up by the members of $\mathcal{R}(\omega)$ in order to realize FfP. Lastly, the type-specific scaling factor $\delta_{\mathcal{T}(\omega)}$ decreases with the share of non-poor individuals in a type $(N_{\mathcal{R}(\omega)}/N_{\mathcal{T}(\omega)})$ and their average (counterfactual) income in excess of the minimum threshold $(\mu^e_{\mathcal{R}(\omega)}\frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})$.

This relation follows from combining the EOp requirement given in (9) with the FfP requirement given in (13) while observing the proportionality requirement given in (14): EOp requires equal average outcomes across types. The higher the total volume of transfers to the poor members of a type, the higher the proportional charge levied on the non-poor members of the same type in order to maintain the EOp requirement.

Equation (15) shows that the fair distribution of incomes Y^r is a function of simple summary statistics of the empirical income distribution Y^e. Some may argue that the normatively desirable distribution of incomes should be independent of the actual distribution of incomes. However, we note that such a dependence is not particular to our measurement approach but characterizes many standard measures of inequality, poverty and inequality of opportunity.[17]

Furthermore, we note that the extent of such dependence can be strengthened or loosened in several ways. In fact, whether and to what extent an insulation of Y^r from Y^e is desirable, depends on the normative intuitions one strives to capture. For illustrative purposes we will give two examples in the following. First, $y_{\min}$ can be set i) in absolute terms or ii) in relative terms as some functional of Y^r. Option i) is preferable if one thinks that the poverty concept applies to basic human needs, while option ii) is preferable if one aims to capture aspects of social deprivation as well (Foster 1998). In our baseline, we choose an absolute poverty threshold and therefore insulate $y_{\min}$ from changes in Y^e but provide sensitivity checks to this choice in section 5.3. Second, $\mathcal{D}^4$ proposes to honor within-type income differences since we interpret them as indicators of differential effort exertion. In line with this normative interpretation, our baseline Y^r is dependent on changes in the intra-type variance of incomes and therefore Y^e. However, in section 3.4 we show how the dependence between Y^r and Y^e can be loosened by harmonizing intra-type variances in Y^r across circumstance types. More generally: While the construction

[17]For example, the standard approach to inequality measurement can be characterized as finding a suitable distance measure between the actual distribution and the norm distribution where every individual has the mean of the distribution. The properties of the distance measure can be further specified (for example, the Pigou-Dalton property, the scale independence property, decomposability, etc.). But as the empirical vector changes, the norm vector also changes. For instance, for the conventional Gini coefficient it holds that $y_i^r = \mu^e$, $\forall\ i \in \mathcal{N}$, implying that Y^r changes with μ^e.

of Y^r may depend on Y^e to varying degrees, the underlying principles that inform the construction of Y^r are always independent of the observed distribution of incomes.

Measure and Comparative Statics. Substituting the norm distribution given in (15) into the divergence measure given in (7), we obtain our baseline measure of unfair inequality:

$$\begin{aligned} D(Y^e||Y^r) =& \frac{1}{N} \sum_{i \in \mathcal{P}(\omega)} \left\{ \ln \tfrac{y_{\min}}{y_i^e} - \left(\tfrac{y_{\min} - y_i^e}{y_{\min}} \right) \right\} \\ &+ \frac{1}{N} \sum_{i \in \mathcal{R}(\omega)} \left\{ \ln \left(\tfrac{y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)}}{y_i^e} \right) - \left(\tfrac{(y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)}) - y_i^e}{y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)}} \right) \right\}, \end{aligned} \tag{16}$$

where $\delta_{\mathcal{T}(\omega)}$ represents the type-specific scaling factor that is applied to $\tilde{y}_i$ – the share of counterfactual income above $y_{\min}$. To further illustrate the properties of this measure, we provide some comparative statics in the following.

(1) Assume $y_{\min} \to 0$. The limiting case of $y_{\min} = 0$ is equivalent to abstracting from the concern for FfP altogether, whereas EOp remains the only normative foundation for inequality aversion. In the limit, this leads to $\mathcal{P}(\omega) = \emptyset$, $\mu^e_{\mathcal{R}(\omega)} = \mu^e_{\mathcal{T}(\omega)}$, and $N_{\mathcal{R}(\omega)} = N_{\mathcal{T}(\omega)}$. As a consequence, $\delta_{\mathcal{T}(\omega)} = 1$, $\forall\ \omega \in \Omega$. The resulting norm vector as well as the ensuing measure of unfair inequality read as follows:

$$y_i^r = y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}},\ \forall\ i \in \mathcal{T}(\omega),\ \forall\ \omega \in \Omega, \tag{17}$$

$$D(Y^e||Y^r) = \frac{1}{N} \sum_{i \in \mathcal{N}} \ln \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}}. \tag{18}$$

With $y_{\min} = 0$, unfair inequality collapses to inequality in the distribution of average outcomes of circumstance types. Hence, as $y_{\min} \to 0$, the measure converges to the standard ex-ante utilitarian measure of inequality of opportunity in which the MLD is applied to a smoothed distribution of type-specific mean incomes.

(2) Assume $N_{\mathcal{P}(\omega)} \to 0,\ \forall\ \omega \in \Omega$. Note the difference to our previous thought experiment in which we abstracted from the concern for FfP altogether. The limiting case of $N_{\mathcal{P}(\omega)} = 0$ corresponds to a society that values FfP below the threshold of $y_{\min}$ but happens to be in the fortunate position of having zero poverty incidence once incomes are corrected for the unequal opportunities faced by people with different circumstances. At the limit, $\mathcal{P}(\omega) = \emptyset$, $\mu^e_{\mathcal{R}(\omega)} = \mu^e_{\mathcal{T}(\omega)}$ and $N_{\mathcal{R}(\omega)} = N_{\mathcal{T}(\omega)}$. As a consequence, $\delta_{\mathcal{T}(\omega)} = 1,\ \forall\ \omega \in \Omega$ and the resulting norm vector as well as the ensuing measure of unfair inequality read as follows:

$$y_i^r = y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}},\ \forall\ i \in \mathcal{T}(\omega),\ \forall\ \omega \in \Omega, \tag{19}$$

$$D(Y^e||Y^r) = \frac{1}{N} \sum_{i \in \mathcal{N}} \ln \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}}. \tag{20}$$

In spite of the fact that the concern for FfP remains intact, opportunity equalization is sufficient to satisfy the criteria of both EOp and FfP if $N_{\mathcal{P}(\omega)} = 0,\ \forall\ \omega \in \Omega$. Hence, the measure of unfair inequality again converges to the standard ex-ante utilitarian measure of inequality of opportunity. The limiting case of $N_{\mathcal{P}(\omega)} = 0,\ \forall\ \omega \in \Omega$ thus illustrates that the measure continues to detect unfairness through violations of EOp even if FfP is perfectly satisfied.

(3) Assume we reduce the number of criteria that constitute unfair outcome determinants from an opportunity-egalitarian perspective. This can be represented by letting the number of circumstance types go to one, i.e. $T \to 1$. At the limit, the entire population would be considered as a single circumstance type and FfP remains the only normative foundation for inequality aversion. $T = 1$ leads to $\mathcal{T}(\omega) = \mathcal{N}$, $\mathcal{P}(\omega) = \mathcal{P}$, and $\mathcal{R}(\omega) = \mathcal{R}$. Furthermore, $N_{\mathcal{P}(\omega)} = N_{\mathcal{P}}$, $\mu^e_{\mathcal{T}(\omega)} = \mu^e$, and $\mu^e_{\mathcal{P}(\omega)} = \mu^e_{\mathcal{P}}$. As a consequence, $\tilde{y}_i = y_i^e - y_{\min}$ and $\delta_{\mathcal{T}(\omega)} = \frac{(\mu^e - y_{\min})}{N_{\mathcal{R}}/N(\mu^e_{\mathcal{R}} - y_{\min})} = \left(1 - \frac{N_{\mathcal{P}}/N(y_{\min} - \mu^e_{\mathcal{P}})}{N_{\mathcal{R}}/N(\mu^e_{\mathcal{R}} - y_{\min})}\right) = \delta$. Thus, the corresponding norm vector as well as the resulting measure of unfair inequality read as follows:

$$
y_i^r = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P}, \\ y_{\min} + (y_i^e - y_{\min}) \underbrace{\left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu_{\mathcal{P}}^e)}{\frac{N_{\mathcal{R}}}{N}(\mu_{\mathcal{R}}^e - y_{\min})}\right)}_{=\delta}, & \forall\, i \in \mathcal{R}, \end{cases} \tag{21}
$$

$$
\begin{aligned} D(Y^e \| Y^r) = & \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}} \ln\left(\frac{y_{\min}}{y_i^e}\right)}_{\text{Watts Index}} - \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}} \left(\frac{y_{\min} - y_i^e}{y_{\min}}\right)}_{\text{Poverty Gap}} \\ & + \frac{1}{N}\sum_{i\in\mathcal{R}} \left\{ \ln\left(\frac{y_{\min} + (y_i^e - y_{\min})\delta}{y_i^e}\right) - \left(\frac{(y_i^e - y_{\min})(\delta - 1)}{y_{\min} + (y_i^e - y_{\min})\delta}\right) \right\}. \end{aligned} \tag{22}
$$

Abstracting from the concern for EOp, leads to a scaling factor δ that is uniform across all $i \in \mathcal{R}$. δ is determined by the ratio of the poverty gap to the amount of excess income above the poverty line. This contrasts with the baseline case in which the transfer rate $\delta_{\mathcal{T}(\omega)}$ is decreasing with the type-specific share of non-poor individuals and their average excess income above the poverty threshold.

The decomposability property of the MN-measures allows us evaluate unfairness in the truncated distribution $Y_{\mathcal{P}}^e = [y_1^e, y_2^e, ..., y_{\min}]$. Up to $y_{\min}$, unfair inequality is characterized by the difference between the Watts index (Zheng 1993) and the poverty gap ratio. Individually, these are well-known measures of poverty. However, also their combination bears a number of desirable properties that have been identified in the literature on poverty measurement (e.g. Ravallion and Chen 2003). These include *monotonicity* (as opposed for example to the headcount ratio), the *principle of transfers* (as opposed for example to the poverty gap taken as a stand-alone measure) and *additive decomposability*. Note that we do not obtain a measure of poverty that satisfies the *focus axiom*. Our approach frames poverty as an aspect of inequality and thus imposes requirements on how the funds to eradicate poverty should be raised – see condition (14). Therefore, it is not indifferent to transfers between individuals with incomes above the poverty line $y_{\min}$ (the third term in equation (22)) and thus violates the *focus axiom*.

(4) Let $\mu^e_{\mathcal{T}(\omega)} \to \mu^e,\ \forall\, \omega \in \Omega$. Note the difference to our previous thought experiment, in which we let $T \to 1$ and abstracted from the concern for EOp altogether. In contrast to the previous case, the normative concern for EOp remains intact, however, the EOp principle is increasingly satisfied as $\mu^e_{\mathcal{T}(\omega)} \to \mu^e,\ \forall\, \omega \in \Omega$. The limiting case corresponds to an equal-opportunity society without disparities in average outcomes across circumstance types. At the limit, $\tilde{y}_i = y^e_i - y_{\min},\ \delta_{\mathcal{T}(\omega)} = \frac{(\mu^e - y_{\min})}{N_{\mathcal{R}(\omega)}/N_{\mathcal{T}(\omega)}(\mu^e_{\mathcal{R}(\omega)} - y_{\min})} = \left(1 - \frac{N_{\mathcal{P}(\omega)}/N_{\mathcal{T}(\omega)}(y_{\min} - \mu^e_{\mathcal{P}(\omega)})}{N_{\mathcal{R}(\omega)}/N_{\mathcal{T}(\omega)}(\mu^e_{\mathcal{R}(\omega)} - y_{\min})}\right)$. The resulting norm vector and the corresponding measure of unfair inequality read as follows:

$$y^r_i = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P},\ \forall\, \omega \in \Omega, \\ y_{\min} + (y^e_i - y_{\min}) \underbrace{\left(1 - \frac{\frac{N_{\mathcal{P}(\omega)}}{N_{\mathcal{T}(\omega)}}(y_{\min} - \mu^e_{\mathcal{P}(\omega)})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)} - y_{\min})}\right)}_{=\delta_{\mathcal{T}(\omega)}}, & \forall\, i \in \mathcal{R},\ \forall\, \omega \in \Omega. \end{cases} \tag{23}$$

$$\begin{aligned} D(Y^e \| Y^r) = & \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}} \ln\left(\tfrac{y_{\min}}{y^e_i}\right)}_{\text{Watts Index}} - \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}} \left(\tfrac{y_{\min} - y^e_i}{y_{\min}}\right)}_{\text{Poverty Gap}} \\ & + \frac{1}{N}\sum_{i\in\mathcal{R}} \left\{ \ln\left(\tfrac{y_{\min} + (y^e_i - y_{\min})\delta_{\mathcal{T}(\omega)}}{y^e_i}\right) - \left(\tfrac{(y^e_i - y_{\min})(\delta_{\mathcal{T}(\omega)} - 1)}{y_{\min} + (y^e_i - y_{\min})\delta_{\mathcal{T}(\omega)}}\right) \right\}. \end{aligned} \tag{24}$$

Since our concern for EOp remains intact we calculate poverty-eradicating transfers across types by reference to the *type-specific* poverty gap and the *type-specific* income share that exceeds $y_{\min}$. The limiting case of $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\, \omega \in \Omega$ shows that our measure continues to detect unfairness through violations of FfP even if EOp is perfectly satisfied.

The previous comparative statics illustrate some particular advantages of our measure of unfair inequality. First, it is easily interpretable since it nests well-known measures of both EOp and FfP. If we abstract from the concern for FfP ($y_{\min} = 0$), we obtain a standard measure for inequality of opportunity. If we abstract from the concern for EOp ($T = 1$), we obtain a combination of the Watts index and the poverty gap ratio, both of which are well-established measures of poverty.

Second, the proposed measure treats EOp and FfP as co-equal principles and therefore detects unfair inequality even if either of the two principles is perfectly satisfied.[18] If there is zero poverty incidence ($N_{\mathcal{P}(\omega)} = 0,\ \forall\ \omega \in \Omega$), it still detects unfair inequality based on average outcome differences across circumstance types. If the income distribution is perfectly opportunity-egalitarian ($\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\ \omega \in \Omega$), it still requires type-specific transfers from rich to poor in order to assure the satisfaction of both FfP and EOp.

3.4 Alternative Conceptualizations

Our baseline measure provides one way of reconciling the principles of EOp and FfP. However, the extensive literature on the measurement of EOp shows that there are different ways of conceptualizing its underlying normative ideas (Roemer and Trannoy 2016). In this section we discuss two alternations to the EOp concept and show how these impact the reconciliation of EOp with FfP.[19]

First, the baseline norm demands the equalization of average incomes across circumstance types. This is a *weak criterion of equality of opportunity* since it only requires the expectation of outcomes to be identically distributed across circumstance types (Lefranc et al. 2009). To the contrary, a *strong criterion of equality of opportunity* requires equality of outcomes conditional on exerting similar levels of effort. For the purpose of formulating a stronger version of the EOp requirement, we follow Roemer (1998) and identify effort tranches by the quantiles of the type-specific income distributions. Hence, i and j are part of the same effort tranche if they both sit at the q-th quantile of their respective type income distribution.[20] Compensation requires to equalize outcomes in each effort tranche,

[18] In contrast, the "opportunity-sensitive poverty" measures proposed by Brunori et al. (2013) do not have this property. Since the EOp principle is a mere weighting factor for incomes below the poverty line, the measure does not detect any violations of the EOp principle once the FfP principle is satisfied.

[19] In addition to varying the conceptualizations of EOp and FfP, our measurement approach allows us to introduce other normative foundations for inequality aversion. These may include affluence aversion due to concerns about political capture by income elites (Piketty 2014) and the emergence of concentrated market structures in which massive returns accrue to an increasingly small number of "superstar" agents (König 2019; Autor et al. 2020). While a precise formulation of these normative concerns is beyond the scope of this paper, we briefly illustrate in Supplementary Material A.4 how additional inequality aversion may be introduced into our framework. Furthermore, we show in Supplementary Material A.5 how the heterogeneity in individual needs could be integrated based on individual-specific deprivation thresholds.

[20] This "Roemerian Identification Assumption" relies on a relative conception of effort. The distribution of absolute effort like the propensity to study or to work long hours may vary across circumstance types.

and hence to equalize all moments of the type-specific income distributions. As such, the strong conceptualization of EOp contrasts with the weak conceptualization embodied in our baseline measure since the latter required equalizing one moment of the type income distributions only. Furthermore, note that the satisfaction of strong EOp implies the satisfaction of weak EOp.

Second, the baseline norm evaluates type-specific opportunity sets by reference to the average incomes of all $i \in \mathcal{T}(\omega)$. Moreover, the (non-)poor fraction of the population is identified by evaluating incomes in a counterfactual income distribution that corrects for unequal opportunities across circumstance types. The baseline norm thus treats EOp and FfP as *non-separable* in their scope of application: The assessment of type advantages (EOp) depends on both poor and non-poor individuals, whereas the identification of poverty (FfP) depends on the counterfactual income an individual would obtain in an opportunity-egalitarian world. In contrast to this conceptualization, one may claim that the requirements of EOp and FfP operate on separate supports of the income distribution Y^e. While FfP characterizes the normative requirement for $\mathcal{P}$, i.e. for people with incomes below $y_{\min}$, the distributional ideal of EOp only applies to $\mathcal{R}$, i.e. to those individuals whose basic needs are satisfied. According to such an argument the normative principles of EOp and FfP are *separable* in their scope of application.

While our baseline measure adheres to *weak EOp* and *non-separability*, we can construct alternative measures by invoking either *strong EOp* or *separability*, or both. These three alternatives are presented in Table 1. Detailed expositions of their construction are provided in Supplementary Material A and comparative statics are shown in Supplementary Material B.

The main features of the alternatives are as follows: First, alternatives (a) and (c) are based on strong EOp. Hence, under the assumption of non-separability (separability) the proportionality requirement for raising funds in the non-deprivation set refers to average

However, the focus on type-specific quantile distributions forces the type-specific effort distributions to be equal. Hence, the absolute effort exertion of individuals is evaluated relative to the distribution of efforts within their circumstance type.

Table 1 – Overview Alternative Conceptualizations

	Weak/Strong	Separability	Norm Distribution
Baseline	Weak	No	$y_i^r = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P}(\omega),\ \forall\, \omega \in \Omega \\ y_{\min} + (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})}, & \forall\, i \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega \end{cases}$
Alternative (a)	Strong	No	$y_i^r = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P}(\theta),\ \forall\, \theta \in \Theta \\ y_{\min} + (\mu^e_{\mathcal{S}(\theta)} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\Theta)}}{N}(\mu^e_{\mathcal{R}(\Theta)} - y_{\min})}, & \forall\, i \in \mathcal{R}(\theta),\ \forall\, \theta \in \Theta \end{cases}$
Alternative (b)	Weak	Yes	$y_i^r = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{T}(\omega) \cap \mathcal{P},\ \forall\, \omega \in \Omega \\ y_{\min} + (y_i^e - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} - y_{\min})}, & \forall\, i \in \mathcal{T}(\omega) \cap \mathcal{R},\ \forall\, \omega \in \Omega \end{cases}$
Alternative (c)	Strong	Yes	$y_i^r = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{S}(\theta) \cap \mathcal{P},\ \forall\, \theta \in \Theta \\ y_{\min} + (\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}, & \forall\, i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\, \theta \in \Theta \end{cases}$

tranche incomes in excess of the deprivation threshold, $\mu^e_{\mathcal{S}(\theta)} - y_{\min}$ ($\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} - y_{\min}$), instead of individual incomes $y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}$ ($y_i^e - y_{\min}$). All else equal, one would expect the measures based on strong EOp to yield higher levels of unfair inequality. Second, alternatives (b) and (c) operate on the assumption of *separability*. Therefore, individuals are not assigned to the deprived and non-deprived fractions of society based on the counterfactual income distributions of a weakly (strongly) opportunity-egalitarian society – indicated by $\mathcal{P}(\omega)$ and $\mathcal{R}(\omega)$ ($\mathcal{P}(\theta)$ and $\mathcal{R}(\theta)$) – but based on the actual income distribution – indicated by $\mathcal{P}$ and $\mathcal{R}$. All else equal, one would expect the measures based on the separability assumption to yield lower levels of unfair inequality.

4 EMPIRICAL APPLICATION

To illustrate the proposed measure of unfair inequality we provide two empirical applications. First, we use the Panel Study of Income Dynamics (PSID) to analyze the development of unfair inequality in the US over the time period 1969-2014. Second, we combine the PSID and the EU Statistics on Income and Living Conditions (EU-SILC) to conduct a cross-sectional analysis in which we benchmark unfair inequality in the US against unfair inequality in 31 European countries in 2010.[21]

[21] Note that much of the recent literature on inequality trends draws on administrative data sources (Burkhauser et al. 2012). However, in the context of this study survey data such as the PSID or EU-SILC provide important advantages since the operationalization of EOp and FfP requires detailed information on individual background characteristics and an accurate representation of the lower tail of the income distribution. Administrative data is restricted in both dimensions since tax returns collect only basic demographic information and because the bottom half of the distribution pays little personal income tax.

4.1 Unfair Inequality in the US over Time

Data Source. The PSID is a main resource for the study of inequality, poverty and intergenerational transmission processes in the US (see Johnson et al. 2018; Smeeding 2018, and the overview articles in the same issue). At its inception in 1968 the PSID consisted of a nationally representative sample of 2,930 families and an oversample of 1,872 low-income families that are tracked until the present day. All individuals who leave their original households automatically become independent units in the PSID sampling frame. To match compositional changes of the US population through post-1968 immigration flows, the PSID added a Latino sample and an immigrant sample in its 1990 and 1997 waves, respectively.[22] Starting in 1997 it has switched from an annual to a biennial survey rhythm. In its most recent waves, the PSID covers the members of more than 9,000 families and provides rich information on their incomes, family background characteristics and living practices.

In this study we focus on individuals aged 25-60 over the survey (income reference) periods 1970-2015 (1969-2014).[23] We will now briefly outline the construction of the inputs to our inequality measure: Y^e, Ω, Θ, and $y_{\min}$. Further detail on the construction of all relevant variables as well as descriptive statistics are disclosed in Supplementary Materials C and E.

Outcome Variable. To assess the distribution of economic resources from a fairness perspective, we use the income components created by the PSID Cross-National Equivalence File (CNEF) to define annual disposable household income as the sum of total household income from labor, asset flows, windfall gains, private transfers, public trans-

[22] We exclude the Latino sample from our investigation as it was dropped in 1995 and did not reflect the full range of post-1968 immigrants.

[23] We employ cross-sectional sample weights for all calculations. However, one may worry that infrequent PSID updates for compositional changes in the US population distort comparisons over time. To address such concerns, we calculate population weights for 48 age-sex-race-cells ($8 \times 2 \times 3$) in the Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC) and rescale the provided PSID individual weights to match their CPS-ASEC counterparts. This rescaling has a negligible effect on our results suggesting that the standard PSID weights do a good job in representing the underlying US population.

fers, private retirement income and social security pensions. We deduct total household taxes as calculated by the NBER TAXSIM calculator (Butrica and Burkhauser 1997).

Our measure of unfairness puts a strong emphasis on the lower end of the income distribution. It is well-known that poverty estimates based on survey data tend to be upward biased due to the under-reporting of government benefit receipts (Meyer and Mittag 2019; Mittag 2019). Furthermore, it has been shown that households with extremely low reported incomes tend to misreport their income from earnings (Brewer et al. 2017; Meyer et al. 2019). To mitigate distortions from benefit under-reporting we use the time series provided in Meyer et al. (2015) to scale reported public transfers by a year-specific under-reporting factor that is calculated based on a comparison between the aggregate level of benefits receipts reported in the PSID and the aggregate expenditure levels from administrative program data. To cushion distortions from the under-reporting of labor incomes we identify individuals that report zero earnings but non-zero working hours in the reporting period. We then replace their reported earnings level by a prediction from a Mincer wage regression, and adjust household labor income by the sum of these correction values over all household members. In total only about 1% of our person-year observations are affected by this imputation procedure.

To account for differences in need and standard of living by household composition we scale all household incomes by the modified OECD equivalence scale. For the sake of inter-period and between-country comparisons we deflate all income figures with the purchasing power parity (PPP) adjustment factors for household consumption provided by the Penn World Tables (Feenstra et al. 2015). Lastly, we curb the influence of outliers by winsorizing at the 1st and the 99.5th-percentile of the year-specific income distribution.

Circumstance Types and Effort Tranches. In an equal-opportunity society there are no differences in outcomes across individuals with different circumstance characteristics but comparable levels of effort. Our measure of unfairness therefore requires to partition the population into circumstance types. Thereby a tension arises. On the one hand, the more parsimonious the type partition, the more we underestimate the influence of individual circumstances on life outcomes (Ferreira and Gignoux 2011). On the other hand, limited degrees of freedom suggest restrictions on the granularity of the type partition to avoid noisy estimates of the relevant type parameters. In this work we use four circumstance variables to partition the population into a maximum of 36 circumstance types.[24] First, we include the biological sex of the respondent. Second, we include a binary indicator differentiating among non-Hispanic white individuals and the remaining population. Third, we construct a categorical variable based on whether the highest educated parent (i) dropped out of secondary education, (ii) attained a secondary school degree, or (iii) acquired at least some tertiary education. Lastly, we proxy the occupational status of parents by grouping them in (i) elementary occupations, (ii) semi-skilled occupations, or (iii) skilled occupations. These are standard circumstances used in the empirical literature on inequality of opportunity. However, we present sensitivity analyses based on alternative type partitions in section 5.2.

Replacing our baseline notion of weak EOp with strong EOp additionally requires the identification of effort tranches. To this end, we further partition each type-specific income distribution into 20 quantiles and replace individual incomes with the within-type average of their respective effort tranche. Hence, for each year we perform our calculations on a maximum population of 36×20 cells, where each cell represents a particular circumstance-effort combination. In Figure S.3 we show that this standardization of income distributions has a negligible impact on conventional inequality and poverty measures in the time period of interest.

Minimum Threshold. The specification of poverty thresholds that allow for meaningful comparisons over time and across countries is a topic of widespread academic debate. For example, the official US poverty line is based on expenditure data from the 1950s to reflect three times the cost of a well-balanced diet. Since then it has been updated only by

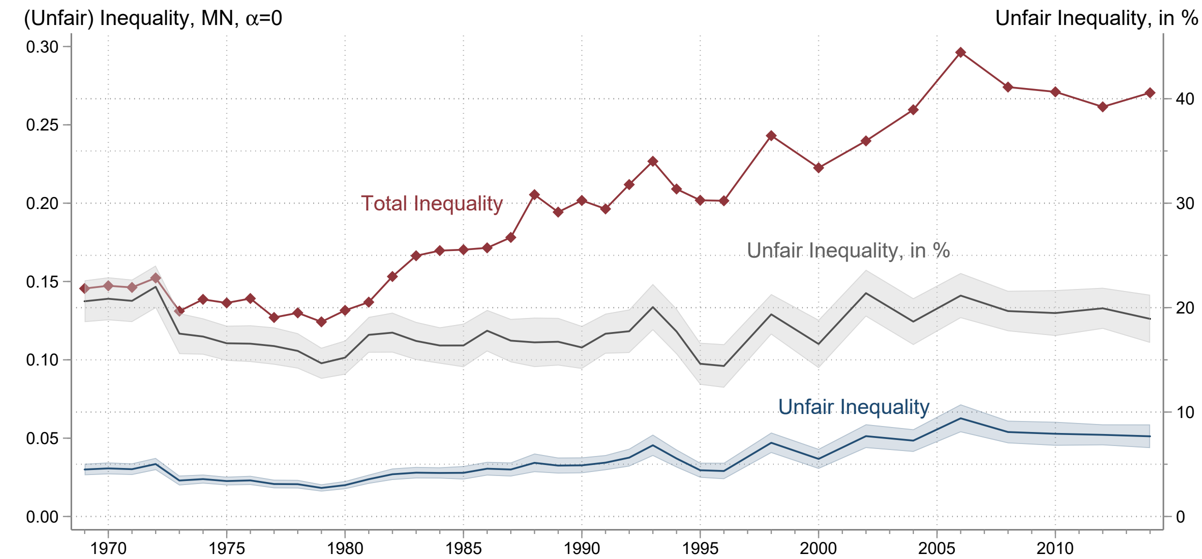
[24]Brunori et al. (2018) use machine learning techniques to find the optimal type partition for the same set of European countries that are used for our second empirical application, see section 4.2. Their results suggest that type partitions with more than 40 types tend to overfit the data. We therefore adhere to a threshold of 36 types.

inflation adjustments without taking account of potential changes in the needs of different family types (Meyer and Sullivan 2012). The international poverty line of the World Bank is currently set at \$1.90 per capita and day in PPP-adjusted dollars. In view of its low value it is criticized for being irrelevant in countries outside of the developing world (Allen 2017). Lastly, both EU and OECD define relative poverty lines as a fraction of median equivalized disposable household income. Poverty measurement based on relative lines, however, may react to changes in the upper percentiles of the distribution irrespective of changes in the shortfall of those in need from what is required to make ends meet (Foster 1998).

For our baseline estimates we rely on a revised set of international poverty lines as calculated by Jolliffe and Prydz (2016) in a two-step procedure. First, they match official national poverty headcounts to the PovcalNet expenditure data of the World Bank and calculate the implied poverty thresholds. Second, they group the resulting range of national poverty lines according to indicators of economic development and take the group median as an internationally comparable poverty line for the respective class of countries. Their procedure recovers the \$1.90 line for the least developed economies but yields more relevant poverty thresholds for economically advanced countries. In our baseline estimate, we take their set of national poverty lines and group countries in quintiles of PPP-adjusted household final consumption expenditure per capita. For single households in the US, this procedure yields a PPP-adjusted poverty line of \$12,874 annually that we hold constant (in real terms) over the period of our analysis. Sensitivity analyses based on alternative poverty thresholds are presented in section 5.3.

Baseline Results. Figure 1 displays the development of (unfair) inequality in the US over the time period 1969-2014. The upper line shows the development of total inequality as measured by the divergence of the empirical income distribution from a perfectly outcome egalitarian distribution in which $y_i^r = \mu^e, \ \forall \ i \in \mathcal{N}$. The time series replicates the well-documented pattern of inequality development in the US (among others Heathcote et al. 2010a; Burkhauser et al. 2012; Piketty et al. 2018): Slight inequality decreases throughout the 1970s are followed by strong inequality increases in the 1980s. This trend continues until the present day, most notably interrupted by the economic crises following the burst of the dot-com bubble at the turn of the century and the global financial crisis in the late 2000s.

Figure 1 – Unfair Inequality in the US, 1969-2014
Baseline Results



Data: PSID.
Note: Own calculations. This figure displays the development of (unfair) inequality in the US over the period 1969-2014. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The shaded areas show bootstrapped 95-% confidence intervals based on 500 draws.

The lower blue line displays the development of unfair inequality as measured by the divergence of the empirical income distribution from a norm distribution in which the ideals of EOp and FfP are realized to their full extent (see equation 16). It is unsurprising that unfair inequality remains at a much lower level than total inequality as the latter provides an upper bound for the former in any given country at any given point in time. However, it is noteworthy that unfair inequality seems to follow a similar time trend as total inequality. Starting with decreases of unfair inequality until 1980, we observe a steady increase of unfairness until the present day and downward movements that are largely coincidental with economic downturns.

The intermediate black line shows the share of total inequality that is in violation of EOp and FfP. It is calculated as the ratio between unfair inequality and total inequality and converted into percentage terms. Starting from a level of approximately 20% in 1969, unfair inequality drops to a share of 15% until 1980. This development suggests that the observed decreases in inequality over the 1970s were accompanied by an even stronger reduction of unfair inequality. In spite of an inequality increase by approximately 50% in the 1980s, the share of inequality attributable to violations of EOp and FfP remained roughly stable at this level until 1990. While the subsequent two decades are characterized by a more erratic pattern, we also note that unfair inequality follows a steeper growth curve than total inequality. Starting at a level of around 16% in 1990, the unfair share of inequality climbs to levels of close to 21% in the mid 2000s and stalls at a level of approximately 19% in the latest period of observation. Some may be surprised by the low relative share of unfair inequality. However, we emphasize that our measures are based on disposable household income and therefore evaluate the remaining unfairness after taking transfers through existing welfare state institutions as well as redistribution within households into account.[25]

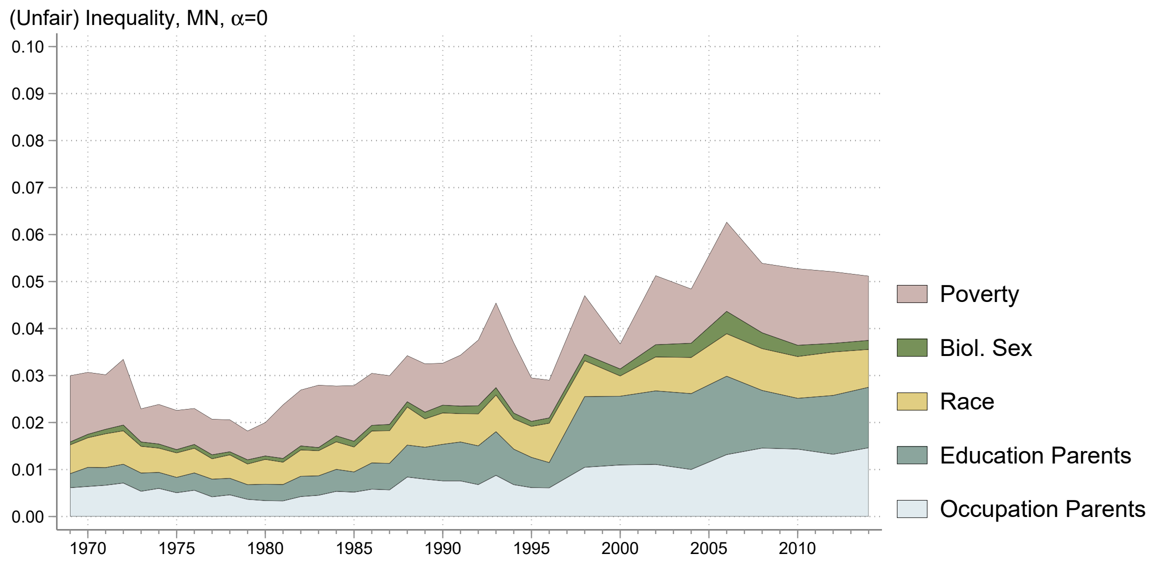
Decomposition. To develop a better understanding for the observed inequality trends, we conduct a Shapley value decomposition (Shorrocks 2012) to identify the contributions of the different components that underpin our normative principles. That is, we quantify the contributions of FfP and EOp, respectively. Furthermore, we decompose the latter into the contributions from the circumstance characteristics biological sex, race, parental education, and parental occupation. This decomposition furthermore allows us to embed our measure of unfairness into the larger literature branches on US trends in poverty, gender income gaps, racial disparities, and social mobility.

The Shapley value procedure quantifies the contribution of each of the aforementioned factors by calculating the average marginal decline in unfair inequality once we eliminate

[25] Moreover, it is well understood in the empirical literature that standard estimates of inequality of opportunity provide only lower bounds of their true value (Ferreira and Gignoux 2011; Hufe et al. 2017).

it from our calculations. For example, one could quantify the marginal impact of FfP on unfair inequality by decreasing $y_{\min}$ from our baseline threshold of $12,874 to $0. Analogously, one could quantify the marginal impact of biological sex by excluding it from the list of variables that define our type partition. However, in both steps the estimate of the marginal impact depends on the specification of the remaining normative criteria. To avoid such path-dependencies, we estimate the individual contribution of each factor by averaging their marginal impacts on unfair inequality across all possible elimination sequences (Shorrocks 2012). The results of this decomposition are shown in Figure 2.

Figure 2 – Unfair Inequality in the US, 1969-2014
Decomposition



Data: PSID.
Note: Own calculations. This figure displays a decomposition of unfair inequality in the US over the period 1969-2014. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. The decomposition is based on the Shapley value procedure proposed in Shorrocks (2012).

At the end of the 1960s, approximately half of unfair inequality, that is 10% of total inequality, could be attributed to violations of the FfP principle. The previously described attenuation of relative unfairness in the 1970s can be almost exclusively attributed to decreased violations of the FfP principle. While EOp shows only a slightly decreasing trend over the 1970s, the contribution of FfP to total inequality is halved, dropping from 0.014 points (10%) to 0.007 points (5%). Following the sharp decreases of the 1970s, the contribution of FfP bounces back to its initial levels in the 1980s and subsequently follows a by and large flat time trend that persists until the present day.[26] In 2014, violations of FfP contribute 0.014 points to our measure of unfairness and explain roughly 5% of total inequality.

At first glance, our results on poverty are in line with official statistics that also show a flat time trend in poverty rates across the period of investigation (U.S. Bureau of the Census 2019). However, the official poverty concept in the US differs from ours in important aspects such that this analogy only holds superficially. Official poverty statistics rely on the poverty headcount ratio applied to an annually adjusted poverty line that is based on the pre-government income of families. To the contrary, we apply a time-constant absolute poverty threshold to disposable household income after taxes and transfers and measure poverty as a linear combination of the poverty gap ratio and the Watts index (Section 3). In fact, applying the headcount ratio to our income concept and the time-constant poverty line, we find that the share of poor individuals drops by more than 40% over time (Figure S.7 and Table S.4).[27] However, while the share of poor households has constantly decreased over time the intensity of poverty as measured by the poverty gap ratio and the Watts index has first decreased in the 1970s and then rebounded since the mid-1990s. As a consequence, we also find a relatively constant poverty trend over time, but for different reasons than the official US government statistics.

The stable poverty trend, however, is superseded by marked increases in the violations of EOp. After slight decreases in the 1970s, the EOp contribution to total inequality increases from 10% in 1980, over 12% (14%) in 1990 (2000) to 14% in the latest period of observation.

Analyzing the EOp component in further detail, we note that the contribution of biological sex to overall inequality is negligible and hovers around the 1%-mark in relative

[26]Note that while the absolute contribution of FfP is rather stable between 1969 and 2014, its relative contribution is halved from 10% to 5%. However, this decrease in the relative contribution follows mechanically from the increase in total inequality. For further illustration, see also Figure S.6 in which we fit locally smoothed time trends for the relative contributions of both EOp and FfP.

[27]See Wimer et al. (2016) for similar results.

terms. Hence, our measure does not reflect the well-documented decrease in earnings differences between males and females (Blau and Kahn 2017). This deviation is not unexpected and follows from our focus on disposable household income. Accounting for resource sharing at the household level evens out any intra-household inequality among males and females. As such, all our results on biological sex are driven by single-headed households. Within this group the flat time trend in the contribution of sex-based differences to total inequality can be rationalized by two countervailing forces that are displayed in Figure S.8. First, income differences among male and female-headed single households have been decreasing over the time period 1969-2014. Second, the prevalence of single-headed households has been steadily increasing for both males and females. While the first trend depresses the contribution of sex-based differences to total inequality, the second trend magnifies the remaining differences leading to relatively time-constant contributions of this component to unfairness in the US.[28]

In analogy to biological sex, the contribution of race to unfairness in the US is largely stagnant at approximately 0.007 points across the time period of observation. In relative terms the contribution of race slightly decreases from 4% to 3%, again reflecting the marked increase of total inequality. This flat trend echoes previous findings that there has been little progress in closing the black-white earnings gap since the 1970s (Bayer and Charles 2018; Derenoncourt and Montialoux 2019).[29]

With the contributions from sex- and race-based differences rather constant over time, the witnessed increase of the EOp component is entirely driven by the increased importance of parental background variables – namely parental education and occupation. While these factors jointly contributed 0.009 points (6%) in 1969, their importance has tripled to 0.028 points (10%) in 2014. Interpreting the covariances between parental education and occupation and individual income as a proxy for social mobility, our findings suggest that the US has become increasingly immobile in the time period from 1969

[28]See also Lundberg et al. (2016) on the interaction between changing gender gaps, family structures and the intergenerational transmission of advantages.

[29]See also Figure S.9 for complementary evidence on the stability of non-white disposable income gaps in our data.

to 2014. This finding is in line with Aaronson and Mazumder (2008) and Davis and Mazumder (2019) who find that the intergenerational elasticity of income has declined for cohorts entering the labor market after 1980 as well as Hilger (2019) who documents a similar time trend for educational mobility. However, we note that the assessment of intergenerational mobility trends in the US is contentious. In contrast to the previously cited works, Lee and Solon (2009), Chetty et al. (2014b), and Song et al. (2019) conclude that intergenerational mobility has stayed constant over the time period of investigation. The disparity of results is explained by various drawbacks of the underlying data sources as well as different measurement choices. While our measurement approach is not strictly comparable to either of these papers, our results are in line with the first set of works.[30]

To summarize: In terms of its trend, unfair inequality largely replicates the development of total inequality in the US. However, due to marked decreases in poverty, unfairness showed an even stronger decrease than total inequality in the 1970s. To the contrary, the steeper growth of unfair inequality since the 1990s is almost exclusively attributable to increased violations of the EOp principle and the growing importance of parental background variables in particular.

4.2 Cross-Country Differences in Unfair Inequality

Data Source. For the purpose of an international comparison we combine the PSID with the 2011 wave of EU-SILC. EU-SILC serves as the official database for monitoring

[30] Mobility measures can be decomposed into i) the copula of parental background characteristics and child outcomes, and ii) the marginal distributions of child outcomes and parental background characteristics, respectively (Chetty et al. 2014b). Rank-mobility measures such as intergenerational correlations (IGC) and rank-rank correlations depend on i) while holding ii) constant. To the contrary, mobility measures like the intergenerational elasticity (IGE) allow for changes in ii). Clearly, our measurement approach is closer to the second class as we compare different marginal distributions in the parent and the child generation that we allow to change over time. However, our measure differs from a typical IGE estimate in at least three important dimensions. i) We model child income as a function of parental education and occupation instead of parental income. ii) We summarize persistence by calculating inequality in a predicted distribution instead of interpreting regression parameters. iii) Child outcomes refer to annual incomes at various points of the life-cycle instead of modeling them so as to mimic lifetime income (Nybom and Stuhler 2016). To provide a closer analogy to standard IGE estimates we re-estimate our measure of unfairness for different age groups at different points in time while excluding all determinants of unfairness except for parental background characteristics. The results, displayed in Figure S.10, suggest that relative mobility has decreased at all points of the individual life-cycle with more pronounced changes at older ages. This pattern is consistent with earnings profiles that fan out over the life-cycle.

inequality, poverty and social exclusion in the EU (see for example Atkinson et al. (2017) and the references cited therein) and covers a total of 31 countries.[31] We use the 2011 cross-sectional wave as it contains a special survey module on parental background information that allows us to construct types from a broad range of circumstance variables.[32] As in the PSID, incomes are reported for the year preceding the survey leading to 2010 as the year of our cross-sectional comparison. The data preparation closely follows the procedures outlined for the PSID. Further detail on the variable construction as well as descriptive statistics are provided in Supplementary Materials C and E.

Outcome Variable. We construct disposable household income as the sum of total household income from labor, asset flows, private transfers, public transfers, private retirement income and social security pensions, and deduct taxes on wealth (if applicable), income and social security contributions. In analogy to the PSID, we scale reported public transfers by a country-specific under-reporting factor and adjust labor incomes by imputing individual labor incomes of respondents with zero labor incomes but non-zero working hours. Only about 1% of respondents are affected by the latter imputation. Furthermore, we deflate household incomes by the modified OECD equivalence scale, adjust for purchasing power parities and winsorize country-specific income distributions at the 1st and 99.5th percentiles.

Circumstance Types and Effort Tranches. For each country we partition the population based on the following circumstance characteristics: i) biological sex, ii) migration background, iii) educational achievement of the highest educated parent, and iv) the highest occupation category of either parent. While circumstances i), iii), and iv) mirror the PSID specification, we replace the binary race variable of the PSID with a binary indi-

[31] The sample consists of Austria (AT), Belgium (BE), Bulgaria (BG), Switzerland (CH), Cyprus (CY), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Greece (EL), Spain (ES), Finland (FI), France (FR), Croatia (HR), Hungary (HU), Ireland (IE), Iceland (IS), Italy (IT), Malta (MT), Lithuania (LT), Luxembourg (LU), Latvia (LV), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), Slovakia (SK), and the United Kingdom (UK).

[32] In contrast to the PSID, EU-SILC consists of rotating panels and each household stays in the data for only 4 years. Hence, one cannot use the panel dimension to construct circumstance variables.

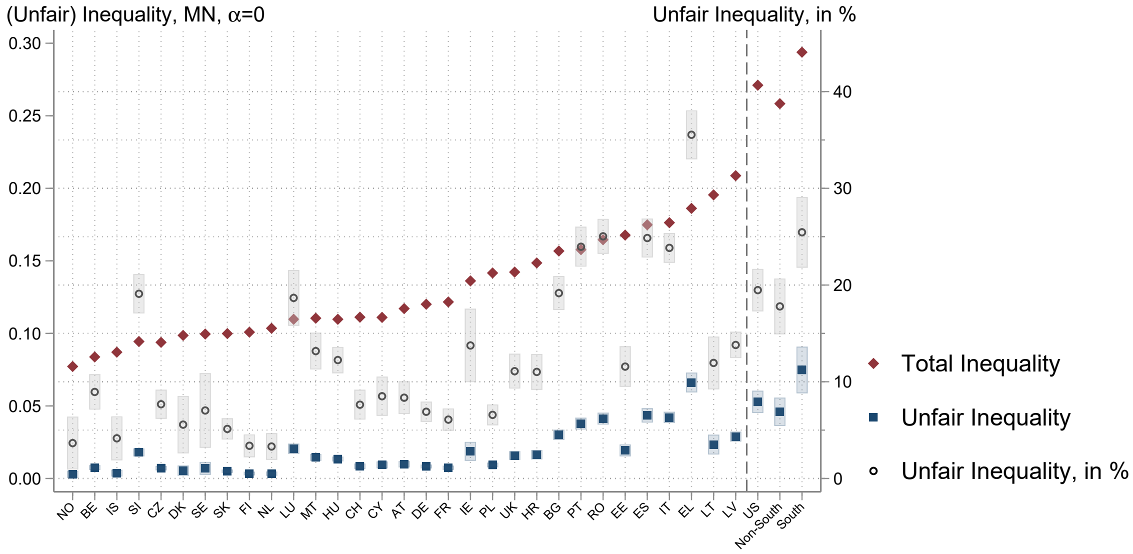
cator for whether respondents were born in their current country of residence. In total we partition the population into 36 circumstance types which we again subdivide into 20 quantiles to identify effort tranches. As evidenced in Figure S.3 this transformation is innocuous with respect to cross-country comparisons of inequality and poverty statistics.

Minimum Threshold. Internationally comparable absolute poverty thresholds are again constructed based on the procedure suggested by Jolliffe and Prydz (2016). 21 out of the 31 European countries belong to the highest quintile of countries in terms of PPP-adjusted household final consumption expenditures per capita and are hence characterized by the same poverty threshold as the US: $12,874 per annum (PPP-adj.). However, 10 Eastern European countries only belong to the second highest quintile and are therefore characterized by a lower poverty threshold of $3,957 per annum (PPP-adj.).

Baseline Results. Figure 3 replicates Figure 1 for the cross-country comparison. The red diamonds indicate total inequality, the blue squares unfair inequality. The black hollow circles show the relative share of unfair inequality. Countries are ordered from left to right by their level of total inequality. The dashed vertical line separates the European countries from the US sample. Acknowledging the special role of the Southern states in terms of intergenerational transmission processes (Chetty et al. 2014a; Bratberg et al. 2017) and poverty prevalence (Ziliak 2006), we also provide results separating the South of the US from the rest of the country (Northeast, Midwest, West) based on the census region groupings of the US Census Bureau.

The US are by far the most unequal society in our country sample with inequality figures about 25% higher than the most unequal European societies. At the other end of the spectrum we find Norway, Iceland and Belgium. The most unfair societies in 2010 are Greece, the US, Spain, Italy, and Romania closely followed by Portugal. Treating the South of the US as a separate country, it would attain the highest level of unfairness of all countries. In relative terms, EOp and FfP explain roughly 25% of total inequality in the European countries of this group – even 35% in Greece. The US attains an unfair share

Figure 3 – Unfair Inequality across Countries, 2010
Baseline Results



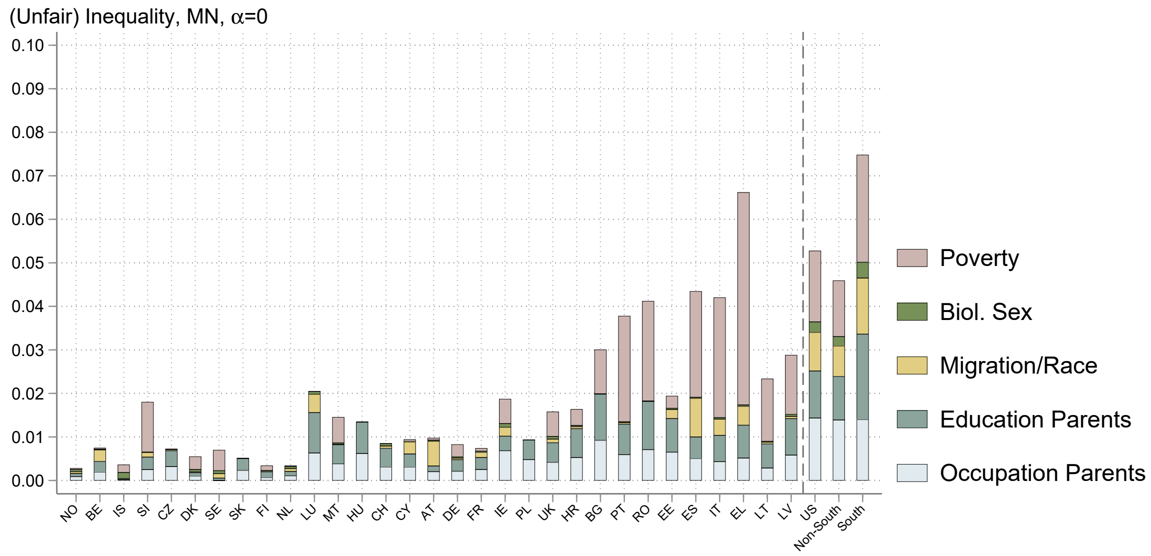
Data: PSID and EU-SILC.
Note: Own calculations. This figure displays cross-country differences in (unfair) inequality in 2010. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The shaded areas show bootstrapped 95-% confidence intervals based on 500 draws.

of approximately 19%. The lower unfairness share of the US follows mechanically from its higher levels of total inequality. The group of countries with the least extent of unfair inequality consists of Scandinavian countries plus the Netherlands. It is important to emphasize that country rankings differ depending on whether we analyze total inequality or unfairness. While for example Belgium is among the top three countries of least total inequality, it is not among the top ten countries of least unfair inequality.

Decomposition. The US differs markedly from its European counterparts in terms the processes that determine unfair inequality. Figure 4 shows the results of a Shapley value decomposition of unfair inequality into its different components.

In the European group of countries with the highest unfairness (Greece, Portugal, Romania, Spain, Italy), violations of the FfP principle consistently explain more than half of the detected unfair inequality. 2010 marks a peak year of the European sovereign debt crisis, and Greece, Portugal, Spain and Italy were among the countries most affected by it. To highlight the differential impact of the economic crisis on unfairness in Europe

Figure 4 – Unfair Inequality across Countries, 2010
Decomposition



Data: PSID and EU-SILC.
Note: Own calculations. This figure displays a decomposition of cross-country differences in unfair inequality in 2010. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. The decomposition is based on the Shapley value procedure proposed in Shorrocks (2012).

and the US, we calculate the difference between the Watts index and the poverty gap ratio for the six most unfair societies in our country sample (Greece, US, Spain, Italy, Romania, Portugal) from 2006 to 2014. Since the FfP component nests the difference between these two poverty measures, it can be interpreted as a proxy statistic for the longitudinal development of FfP in these countries. The results are displayed in Figure S.11. Romania is the least economically developed country in the considered country group. In Romania the financial crisis ended a trend of decreasing poverty and led to increased violations of the FfP principle in its aftermath. Similarly, in the group of Southern European countries the FfP proxy increases markedly after 2008. This evidence suggests that the high levels of unfair inequality among the European countries in 2010 followed from the economic downturn that accompanied the financial crisis and which in turn led to increased violations of the FfP principle.

In contrast to the European group, the difference between Watts index and poverty gap ratio is completely flat in the US over the crisis years. Instead, Figure 4 shows that unfairness in the US is strongly driven by the EOp component. This difference is not caused by the differential importance of biological sex. Due to our focus on disposable household income, income differences across the sexes have a negligible impact on unfair inequality in Europe and the US alike. Neither is this difference a mere consequence of replacing the race indicator with the immigration background indicator. Even abstracting from the migration/race circumstance, the US would be characterized by the highest degree of unequal opportunities in our country sample. It is the contributions of parental education and occupation that are the highest among all countries under consideration and place the US among the most unfair societies in our country sample. In line with the findings of Chetty et al. (2014a) and Hilger (2019) the lack of social mobility is particularly pronounced in the Southern states of the US. However, even when focusing on the non-Southern states only, the US ranks among the countries with the highest intergenerational persistence in our country sample (see also Corak 2013).

5 SENSITIVITY ANALYSIS

In this section, we investigate the sensitivity of our baseline results to alternative normative assumptions. First, we provide empirical results for all three alternative conceptualizations laid out in Table 1.

Second, in principle the measurement approach adopted in this paper takes a neutral stance on the specification of the model primitives Ω, Θ, and $y_{\min}$. Hence, it may accommodate a wide array of different views on the responsibility cut as well as the appropriate minimum threshold $y_{\min}$. Yet, we acknowledge that the precise cut between circumstances and effort, as well as the choice of $y_{\min}$ are normatively contentious. While it is not the ambition of this paper to resolve such disagreement, we provide results for alternative choices of Ω, Θ, and $y_{\min}$ in sections 5.2 and 5.3, respectively.

Third, differences between Y^r and Y^e may be aggregated by different divergence measures that put different weights on positive and negative divergences from norm incomes, respectively. We therefore provide robustness analyses with respect to the use of different divergence measures in section 5.4.

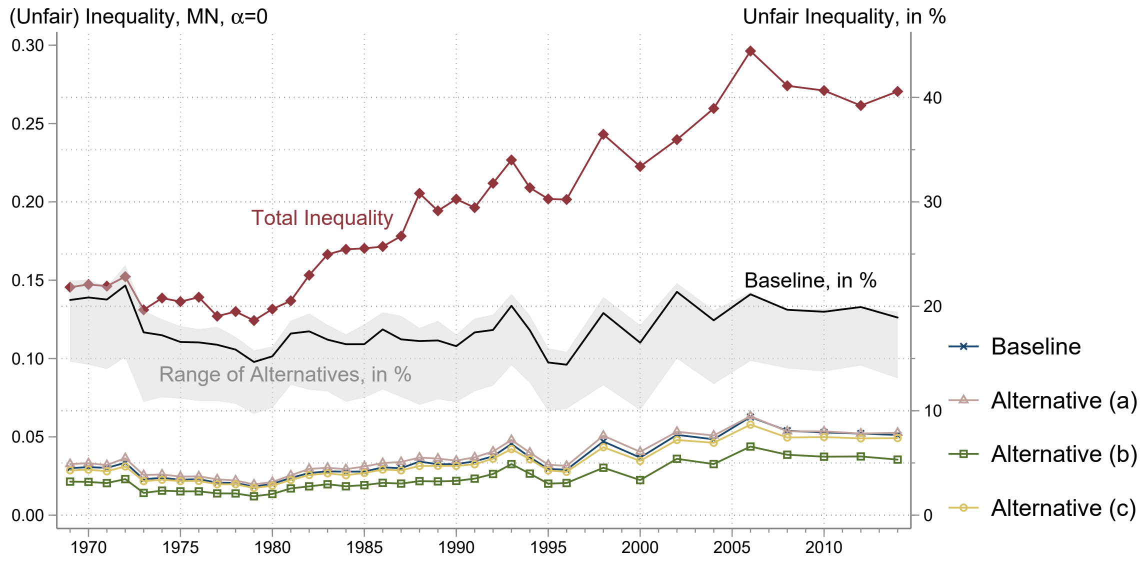
For brevity, we only present robustness checks for the longitudinal analysis of the US in the main body of this paper. However, every sensitivity check is conducted in an analogous way for the cross-country comparison – see Figures S.12-S.15 and Table S.6 in the Supplementary Material.

5.1 *Alternative Norm Distributions*

Our baseline estimates of unfair inequality rely on a measure that is based on a weak conceptualization of EOp and reconciles EOp and FfP in a non-separable way. In Table 1 we have presented alternative norm distributions that divert from the baseline by operating on a strong notion of EOp (Alternatives (a) and (c)) and/or assume separability between EOp and FfP (Alternatives (b) and (c)). Figure 5 presents the development of (unfair) inequality in the US with the upper line again marking the development of total inequality and the lower lines marking unfair inequality under each of these different conceptualizations. The black line marks the relative share of unfair inequality from our baseline estimate. The gray area shows the range between the lower and the upper envelope of the relative share of unfairness according to the alternative measurement specifications.

We note that our conclusions with respect to the time trend of unfair inequality in the US is robust to the different conceptualizations: A decrease in the relative share of unfair inequality until 1980 is followed by a stagnation throughout the following decade and increases throughout the 1990s until the present day. However, level differences exist. While Alternatives (a) and (c) yield results that are largely congruent to our baseline, Alternative (b) consistently detects lower levels of unfair inequality than the remaining measures. This result directly follows from the separability assumption according to which (i) opportunity sets of circumstance types are evaluated by excess incomes above $y_{\min}$ only, and ii) excluding empirically poor individuals from compensation through opportunity-equalizing transfers beyond the poverty line. Both features make the distribution of type-specific advantages more homogeneous and therefore require less transfers across types to attain the normatively desirable distribution of incomes. If one prefers the

Figure 5 – Unfair Inequality in the US, 1969-2014
Alternative Norm Distributions



Data: PSID.
Note: Own calculations. This figure displays the development of (unfair) inequality in the US over the period 1969-2014 according to the alternative norm distributions outlined in Table 1. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

conceptualization of Alternative (b) over our baseline measure, one would conclude that unfairness amounts to 13% instead of 19% of total inequality in 2014.

5.2 Alternative Responsibility Cuts

Any measurement of a responsibility-sensitive version of egalitarianism requires a stance on the features of life for which people should be held responsible. In our baseline estimates we assume that people should not be held responsible for i) their biological sex, ii) their race, iii) the occupation of their parents, and iv) the education of their parents. However, there may be further characteristics beyond individual control that evoke normative concern. Examples could be the quality of neighborhoods in which people grew up (Chetty et al. 2016), parenting practices (Doepke et al. 2019) or even genetic endowments (Papageorge and Thom 2019).

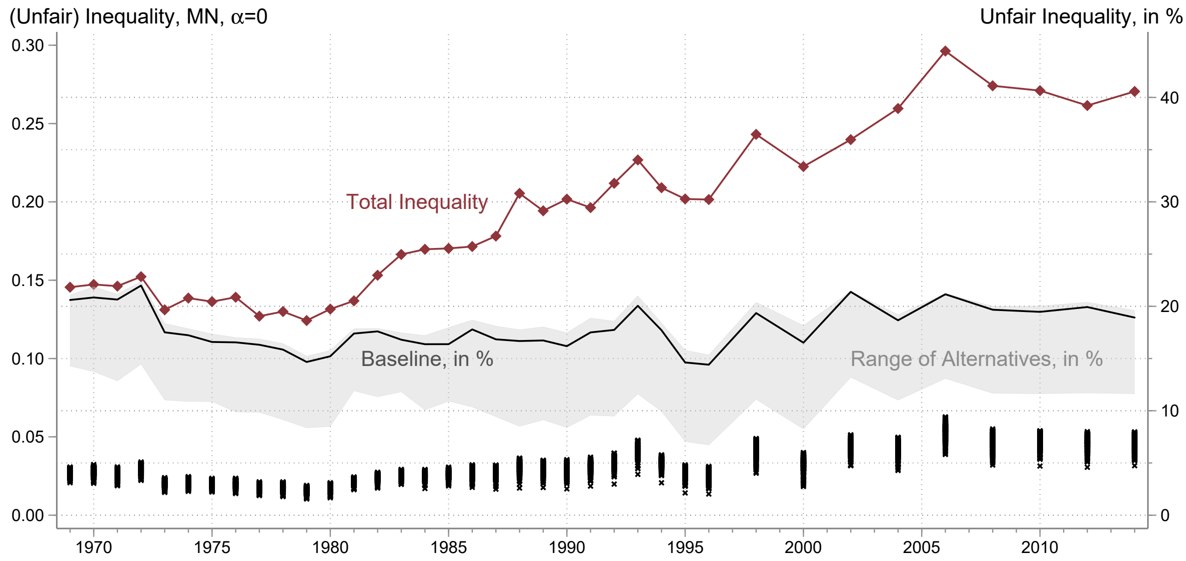
To be sure, the PSID puts strong constraints on testing the influence of different circumstance characteristics.[33] We therefore proceed as follows: First, we extract two additional circumstances that are consistently measured across the period of our analysis: i) the census region in which respondents grew up, and ii) the migration background of parents. We convert both variables into a vector of binary indicators and add them to our set of circumstances. Second, we repeat our analysis for all circumstance combinations that yield the same number of types as in our baseline analysis (36 types).[34] Hence, we repeat our analysis for 210 different specifications of Ω. The results are presented in Figure 6, where each black cross represents a different specification of Ω in any given year. The black line again marks the relative share of unfair inequality from our baseline estimate while the gray area shows the range between the lower and the upper envelope of the relative share of unfairness according to the alternative measurement specifications.

Our conclusions with respect to the time trend of unfair inequality in the US remains unaffected by the specification of Ω. However, we again register level differences depending on the factors for which we hold people responsible. According to the most conservative specification of Ω, unfair inequality in the US amounts to roughly 12% of total inequality in 2014 (with the upper range being 20%). We acknowledge that the alternative circumstance information in the PSID remains limited to geographical and migration background information. EU-SILC avails a broader range of circumstance characteristics from different domains that are consistently elicited across all sample countries. These include i) the relationship status of parents, ii) the number of siblings, iii) the financial situation of the parental household, as well as iv) property ownership of parents. We again test 210 different specifications of Ω for the EU-SILC countries holding the maximum number of types constant at 36. However, Figure S.13 reveals that in spite of level differences the

[33] The PSID has introduced the Child and Development Supplement (CDS) in 1997 with follow-up waves in 2002/03 and 2007/08. The CDS provides very detailed information on the living environments of 3,563 children aged 0-12 in the initial wave. However, even the oldest children from the 1997 CDS cohort are only now in their early 30s – an age that is commonly believed to be the minimum threshold to approximate long-term earnings potential. Respecting sensible age thresholds and due to sample attrition over time, the CDS sample is too small to exploit its richer circumstance information for the income decompositions that underlie our empirical analysis – see also our discussion in section 4.1.

[34] We keep the granularity of the type partition constant to ensure the comparability to our baseline results and to balance the concerns for underestimating the influence of circumstances and noisy estimates of the relevant type parameters – see also our discussion in section 4.1.

Figure 6 – Unfair Inequality in the US, 1969-2014
Alternative Circumstance Sets

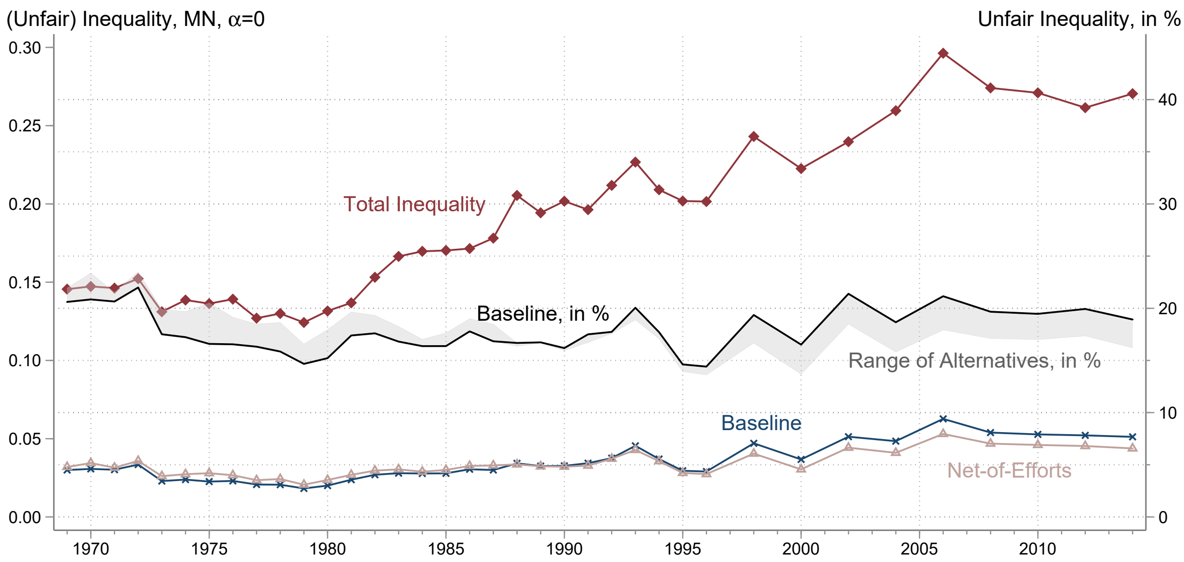


Data: PSID.
Note: Own calculations. This figure displays the development of (unfair) inequality in the US over the period 1969-2014 according to alternative specifications of the circumstance set Ω. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

general conclusions from our cross-country comparison remain robust to this broader set of alternative circumstance characteristics.

Another normative assumption relates to the correlation between circumstances Ω and efforts Θ. In our baseline measure we treat the correlation between both components as morally objectionable. For example, part of the income gap between whites and non-whites can be explained by differences in educational attainment (Gelbach 2016) which itself is at least partially under the control of individuals. Circumstances thus exert a direct and an indirect effect on life outcomes. While in our baseline we follow Roemer (1998) and consider both effects as normatively objectionable, others have suggested to hold people responsible for effort and preference variables regardless of how they are formed (Barry 2005). To test the sensitivity of our baseline results to this alternative normative stance, we repeat our analysis while partialling out the indirect effect that circumstances exert through individual efforts. To this end, we consider two variables that are partially under the control of individuals and highly predictive of incomes – i) educational attainment, and ii) annual working hours – and clean circumstances from their correlation with these effort variables before repeating our analysis.[35] If circumstances had no impact independent of the considered efforts, we would see a sharp drop of unfair inequality in comparison to our baseline results.

Figure 7 – Unfair Inequality in the US, 1969-2014
Accounting for Preferences



Data: PSID.
Note: Own calculations. This figure displays the development of (unfair) inequality in the US over the period 1969-2014 according to alternative treatments of the correlation between the effort set Θ and the circumstance set Ω. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

Figure 7 shows the differences between our baseline and the alternative responsibility cut. We note a moderation of the previously described time trend when holding people responsible for the correlation between circumstances Ω and efforts Θ. In contrast to our baseline, unfair inequality starts at higher levels in 1969 and increases much more moderately in the 1990s. Combining this moderation of the time trend in absolute unfair inequality with the increasing slope of total inequality, the relative share of unfairness decreases over time and remains slightly above the 15%-mark in 2014. The differential development of our baseline and the alternative measure is consistent with evidence on increasing college wage premia (Heathcote et al. 2010b), longer working hours among the

[35] We describe the exact steps of this procedure in Supplementary Material F.

highly educated (Fuentes and Leamer 2019) and the increasing stratification of college completion by parental background characteristics (Davis and Mazumder 2019; Hilger 2019). Once we shut down educational attainment and working hours as channels of circumstance influence, unfairness does no longer reflect the growing importance of these factors for the determination of incomes over time.

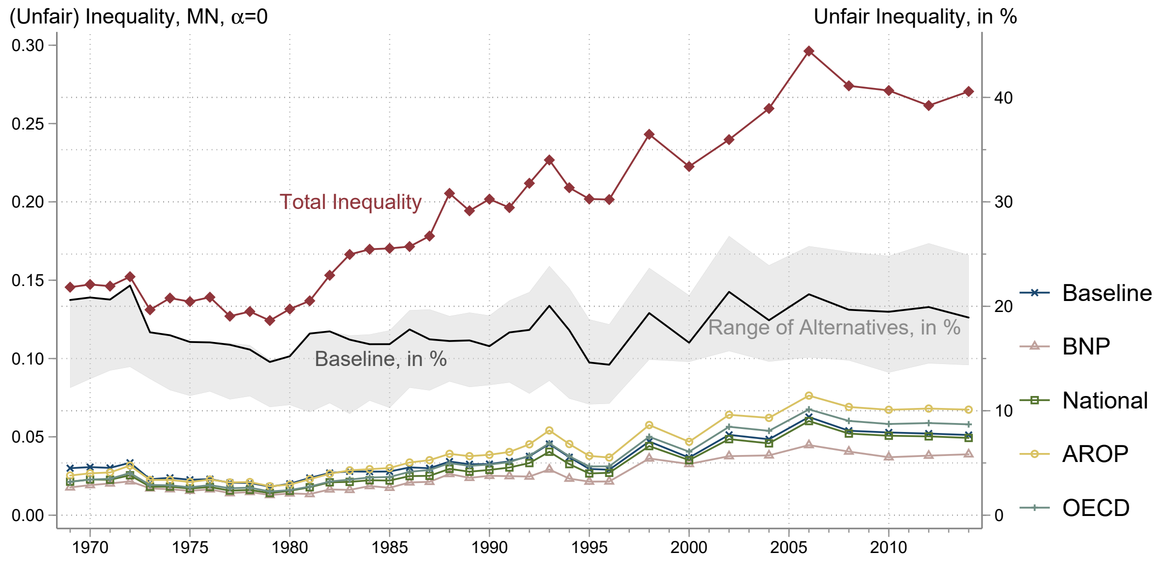
5.3 Alternative Minimum Thresholds

There is no clear consensus on how to set an income threshold that captures the material requirements of what it takes to make ends meet. Acknowledging the arbitrariness of any threshold, Foster (1998) suggests to move beyond normative and empirical disagreements on the correct value of y_{min} and to show the robustness of the main conclusions based on different plausible specifications of y_{min} instead. In this spirit we provide alternative measures of unfair inequality based on four different poverty lines. First, Allen (2017) uses a linear programming approach to calculate the PPP-adjusted minimal cost of a basic needs consumption basket containing food to satisfy nutritional requirements, as well as fuel for heating, clothing and shelter for different climatic regions of the world. For the four countries overlapping with our sample (US, Lithuania, UK, France) he calculates an average basic needs poverty (BNP) line of \$3.96 (PPP-adj.) per capita and day which we apply to all countries and years in our sample. Second, we repeat our analysis by using the official country-year-specific national poverty lines of the US Census Bureau and EUROSTAT. Third, we calculate relative poverty lines based on the suggestions of the OECD and EUROSTAT. While the OECD proposes a poverty line at 50% of the median equivalized disposable household income, EUROSTAT proposes an at-risk-of-poverty (AROP) line at 60% of the median of the same distribution.[36] The results for these different poverty thresholds are shown in Figure 8.

We note that our general conclusions with respect to the trend of unfairness in the

[36] Note that the official poverty statistics of EUROSTAT are also calculated by reference to the AROP threshold. The AROP lines presented in this work differ nevertheless from the national poverty lines provided by EUROSTAT since we calculate them by observing the sample restrictions and variable definitions used in this paper.

Figure 8 – Unfair Inequality in the US, 1969-2014
Alternative Minimum Thresholds



Data: PSID.
Note: Own calculations. This figure displays the development of (unfair) inequality in the US over the period 1969-2014 according to alternative specifications of the poverty threshold $y_{\min}$. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications. The construction of the alternative minimum thresholds is discussed in Supplementary Material C.

US are insensitive to the specification of the poverty threshold. If anything, the relative poverty thresholds of the OECD and AROP tend to magnify the relative increase of unfairness since the 1990s. However, unsurprisingly we observe sharp level differences in unfair inequality depending on the stringency of the poverty threshold. Proponents of the AROP threshold ($18,737) would conclude that unfairness explained 25% of total inequality in the US in 2014, while proponents of the BNP ($1,445) threshold would detect a relative share of 14%.

5.4 Alternative Divergence Measures

Our baseline measure of unfair inequality employs the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$. In addition to alternations in the weighting parameter α, we now present results based on the measures put forward by Cowell (1985) and Almås et al. (2011). The family put forward by Cowell (1985) is another generalization of the entropy class of inequality indexes that varies with an inequality aversion parameter

α. The Cowell-family and the MN-family coincide exactly for $\alpha = 1$. Moreover, we employ the unfairness Gini proposed by Almås et al. (2011) which tends to put relatively less weight on large negative divergences from the reference distribution.

In spite of their differences, all measures yield highly comparable results in terms of cross-period comparisons of unfair inequality. Table 2 shows rank-correlations for the different measures and their parameterizations for the US sample. All correlation coefficients are at a level of at least 0.96. Hence, we conclude that our results are robust to alternations in the way in which divergences between Y^e and Y^r are aggregated.

Table 2 – Rank Correlation across Years, US

	Magdalou and Nock			Cowell			Almås et al.
	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$	
Magdalou and Nock							
$\alpha = 0$	1.00	.	.	.	.	.	.
$\alpha = 1$	0.99	1.00	.	.	.	.	.
$\alpha = 2$	0.97	0.99	1.00	.	.	.	.
Cowell							
$\alpha = 0$	0.99	1.00	0.98	1.00	.	.	.
$\alpha = 1$	0.99	1.00	0.99	1.00	1.00	.	.
$\alpha = 2$	0.98	1.00	0.99	1.00	1.00	1.00	.
Almås et al.							
	0.96	0.98	1.00	0.98	0.98	0.98	1.00

Data: PSID.
Note: Own calculations. This table displays rank correlations for unfair inequality across years based on different divergence measures. Unfair inequality is calculated based on the divergence measures proposed by Magdalou and Nock (2011), Cowell (1985), and Almås et al. (2011).

6 CONCLUSION

In this paper we have provided a new measure of unfair inequality that reconciles the ideals of equality of opportunity (EOp) and freedom from poverty (FfP). In fact, we provide the first work that combines these widely-endorsed principles of justice into a joint measure of unfair inequality by treating both as co-equal grounds for compensation.

Next to illustrating our measurement approach and showcasing its flexibility to various normative alternations, we provide two empirical applications. First, we analyze the development of inequality in the US over the time period 1969-2014 from the normative perspective of our unfairness measure. Second, we provide a corresponding international comparison between the US and 31 European countries in 2010. In combination, both analyses yield important implications for current debates on inequality. First, the US trend in unfair inequality has largely traced the marked increase of total inequality since the beginning of the 1980s. Second, since the 1990s unfair inequality follows a steeper growth curve than total inequality. Third, this trend is mainly driven by a less equal distribution of opportunities across people that face different circumstances beyond their individual control. Fourth, unfairness in the US shows a remarkably different structure than in comparable European societies. While unfairness in Europe in 2010 seems to be largely driven by the consequences of European debt crisis, unfairness in the US is driven by the intergenerational transmission of disadvantages. The underlying determinants of the latter are arguably much more persistent than income shortfalls due to economic downturns which illustrates the enormous challenge presented to policymakers willing to address unfairness in the US.

While we provide comprehensive robustness checks for our findings, there are shortcomings which suggest a wide avenue for further research. At the empirical level, it includes addressing the well-known drawbacks of survey data by the use of suitable administrative datasets. Furthermore, we have shown in this work that our measurement approach lends itself to various refinements and extensions with respect to the conceptualization of unfairness. While we were careful to choose our guiding principles to broadly match the fairness perceptions of a larger public, we look forward to tailor our approach even stronger to forthcoming empirical evidence on the normative preferences upheld by individuals.

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A PROOF

Proof of Proposition 1. The proposition is trivially true for the (counterfactually) poor population $\mathcal{P}(\omega)$ as their norm incomes are prescribed by the FfP condition (13). Furthermore, for each type $\mathcal{T}(\omega)$ we can use (14) to rewrite y_i^r for the non-poor population $\mathcal{R}(\omega)$:

$$y_i^r = y_{\min} + \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}} (y_j^r - y_{\min}). \tag{25}$$

We use this expression together with the FfP condition ($y_i^r = y_{\min}, \ \forall \ i \in \mathcal{P}(\omega)$) in the EOp condition (9):

$$\underbrace{\frac{1}{N_{\mathcal{T}(\omega)}} \left[\sum_{i \in \mathcal{P}(\omega)} y_{\min} + \sum_{i \in \mathcal{R}(\omega)} \left(y_{\min} + \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}} (y_j^r - y_{\min}) \right) \right]}_{= \mu^r_{\mathcal{T}(\omega)}} = \mu^e. \tag{26}$$

We simplify (26) as follows:

$$\begin{aligned}
y_{\min} + \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{R}(\omega)} \frac{y_j^r - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}} (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) &= \mu^e \\
y_{\min} + \frac{y_j^r - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}} \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{R}(\omega)} (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) &= \mu^e \\
y_{\min} + \frac{y_j^r - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}} \frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) &= \mu^e.
\end{aligned}$$

We solve for y_j^r to obtain the norm income of any $j \in \mathcal{R}(\omega)$:

$$y_j^r = y_{\min} + (y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})}. \tag{27}$$

As evidenced by (26), $\mu^r_{\mathcal{T}(\omega)}$ is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{\min}, \infty)$. It is straightforward that $\mu^r_{\mathcal{T}(\omega)} \to y_{\min}$ for $y_j^r \to y_{\min}$ and $\mu^r_{\mathcal{T}(\omega)} \to \infty$ for $y_j^r \to \infty$. Under the assumption that $\mu^e > y_{\min}$ and invoking the intermediate value theorem, it follows that there is a unique value of y_j^r for which (26) holds. Since the choice of $i, j \in \mathcal{R}(\omega)$ was arbitrary, expressions (27) and (15) hold for all $i, j \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega$.

However, such a unique value only exists if $\mu^e > y_{\text{min}}$. Assume this was not true, i.e. $\mu^e \leq y_{\text{min}}$. Then, it would still hold that $\mu^r_{\mathcal{T}(\omega)} \to y_{\text{min}}$ for $y_j^r \to y_{\text{min}}$ and $\mu^r_{\mathcal{T}(\omega)} \to \infty$ for $y_j^r \to \infty$. Hence, $\mu^r_{\mathcal{T}(\omega)} \in (y_{\text{min}}, \infty)$. However, from the EOp requirement (9) we also know that $\mu^r_{\mathcal{T}(\omega)} = \mu^e$. If $\mu^e \leq y_{\text{min}}$, either of these statements must be false and hence $\cap_{h=1}^4 \mathcal{D}^h = \emptyset$. Intuitively, if $\mu^e \leq y_{\text{min}}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^3$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^4$), while maintaining the equal resource requirement ($\mathcal{D}^1$).

■

Measuring Unfair Inequality: Reconciling Equality of Opportunity and Freedom from Poverty

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Supplementary Material

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A ALTERNATIVE CONCEPTUALIZATIONS

In this appendix we provide the formal derivations of the alternative norm distributions discussed in section 3.4 and displayed in Table 1. Furthermore, we show how additional inequality aversion may be introduced into our framework and how to operationalize the FfP concept based on individual-specific deprivation thresholds.

A.1 *Alternative (a).*

For this alternative measure we divert from the baseline by replacing weak EOp with strong EOp. The satisfaction of strong EOp requires the equalization of all moments of the type-specific income distribution. We therefore reformulate (9) as follows:

$$\mathcal{D}^{2a} = \left\{ d \in \mathcal{D} \;\middle|\; y_i^r = \tfrac{1}{N_{\mathcal{S}(\theta)}} \sum_{j \in \mathcal{S}(\theta)} y_j^r = \mu^r_{\mathcal{S}(\theta)},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta \right\}. \tag{28}$$

Since we adhere to non-separability, invoking strong EOp requires a subsequent redefinition of the poor and the non-poor fraction of the population. As in the baseline, we construct a counterfactual income distribution that complies with the EOp principle in order to identify those below the poverty threshold y_{min}:

$$\mathcal{P}(\theta) = \left\{ i \in \mathcal{S}(\theta) \;\middle|\; y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e} \leq y_{\text{min}} \right\},\ \forall\ \theta \in \Theta, \tag{29}$$

$$\mathcal{R}(\theta) = \left\{ i \in \mathcal{S}(\theta) \;\middle|\; y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e} > y_{\text{min}} \right\},\ \forall\ \theta \in \Theta. \tag{30}$$

Furthermore, we define $\mathcal{R}(\Theta) = \cup_h \mathcal{R}(\theta)$.

As a consequence, the FfP and the proportionality requirement are formulated with respect to the counterfactual distribution in which strong EOp is realized:

$$\mathcal{D}^{3a} = \left\{ d \in \mathcal{D} \;\middle|\; y_i^r = y_{\text{min}},\ \forall\ i \in \mathcal{P}(\theta),\ \forall\ \theta \in \Theta \right\}, \tag{31}$$

$$\mathcal{D}^{4a} = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y_i^r - y_{\text{min}}}{y_j^r - y_{\text{min}}} = \frac{\mu^e_{\mathcal{S}(\theta)} - y_{\text{min}}}{\mu^e_{\mathcal{S}(\theta')} - y_{\text{min}}},\ \forall\ i \in \mathcal{R}(\theta),\ \forall\ j \in \mathcal{R}(\theta'),\ \forall\ \theta \in \Theta \right\}. \tag{32}$$

Invoking strong EOp leads to the following proposition:

Proposition 2. *Suppose $\mu^e > y_{min}$. Then, the intersection $\mathcal{D}^1 \cap \mathcal{D}^{2a} \cap \mathcal{D}^{3a} \cap \mathcal{D}^{4a}$ yields a singleton which defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{min}, & \forall\ i \in \mathcal{P}(\theta),\ \forall\ \theta \in \Theta, \\ y_{min} + (\mu^e_{\mathcal{S}(\theta)} - y_{min}) \frac{(\mu^e - y_{min})}{\frac{N_{\mathcal{R}(\Theta)}}{N}(\mu^e_{\mathcal{R}(\Theta)} - y_{min})}, & \forall\ i \in \mathcal{R}(\theta),\ \forall\ \theta \in \Theta. \end{cases} \tag{33}$$

Conversely, if $\mu^e \leq y_{min}$, then $\mathcal{D}^1 \cap \mathcal{D}^{2a} \cap \mathcal{D}^{3a} \cap \mathcal{D}^{4a} = \emptyset$.

Proof of Proposition 2. The proof proceeds in analogy to the proof of Proposition 1. The proposition is trivially true for the (counterfactually) poor population $\mathcal{P}(\theta)$ as their norm incomes are prescribed by (31). We can use (32) to rewrite y_i^r for the members of tranches that are non-poor on average and use this expression in the constant resources constraint (8):

$$\underbrace{\frac{1}{N} \sum_{\theta \in \Theta} \left[\sum_{i \in \mathcal{P}(\theta)} y_{\text{min}} + \sum_{i \in \mathcal{R}(\theta)} \left(y_{\text{min}} + \frac{\mu^e_{\mathcal{S}(\theta)} - y_{\text{min}}}{\mu^e_{\mathcal{S}(\theta')} - y_{\text{min}}} (y_j^r - y_{\text{min}}) \right) \right]}_{=\mu^r} = \mu^e. \tag{34}$$

Solving for y_j^r we obtain:

$$y_j^r = y_{\text{min}} + (\mu^e_{\mathcal{S}(\theta')} - y_{\text{min}}) \frac{(\mu^e - y_{\text{min}})}{\frac{N_{\mathcal{R}(\Theta)}}{N}(\mu^e_{\mathcal{R}(\Theta)} - y_{\text{min}})}. \tag{35}$$

As evidenced by (34), μ^r is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{\text{min}}, \infty)$. Under the assumption that $\mu^e > y_{\text{min}}$ and invoking the intermediate value theorem, it follows that there is a unique value of y_j^r for which (8) holds. Since the choice of $i \in \mathcal{R}(\theta)$ and $j \in \mathcal{R}(\theta')$ was arbitrary, expression (33) holds $i \in \mathcal{R}(\theta), j \in \mathcal{R}(\theta'),\ \forall\ \theta \in \Theta$.

However, such a unique value only exists if $\mu^e > y_{\text{min}}$. Assume this was not true, i.e. $\mu^e \leq y_{\min}$. Then, it would still hold that $\mu^r \to y_{\min}$ for $y_j^r \to y_{\min}$ and $\mu^r \to \infty$ for $y_j^r \to \infty$. Hence, $\mu^r \in (y_{\min}, \infty)$. However, from the constant resources requirement (8) we also know that $\mu^r = \mu^e$. If $\mu^e < y_{\min}$, either of these statements must be false and hence $\mathcal{D}^1 \cap \mathcal{D}^{2a} \cap \mathcal{D}^{3a} \cap \mathcal{D}^{4a} = \emptyset$. Intuitively, if $\mu^e < y_{\min}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^{3a}$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^{4a}$), while maintaining the equal resource requirement ($\mathcal{D}^1$). ■

A.2 Alternative (b).

For this alternative measure we divert from the baseline by replacing non-separability with separability. In line with this normative assumption we reformulate the EOp requirement as follows:

$$\mathcal{D}^{2b} = \left\{ d \in \mathcal{D} \;\middle|\; \underbrace{\frac{1}{N_{\mathcal{T}(\omega)\cap\mathcal{R}}} \sum_{i \in \mathcal{T}(\omega)\cap\mathcal{R}} y_i^r}_{=\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}}} = \underbrace{\frac{1}{N_{\mathcal{R}}} \sum_{j \in \mathcal{R}} y_j^e \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right)}_{=\mu^r_{\mathcal{R}}}, \; \forall \, \omega \in \Omega \right\}. \tag{36}$$

Instead of rating type-specific advantages by $\mu^e_{\mathcal{T}(\omega)}$, (36) draws on the average excess income above the poverty line, $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}}$, to evaluate opportunity sets. Note that the type-specific average income above $y_{\min}$ must be equalized with respect to the norm (not the empirical) income of the rich population. This is a direct consequence of the constant resource restriction given in (8): Maintaining constant resources it is impossible to satisfy FfP without reducing the resources of the non-poor fraction $\mathcal{R}$ accordingly.

Separability of EOp and FfP entails that the incomes of $i \in \mathcal{P}$ are compared to a norm income of $y_{\min}$, while the gains from opportunity equalization only accrue to $i \in \mathcal{R}$. As a consequence, the FfP and the proportionality requirement are formulated with respect to the sets $\mathcal{P}$ and $\mathcal{R}$ instead of their counterfactual analogues $\mathcal{P}(\omega)$ and $\mathcal{R}(\omega)$:

$$\mathcal{D}^{3b} = \left\{ d \in \mathcal{D} \;\middle|\; y_i^r = y_{\min}, \; \forall \, i \in \mathcal{P} \right\}, \tag{37}$$

$$\mathcal{D}^{4b} = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y_i^r - y_{\min}}{y_j^r - y_{\min}} = \frac{y_i^e - y_{\min}}{y_j^e - y_{\min}},\ \forall\, i, j \in \mathcal{T}(\omega) \cap \mathcal{R},\ \forall\, \omega \in \Omega \right\}. \tag{38}$$

Invoking the separability assumption leads to the following proposition:

Proposition 3. *Suppose $\mu^e > y_{min}$. Then, the intersection $\mathcal{D}^1 \cap \mathcal{D}^{2b} \cap \mathcal{D}^{3b} \cap \mathcal{D}^{4b}$ yields a singleton which defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{min}, & \forall\, i \in \mathcal{T}(\omega) \cap \mathcal{P},\ \forall\, \omega \in \Omega, \\ y_{min} + (y_i^e - y_{min}) \frac{(\mu^e - y_{min})}{\frac{N_\mathcal{R}}{N}(\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} - y_{min})}, & \forall\, i \in \mathcal{T}(\omega) \cap \mathcal{R},\ \forall\, \omega \in \Omega. \end{cases} \tag{39}$$

Conversely, if $\mu^e \leq y_{min}$, then $\mathcal{D}^1 \cap \mathcal{D}^{2b} \cap \mathcal{D}^{3b} \cap \mathcal{D}^{4b} = \emptyset$.

Proof of Proposition 3. The proof proceeds in analogy to the proof of Proposition 1. The proposition is trivially true for the poor population $\mathcal{P}$ as their norm incomes are prescribed by (37). For each type $\mathcal{T}(\omega)$ we can use (38) to rewrite y_i^r for the non-poor population and use this expression in the reformulated EOp condition (36):

$$\underbrace{\frac{1}{N_{\mathcal{T}(\omega)\cap\mathcal{R}}} \left[\sum_{i \in \mathcal{T}(\omega)\cap\mathcal{R}} \left(y_{\min} + \frac{y_i^e - y_{\min}}{y_j^e - y_{\min}} (y_j^r - y_{\min}) \right) \right]}_{=\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}}} = \mu^r_\mathcal{R}. \tag{40}$$

We use the constant resource condition (8) to express $\mu^r_\mathcal{R}$ in terms of observable quantities:

$$\frac{1}{N_{\mathcal{T}(\omega)\cap\mathcal{R}}} \left[\sum_{i \in \mathcal{T}(\omega)\cap\mathcal{R}} \left(y_{\min} + \frac{y_i^e - y_{\min}}{y_j^e - y_{\min}} (y_j^r - y_{\min}) \right) \right] = \frac{\mu^e - \frac{N_\mathcal{P}}{N} y_{\min}}{\frac{N_\mathcal{R}}{N}}. \tag{41}$$

Solving for y_j^r we obtain:

$$y_j^r = y_{\min} + (y_j^e - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_\mathcal{R}}{N} (\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} - y_{\min})}. \tag{42}$$

As evidenced by (41), $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}}$ is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{\min}, \infty)$. Invoking the proportionality condition (38) it must also be that $\mu^r_\mathcal{R} > y_{\min}$. Under the assumption that $\mu^e > y_{\min}$ and invoking the intermediate value theorem, it follows that there is a unique value of y^r_j for which (36) holds. Since the choice of $i, j \in \mathcal{T}(\omega) \cap \mathcal{R}$ was arbitrary, expression (39) holds $\forall\ i, j \in \mathcal{T}(\omega) \cap \mathcal{R},\ \forall\ \omega \in \Omega$.

However, such a unique value only exists if $\mu^e > y_{\min}$. Assume this was not true, i.e. $\mu^e \leq y_{\min}$. Then, it would still hold that $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} \to y_{\min}$ for $y^r_j \to y_{\min}$ and $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} \to \infty$ for $y^r_j \to \infty$. Hence, $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} \in (y_{\min}, \infty)$. However, from the reformulated EOp requirement (36) we also know that $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^r_{\mathcal{R}} \left(= (\mu^e - \frac{N_{\mathcal{P}}}{N} y_{\min}) / \frac{N_{\mathcal{R}}}{N}\right)$. If $\mu^e \leq y_{\min}$, either of these statements must be false and hence $\mathcal{D}^1 \cap \mathcal{D}^{2b} \cap \mathcal{D}^{3b} \cap \mathcal{D}^{4b} = \emptyset$. Intuitively, if $\mu^e \leq y_{\min}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^{3b}$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^{4b}$), while maintaining the equal resource requirement ($\mathcal{D}^1$). ■

A.3 Alternative (c).

For this alternative measure we divert from the baseline by adhering to both strong EOp and separability. We therefore reformulate (9) as follows:

$$\mathcal{D}^{2c} = \left\{ d \in \mathcal{D} \;\middle|\; y^r_i = \frac{1}{N_{\mathcal{S}(\theta)\cap\mathcal{R}}} \sum_{j \in \mathcal{S}(\theta)\cap\mathcal{R}} y^r_j = \mu^r_{\mathcal{S}(\theta)\cap\mathcal{R}},\ \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\ \theta \in \Theta \right\}. \quad (43)$$

Separability of EOp and FfP entails that the incomes of $i \in \mathcal{P}$ are compared to a norm income of $y_{\min}$, while the gains from opportunity equalization only accrue to $i \in \mathcal{R}$. As a consequence, the FfP and the proportionality requirement are formulated with respect to the sets $\mathcal{P}$ and $\mathcal{R}$ instead of a counterfactual analogue:

$$\mathcal{D}^{3c} = \left\{ d \in \mathcal{D} \;\middle|\; y^r_i = y_{\min},\ \forall\ i \in \mathcal{P} \right\}, \quad (44)$$

$$\mathcal{D}^{4c} = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y^r_i - y_{\min}}{y^r_j - y_{\min}} = \frac{\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} - y_{\min}}{\mu^e_{\mathcal{S}(\theta')\cap\mathcal{R}} - y_{\min}},\ \forall\ i \in \mathcal{R}(\theta),\ \forall\ j \in \mathcal{R}(\theta'),\ \forall\ \theta \in \Theta \right\}. \quad (45)$$

Invoking strong EOp and the separability assumption leads to the following proposition:

Proposition 4. *Suppose $\mu^e > y_{min}$. Then, the intersection $\mathcal{D}^1 \cap \mathcal{D}^{2c} \cap \mathcal{D}^{3c} \cap \mathcal{D}^{4c}$ yields a singleton which defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{min}, & \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{P},\ \forall\ \theta \in \Theta, \\ y_{min} + (\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} - y_{min}) \frac{(\mu^e - y_{min})}{\frac{N_\mathcal{R}}{N}(\mu^e_\mathcal{R} - y_{min})}, & \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\ \theta \in \Theta. \end{cases} \tag{46}$$

Conversely, if $\mu^e \leq y_{min}$, then $\mathcal{D}^1 \cap \mathcal{D}^{2c} \cap \mathcal{D}^{3c} \cap \mathcal{D}^{4c} = \emptyset$.

Proof of Proposition 4. The proof proceeds in analogy to the proof of Proposition 1. The proposition is trivially true for the poor population $\mathcal{P}$ as their norm incomes are prescribed by (44). We can use (45) to rewrite y_i^r for the non-poor members of each effort tranche and use this expression in the constant resources constraint (8):

$$\underbrace{\frac{1}{N} \sum_{\theta\in\Theta} \left[\sum_{i\in\mathcal{S}(\theta)\cap\mathcal{P}} y_{\min} + \sum_{i\in\mathcal{S}(\theta)\cap\mathcal{R}} \left(y_{\min} + \frac{\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} - y_{\min}}{\mu^e_{\mathcal{S}(\theta')\cap\mathcal{R}} - y_{\min}} (y_j^r - y_{\min}) \right) \right]}_{=\mu^r} = \mu^e. \tag{47}$$

Solving for y_j^r we obtain:

$$y_j^r = y_{\min} + (\mu^e_{\mathcal{S}(\theta')\cap\mathcal{R}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_\mathcal{R}}{N}(\mu^e_\mathcal{R} - y_{\min})}. \tag{48}$$

As evidenced by (47), μ^r is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{\min}, \infty)$. Under the assumption that $\mu^e > y_{\min}$ and invoking the intermediate value theorem, it follows that there is a unique value of y_j^r for which (8) holds. Since the choice of $i \in \mathcal{S}(\theta) \cap \mathcal{R}$ and $j \in \mathcal{S}(\theta') \cap \mathcal{R}$ was arbitrary, expression (46) holds for all $i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\ j \in \mathcal{S}(\theta') \cap \mathcal{R},\ \forall\ \theta \in \Theta$.

However, such a unique value only exists if $\mu^e > y_{\min}$. Assume this was not true, i.e. $\mu^e \leq y_{\min}$. Then, it would still hold that $\mu^r \to y_{\min}$ for $y_j^r \to y_{\min}$ and $\mu^r \to \infty$ for $y_j^r \to \infty$. Hence, $\mu^r \in (y_{\min}, \infty)$. However, from the constant resources requirement (8) we also know that $\mu^r = \mu^e$. If $\mu^e \leq y_{\text{min}}$, either of these statements must be false and hence $\mathcal{D}^1 \cap \mathcal{D}^{2c} \cap \mathcal{D}^{3c} \cap \mathcal{D}^{4c} = \emptyset$. Intuitively, if $\mu^e \leq y_{\text{min}}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^{3c}$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^{4c}$), while maintaining the equal resource requirement ($\mathcal{D}^1$). ■

A.4 Additional Progressiveness

We are able to accommodate additional inequality aversion by relaxing the proportionality assumption and allowing for additional progressiveness in the intra-type distribution of excess income above y_{min}. To this end, let us reformulate the proportionality restriction as follows:

$$\mathcal{D}^{4d} = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y_i^r - y_{\text{min}}}{y_j^r - y_{\text{min}}} = \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \mathcal{W}_i(\sigma) - y_{\text{min}}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \mathcal{W}_j(\sigma) - y_{\text{min}}},\ \forall\ i, j \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega \right\}, \tag{49}$$

where $\mathcal{W}_i(\sigma)$ is an income weight subject to the parameter $\sigma \in [0, 1] : \mathcal{W}_i(\sigma) = \left(1 - \sigma \frac{y_i^e - \mu^e_{\mathcal{R}(\omega)}}{y_i^e}\right)$.

Accounting for additional inequality aversion in the upper end of the income distribution leads to the following proposition:

Proposition 5. *Suppose $\mu^e > y_{min}$. Then, the intersection $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^3 \cap \mathcal{D}^{4d}$ yields a singleton which uniquely defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega, \\ y_{min} + (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \mathcal{W}_i(\sigma) - y_{min}) \frac{(\mu^e - y_{min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{min})}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega. \end{cases} \tag{50}$$

Conversely, if $\mu \leq y_{min}$, then $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^3 \cap \mathcal{D}^{4d} = \emptyset$.

Proof of Proposition 5. The proof proceeds in analogy to the proof of Proposition 1. The proposition is trivially true for the (counterfactually) poor population $\mathcal{P}(\omega)$ as their norm incomes are prescribed by (13). For each type $\mathcal{T}(\omega)$ we can use (49) to rewrite y_i^r for the non-poor population and use this expression together with the FfP condition (13) in the

EOp condition (9):

$$\underbrace{\frac{1}{N_{\mathcal{T}(\omega)}}\left[\sum_{i\in\mathcal{P}(\omega)} y_{\min} + \sum_{i\in\mathcal{R}(\omega)}\left(y_{\min} + \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}}\mathcal{W}_i(\sigma) - y_{\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}}\mathcal{W}_j(\sigma) - y_{\min}}(y_j^r - y_{\min})\right)\right]}_{=\mu^r_{\mathcal{T}(\omega)}} = \mu^e. \tag{51}$$

Solving for y_j^r we obtain:

$$y_j^r = y_{\min} + (y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}}\mathcal{W}_j(\sigma) - y_{\min})\frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)}\frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})}. \tag{52}$$

As evidenced by (51), $\mu^r_{\mathcal{T}(\omega)}$ is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{\min}, \infty)$. Under the assumption that $\mu^e > y_{\min}$ and invoking the intermediate value theorem, it follows that there is a unique value of y_j^r for which (9) holds. Since the choice of $i, j \in \mathcal{R}(\omega)$ was arbitrary, expression (50) holds $\forall\, i, j \in \mathcal{R}(\omega)$, $\forall\, \omega \in \Omega$.

However, such a unique value only exists if $\mu^e > y_{\min}$. Assume this was not true, i.e. $\mu^e \leq y_{\min}$. Then, it would still hold that $\mu^r_{\mathcal{T}(\omega)} \to y_{\min}$ for $y_j^r \to y_{\min}$ and $\mu^r_{\mathcal{T}(\omega)} \to \infty$ for $y_j^r \to \infty$. Hence, $\mu^r_{\mathcal{T}(\omega)} \in (y_{\min}, \infty)$. However, from the EOp requirement (9) we also know that $\mu^r_{\mathcal{T}(\omega)} = \mu^e$. If $\mu^e \leq y_{\min}$, either of these statements must be false and hence $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^3 \cap \mathcal{D}^{4d} = \emptyset$. Intuitively, if $\mu^e \leq y_{\min}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^3$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^{4d}$), while maintaining the equal resource requirement ($\mathcal{D}^1$). ■

Note that σ can be interpreted as an inequality aversion parameter with respect to excess income above $y_{\min}$.[1] To see this, note that $\frac{\partial y_i^r}{\partial \sigma} > 0$ ($\frac{\partial y_i^r}{\partial \sigma} < 0$) if $y_i^e < \mu^e_{\mathcal{R}(\omega)}$ ($y_i^e > \mu^e_{\mathcal{R}(\omega)}$) and $\frac{\partial^2 y_i^r}{\partial \sigma \partial y_i^e} < 0$. Hence, increasing σ leads to higher norm incomes for those below the type-specific mean of excess income. The positive effect monotonically decreases for increasing y_i^e until it turns negative for incomes above the type-specific mean of excess income.

Letting σ travel to one, $\mathcal{W}_i(\sigma) \to \mu^e_{\mathcal{R}(\omega)}/y_i^e$ and the norm distribution collapses to the

[1]For the sake of illustration we treat σ as a uniform parameter for all $\omega \in \Omega$. However, it is easy to allow for heterogeneity in σ across types.

following expression:

$$\lim_{\sigma \to 1} y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega, \\ y_{\min} + (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \mathcal{W}_i(\sigma) - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega, \end{cases} \tag{53}$$

$$= \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega, \\ y_{\min} + \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega, \end{cases} \tag{54}$$

$$= \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega, \\ \mu^r_{\mathcal{R}(\omega)}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega. \end{cases} \tag{55}$$

Hence, increasing σ indicates increasing inequality aversion with respect to income disparities among the non-poor population of a particular type. With $\sigma = 1$, the norm income of each non-poor type member is given by the average norm income of the non-poor constituents of its respective type. As a consequence, average income differences between the poor and the non-poor members of each type remain as the sole justifiable source of inequality. Reversely, taking limits towards zero inequality aversion, $\mathcal{W}_i(\sigma) \to 1$, and we obtain the baseline norm (see equation (15)) according to which excess norm incomes above $y_{\min}$ are distributed proportionally to their empirical analogues.

A.5 Individual Minimum Thresholds

In our baseline analysis we account for differential needs across individuals by applying an equivalence scale. Alternatively, one could also account for differential needs by replacing the population-wide minimum threshold $y_{\min}$ with individual-specific minimum thresholds $y_{i,\min}$. As a consequence, one would have to redefine the set of poor and non-poor individuals as follows:

$$\mathcal{P}(\omega) = \left\{ i \in \mathcal{N} \;\middle|\; y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} \leq y_{i,\min} \right\}, \;\forall\, \omega \in \Omega \tag{56}$$

$$\mathcal{R}(\omega) = \left\{ i \in \mathcal{N} \;\middle|\; y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} > y_{i,\min} \right\}, \;\forall\, \omega \in \Omega. \tag{57}$$

Similarly, the FfP principle and the proportionality requirement would have to be redefined in terms of the individual-specific minimum thresholds $y_{i,\min}$:

$$\mathcal{D}^{3e} = \left\{ d \in \mathcal{D} \;\middle|\; y_i^r = y_{i,\min}, \;\forall\, i \in \mathcal{P}(\omega), \;\forall\, \omega \in \Omega \right\}. \tag{58}$$

$$\mathcal{D}^{4e} = \left\{ d \in \mathcal{D} \;\middle|\; \frac{y_i^r - y_{i,\min}}{y_j^r - y_{j,\min}} = \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{i,\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{j,\min}}, \;\forall\, i,j \in \mathcal{R}(\omega), \;\forall\, \omega \in \Omega \right\}. \tag{59}$$

In addition let us define the type-specific average of poverty thresholds $\mu^{\min}_{\mathcal{T}(\omega)} = \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{T}(\omega)} y_{i,\min}$ and the type-specific average of poverty thresholds among its non-poor constituents $\mu^{\min}_{\mathcal{R}(\omega)} = \frac{1}{N_{\mathcal{R}(\omega)}} \sum_{i \in \mathcal{R}(\omega)} y_{i,\min}$.

These reformulations lead to the following proposition:

Proposition 6. *Suppose $\mu^e > \mu^{min}_{\mathcal{T}(\omega)}, \;\forall\, \omega \in \Omega$. Then, the intersection $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^{3e} \cap \mathcal{D}^{4e}$ yields a singleton which uniquely defines the norm distribution Y^r:*

$$y_i^r = \begin{cases} y_{i,min}, & \forall\, i \in \mathcal{P}(\omega), \;\forall\, \omega \in \Omega, \\ y_{i,min} + \left(y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{i,min}\right) \frac{(\mu^e - \mu^{min}_{\mathcal{T}(\omega)})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} \left(\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - \mu^{min}_{\mathcal{R}(\omega)}\right)}, & \forall\, i \in \mathcal{R}(\omega), \;\forall\, \omega \in \Omega. \end{cases} \tag{60}$$

Conversely, if $\exists\, \omega \in \Omega \colon \mu^e \leq \mu^{min}_{\mathcal{T}(\omega)}$, then $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^{3e} \cap \mathcal{D}^{4e} = \emptyset$.

Proof of Proposition 6. The proof proceeds in analogy to the proof of Proposition 1. The proposition is trivially true for the (counterfactually) poor population $\mathcal{P}(\omega)$ as their norm incomes are prescribed by (58). For each type $\mathcal{T}(\omega)$ we can use (59) to rewrite y_i^r for the non-poor population and use this expression together with the FfP condition (58) in the

EOp condition (9):

$$\underbrace{\frac{1}{N_{\mathcal{T}(\omega)}}\left[\sum_{i\in\mathcal{P}(\omega)} y_{i,\min} + \sum_{i\in\mathcal{R}(\omega)}\left(y_{i,\min} + \frac{y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{i,\min}}{y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{j,\min}}(y_j^r - y_{j,\min})\right)\right]}_{=\mu^r_{\mathcal{T}(\omega)}} = \mu^e. \tag{61}$$

Solving for y_j^r we obtain:

$$y_j^r = y_{j,\min} + (y_j^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{j,\min}) \frac{(\mu^e - \mu^{\min}_{\mathcal{T}(\omega)})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - \mu^{\min}_{\mathcal{R}(\omega)})}. \tag{62}$$

As evidenced by (61), $\mu^r_{\mathcal{T}(\omega)}$ is a continuous and monotonically increasing function of y_j^r and we know that $y_j^r \in (y_{j,\min}, \infty)$. Under the assumption that $\mu^e > \mu^{\min}_{\mathcal{T}(\omega)}$, $\forall\, \omega \in \Omega$ and invoking the intermediate value theorem, it follows that there is a unique value of y_j^r for which (9) holds. Since the choice of $i, j \in \mathcal{R}(\omega)$ was arbitrary, expression (60) holds $\forall\, i, j \in \mathcal{R}(\omega)$, $\forall\, \omega \in \Omega$.

However, such a unique value only exists if $\mu^e > \mu^{\min}_{\mathcal{T}(\omega)}$, $\forall\, \omega \in \Omega$. Assume this was not true, i.e. $\exists\, \omega \in \Omega$: $\mu^e \leq \mu^{\min}_{\mathcal{T}(\omega)}$. Then, it would still hold that $\mu^r_{\mathcal{T}(\omega)} \to \mu^{\min}_{\mathcal{T}(\omega)}$ for $y_j^r \to y_{j,\min}$ and $\mu^r_{\mathcal{T}(\omega)} \to \infty$ for $y_j^r \to \infty$. Hence, $\mu^r_{\mathcal{T}(\omega)} \in \left(\mu^{\min}_{\mathcal{T}(\omega)}, \infty\right)$. However, from the EOp requirement (9) we also know that $\mu^r_{\mathcal{T}(\omega)} = \mu^e$. If $\mu^e \leq \mu^{\min}_{\mathcal{T}(\omega)}$, either of these statements must be false and hence $\mathcal{D}^1 \cap \mathcal{D}^2 \cap \mathcal{D}^{3e} \cap \mathcal{D}^{4e} = \emptyset$. Intuitively, if $\exists\, \omega \in \Omega$: $\mu^e \leq \mu^{\min}_{\mathcal{T}(\omega)}$ one cannot lift all people above the minimum threshold ($\mathcal{D}^{3e}$), without drawing non-poor people below the minimum threshold ($\mathcal{D}^{4e}$), while maintaining the equal resource requirement ($\mathcal{D}^1$). ■

B COMPARATIVE STATICS

In this appendix we give a comprehensive overview over the comparative statics of all norms listed in Table 1. A general overview can be found in Table S.1. Each of the illustrated comparative static scenarios is discussed verbally in the following.

(a) EOp or FfP Only

(1) Assume $y_{\text{min}} \to 0$. The limit case with $y_{\text{min}} = 0$ is equivalent to abstracting from the concern for FfP altogether.

- **Baseline**: Leads to $\mathcal{P}(\omega) = \emptyset$, $\mu^e_{\mathcal{R}(\omega)} = \mu^e_{\mathcal{T}(\omega)}$, $N_{\mathcal{R}(\omega)} = N_{\mathcal{T}(\omega)}$, $\forall\ \omega \in \Omega$. As a consequence, realizing weak EOp remains the only normative concern.

- **Alternative (a)**: Leads to $\mathcal{P}(\theta) = \emptyset$, $\mu^e_{\mathcal{R}(\theta)} = \mu^e$, $N_{\mathcal{R}(\theta)} = N$, $\forall\ \theta \in \Theta$. As a consequence, realizing strong EOp remains the only normative concern.

- **Alternative (b)**: Leads to $\mathcal{P} = \emptyset$, $N_{\mathcal{R}} = N$, and $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{T}(\omega)}$, $\forall\ \omega \in \Omega$. As a consequence, realizing weak EOp remains the only normative concern.

- **Alternative (c)**: Leads to $\mathcal{P} = \emptyset$, $N_{\mathcal{R}} = N$, and $\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} = \mu^e_{\mathcal{S}(\theta)}$, $\forall\ \theta \in \Theta$. As a consequence, realizing strong EOp remains the only normative concern.

(2) Assume $T \to 1$. The limit case with $T = 1$ is equivalent to abstracting from the concern for EOp altogether. It also leads to $\mathcal{P}(\omega) = \mathcal{P} = \mathcal{P}(\theta)$.

- **Baseline**: Leads to $N_{\mathcal{R}(\omega)} = N_{\mathcal{R}}$, $N_{\mathcal{T}(\omega)} = N$, $\mu^e_{\mathcal{R}(\omega)} = \mu^e_{\mathcal{R}}$, $\mu^e_{\mathcal{T}(\omega)} = \mu^e$, $\forall\ \omega \in \Omega$. As a consequence, poverty eradication through a linear transfer rate on excess income above y_{min} remains the only normative concern.

- **Alternative (a)**: Leads to $N_{\mathcal{R}(\Theta)} = N_{\mathcal{R}}$, $\mu^e_{\mathcal{R}(\Theta)} = \mu^e_{\mathcal{R}}$, $\mu^e_{\mathcal{S}(\theta)} = y^e_i$, $\forall\ i \in \mathcal{S}(\theta)$, $\forall\ \theta \in \Theta$. As a consequence, poverty eradication through a linear transfer rate on excess income above y_{min} remains the only normative concern.

- **Alternative (b)**: Leads to $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$. As a consequence, poverty eradication through a linear transfer rate on excess income above y_{min} remains the only normative concern.

- **Alternative (c)**: Leads to $\mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}} = y^e_i$, $\forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R}$, $\forall\ \theta \in \Theta$. As a consequence, poverty eradication through a linear transfer rate on excess income above y_{min} remains the only normative concern.

(b) Freedom from Poverty

(3) Assume $N_{\mathcal{P}(\omega)} \to 0$, $\forall \omega \in \Omega$. The limit case with $N_{\mathcal{P}(\omega)} = 0$ is equivalent to zero poverty incidence if resources were distributed in accordance with weak EOp.

- **Baseline**: Leads to $\mathcal{P}(\omega) = \emptyset$, $\mu^e_{\mathcal{R}(\omega)} = \mu^e_{\mathcal{T}(\omega)}$, $N_{\mathcal{R}(\omega)} = N_{\mathcal{T}(\omega)}$, $\forall\ \omega \in \Omega$. As a consequence, realizing weak EOp remains the only normative concern.

- **Alternative (a)**: $\cup_k \mathcal{P}(\omega) = \emptyset$ implies $\cup_l \mathcal{P}(\theta) = \emptyset$. Hence, $\mu^e_{\mathcal{R}(\Theta)} = \mu^e$, and $N_{\mathcal{R}(\Theta)} = N$. As a consequence, realizing strong EOp remains the only normative concern.

- **Alternative (b)**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}$. Since $\cup_k \mathcal{P}(\omega) = \emptyset$ does not imply $\mathcal{P} = \emptyset$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (c)**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}$. Since $\cup_k \mathcal{P}(\omega) = \emptyset$ does not imply $\mathcal{P} = \emptyset$ the calculation of the norm remains unaffected even in the limit case

(4) Assume $N_{\mathcal{P}} \to 0$. The limit case with $N_{\mathcal{P}} = 0$ is equivalent to zero poverty incidence in the empirical income distribution.

- **Baseline**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}(\omega)$. Since $\mathcal{P} = \emptyset$ does not imply $\cup_k \mathcal{P}(\omega) = \emptyset$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (a)**: $\mathcal{P} = \emptyset$ implies $\cup_l \mathcal{P}(\theta) = \emptyset$. Hence, $\mu^e_{\mathcal{R}(\Theta)} = \mu^e$, and $N_{\mathcal{R}(\Theta)} = N$. As a consequence, realizing strong EOp remains the only normative concern.

- **Alternative (b)**: Leads to $N_{\mathcal{R}} = N$, and $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{T}(\omega)}$, $\forall\ \omega \in \Omega$. As a consequence, realizing weak EOp through a type-specific linear transfer rate on excess income above y_{min} remains the only normative concern.

- **Alternative (c)**: Leads to $N_{\mathcal{R}} = N$, and $\mu^e_{R} = \mu^e$, $\mu^e_{\mathcal{S}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{S}(\omega)}$, $\forall\ \theta \in \Theta$. As a consequence, realizing strong EOp remains the only normative concern.

(5) Assume $N_{\mathcal{P}(\theta)} \to 0$, $\forall\ \theta \in \Theta$. The limit case with $N_{\mathcal{P}(\theta)} = 0$ is equivalent to zero poverty incidence if resources were distributed in accordance with strong EOp.

- **Baseline**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}(\omega)$. Since $\cup_l \mathcal{P}(\theta) = \emptyset$ does not imply $\cup_k \mathcal{P}(\omega) = \emptyset$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (a)**: Leads to $\mu^e_{\mathcal{R}(\Theta)} = \mu^e$, $N_{\mathcal{R}(\Theta)} = N$. As a consequence, realizing strong EOp remains the only normative concern.

- **Alternative (b)**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}$. Since $\cup_l \mathcal{P}(\theta) = \emptyset$ does not imply $\mathcal{P} = \emptyset$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (c)**: No difference. The poor are identified and tied to a norm income of y_{min} based on $\mathcal{P}$. Since $\cup_l \mathcal{P}(\theta) = \emptyset$ does not imply $\mathcal{P} = \emptyset$ the calculation of the norm remains unaffected even in the limit case.

(c) Equality of Opportunity

(6) Assume $\mu^e_{\mathcal{T}(\omega)} \to \mu^e$, $\forall\ \omega \in \Omega$. The limit case with $\mu^e_{\mathcal{T}(\omega)} = \mu^e$, $\forall\ \omega \in \Omega$ corresponds to a society in which weak EOp is realized. It also leads to $\cup_k \mathcal{P}(\omega) = \mathcal{P}$.

- **Baseline**: Weak EOp under the non-separability assumption is realized by assumption. As a consequence, poverty eradication through a type-specific linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

- **Alternative (a)**: No difference. Strong EOp under the non-separability assumption requires equalizing all moments of the type distribution. Since $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\ \omega \in \Omega$ does not imply $y^e_i = y^e_j = \mu^e_{\mathcal{S}(\theta)},\ \forall\ i,j \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (b)**: No difference. Weak EOp under the separability assumption requires equalizing type mean incomes above $y_{\min}$ only. Since $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\ \omega \in \Omega$ does not imply $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^r_{\mathcal{R}},\ \forall\ \omega \in \Omega$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (c)**: No difference. Strong EOp under the separability assumption requires equalizing all incomes of the non-poor tranche members. Since $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\ \omega \in \Omega$ does not imply $y^e_i = y^e_j = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}},\ \forall\ i,j \in \mathcal{S}(\theta)\cap\mathcal{R},\ \forall\ \theta \in \Theta$ the calculation of the norm remains unaffected even in the limit case.

(7) Assume $y^e_i \to \mu^e_{\mathcal{S}(\theta)},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$. The limit case with $y^e_i = \mu^e_{\mathcal{S}(\theta)},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$ corresponds to a society in which strong EOp is realized. It also leads to $\cup_k \mathcal{P}(\omega) = \mathcal{P} = \cup_l \mathcal{P}(\theta)$.

- **Baseline**: Weak EOp under the non-separability assumption requires equalizing type mean incomes. $y^e_i = \mu^e_{\mathcal{S}(\theta)},\ \forall\, i \in \mathcal{S}(\theta),\ \forall\, \theta \in \Theta$ implies $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\, \omega \in \Omega$. As a consequence, poverty eradication through a linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

- **Alternative (a)**: Strong EOp under the non-separability assumption is realized by assumption. As a consequence, poverty eradication through a linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

- **Alternative (b)**: Weak EOp under the separability assumption requires equalizing type mean incomes above $y_{\min}$ only. $y_i^e = y_j^e = \mu^e_{\mathcal{S}(\theta)}$, $\forall\ i,j \in \mathcal{S}(\theta)$, $\forall\ \theta \in \Theta$ implies $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$. As a consequence, poverty eradication through a linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

- **Alternative (c)**: Strong EOp under the separability assumption requires equalizing all incomes of the non-poor tranche members. $y_i^e = y_j^e = \mu^e_{\mathcal{S}(\theta)}$, $\forall\ i,j \in \mathcal{S}(\theta)$, $\forall\ \theta \in \Theta$ implies $y_i^e = y_j^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i,j \in \mathcal{S}(\theta)\cap\mathcal{R}$, $\forall\ \theta \in \Theta$. As a consequence, poverty eradication through a linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

(8) Assume $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} \rightarrow \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$. The limit case corresponds to a society in which weak EOp is realized under the separability assumption.

- **Baseline**: No difference. Weak EOp under the non-separability assumption requires equalizing type mean incomes. Since $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$ does not imply $\mu^e_{\mathcal{T}(\omega)} = \mu^e$, $\forall\ \omega \in \Omega$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (a)**: No difference. Strong EOp under the non-separability assumption requires equalizing all moments of the type distribution. Since $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$ does not imply $y_i^e = y_j^e = \mu^e_{\mathcal{S}(\theta)}$, $\forall\ i,j \in \mathcal{S}(\theta)$, $\forall\ \theta \in \Theta$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (b)**: Weak EOp under the separability assumption is realized by assumption. As a consequence, poverty eradication through a linear transfer rate on excess income above $y_{\min}$ remains the only normative concern.

- **Alternative (c)**: No difference. Strong EOp under the separability assumption requires equalizing all incomes of the non-poor tranche members. Since $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}}$, $\forall\ \omega \in \Omega$ does not imply $y_i^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i \in \mathcal{S}(\theta)\cap\mathcal{R}$, $\forall\ \theta \in \Theta$ the calculation of the norm remains unaffected even in the limit case.

(9) Assume $y_i^e \to \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R}$, $\forall\ \theta \in \Theta$. The limit case corresponds to a society in which strong EOp is realized under the separability assumption.

- **Baseline**: No difference. Weak EOp under the non-separability assumption requires equalizing type mean incomes. Since $y_i^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R}$, $\forall\ \theta \in \Theta$ does not imply $\mu^e_{\mathcal{T}(\omega)} = \mu^e$, $\forall\ \omega \in \Omega$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (a)**: No difference. Strong EOp under the non-separability assumption requires equalizing all moments of the type distribution. Since $y_i^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R}$, $\forall\ \theta \in \Theta$ does not imply $y_i^e = y_j^e = \mu^e_{\mathcal{S}(\theta)}$, $\forall\ i, j \in \mathcal{S}(\theta)$, $\forall\ \theta \in \Theta$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (b)**: No difference. Weak EOp under the separability assumption requires equalizing type mean incomes above y_{min} only. Since $y_i^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}}$, $\forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R}$, $\forall\ \theta \in \Theta$ does not imply $\mu^r_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^r_{\mathcal{R}}$, $\forall\ \omega \in \Omega$ the calculation of the norm remains unaffected even in the limit case.

- **Alternative (c)**: Strong EOp under the separability assumption is realized by assumption. As a consequence, poverty eradication through a linear transfer rate on excess income above y_{min} remains the only normative concern.

Table S.1 – Overview Comparative Statics

	Baseline	Alternative (a)	Alternative (b)	Alternative (c)
Norm Distribution Y^r				
	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega \\ y_{\min} + (y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)} \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}} - y_{\min})}, & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\theta),\ \forall\ \theta \in \Theta \\ y_{\min} + (\mu^e_{\mathcal{S}(\theta)} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}(\Theta)}}{N}(\mu^e_{\mathcal{R}(\Theta)} - y_{\min})}, & \forall\ i \in \mathcal{R}(\theta),\ \forall\ \theta \in \Theta \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{T}(\omega) \cap \mathcal{P},\ \forall\ \omega \in \Omega \\ y_{\min} + (y_i^e - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} - y_{\min})}, & \forall\ i \in \mathcal{T}(\omega) \cap \mathcal{R},\ \forall\ \omega \in \Omega \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{P},\ \forall\ \theta \in \Theta, \\ y_{\min} + (\mu^e_{\mathcal{S}(i)\cap\mathcal{R}} - y_{\min}) \frac{(\mu^e - y_{\min})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}, & \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\ \theta \in \Theta \end{cases}$
(a) EOp or FfP Only				
(1) $y_{\min} = 0$	$y_i^r = y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}},\ \forall\ i \in \mathcal{T}(\omega),\ \forall\ \omega \in \Omega$	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$	$y_i^r = y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}},\ \forall\ i \in \mathcal{T}(\omega),\ \forall\ \omega \in \Omega$	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$
(2) $T = 1$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$
(b) Freedom from Poverty				
(3) $\mathcal{P}(\omega) = 0,\ \forall\ \omega \in \Omega$	$y_i^r = y_i^e \frac{\mu^e}{\mu^e_{\mathcal{T}(\omega)}},\ \forall\ i \in \mathcal{T}(\omega),\ \forall\ \omega \in \Omega$	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$	No difference	No difference
(4) $\mathcal{P} = 0$	No difference	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$	$y_i^r = y_{\min} + (y_i^e - y_{\min}) \frac{(\mu^e - y_{\min})}{(\mu^e_{\mathcal{T}(\omega)} - y_{\min})},\ \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega$	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$
(5) $\mathcal{P}(\theta) = 0,\ \forall\ \theta \in \Theta$	No difference	$y_i^r = y_i^e \frac{\mu^e_{\mathcal{S}(\theta)}}{y_i^e},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$	No difference	No difference
(c) Equality of Opportunity				
(6) $\mu^e_{\mathcal{T}(\omega)} = \mu^e,\ \forall\ \omega \in \Omega$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P}(\omega),\ \forall\ \omega \in \Omega \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}(\omega)}}{N_{\mathcal{T}(\omega)}}(y_{\min} - \mu^e_{\mathcal{P}(\omega)})}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}}(\mu^e_{\mathcal{R}(\omega)} - y_{\min})}\right), & \forall\ i \in \mathcal{R}(\omega),\ \forall\ \omega \in \Omega \end{cases}$	No difference	No difference	No difference
(7) $y_i^e = \mu^e_{\mathcal{S}(\theta)},\ \forall\ i \in \mathcal{S}(\theta),\ \forall\ \theta \in \Theta$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$
(8) $\mu^e_{\mathcal{T}(\omega)\cap\mathcal{R}} = \mu^e_{\mathcal{R}},\ \forall\ \omega \in \Omega$	No difference	No difference	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$	No difference
(9) $y_i^e = \mu^e_{\mathcal{S}(\theta)\cap\mathcal{R}},\ \forall\ i \in \mathcal{S}(\theta) \cap \mathcal{R},\ \forall\ \theta \in \Theta$	No difference	No difference	No difference	$y_i^r = \begin{cases} y_{\min}, & \forall\ i \in \mathcal{P} \\ y_{\min} + (y_i^e - y_{\min}) \left(1 - \frac{\frac{N_{\mathcal{P}}}{N}(y_{\min} - \mu^e_{\mathcal{P}})}{\frac{N_{\mathcal{R}}}{N}(\mu^e_{\mathcal{R}} - y_{\min})}\right), & \forall\ i \in \mathcal{R} \end{cases}$

C DATA APPENDIX

C.1 Disposable Household Income

PSID. We construct disposable household income as the sum of household labor income, household asset income, household private transfers, household private pensions, other household income, household public pensions, household public cash assistance minus total household taxes. These income aggregates are calculated and provided by PSID CNEF.

In view of changes in the handling of negative incomes across waves, we consistently set household asset income and household private transfers to zero if they are negative or missing.

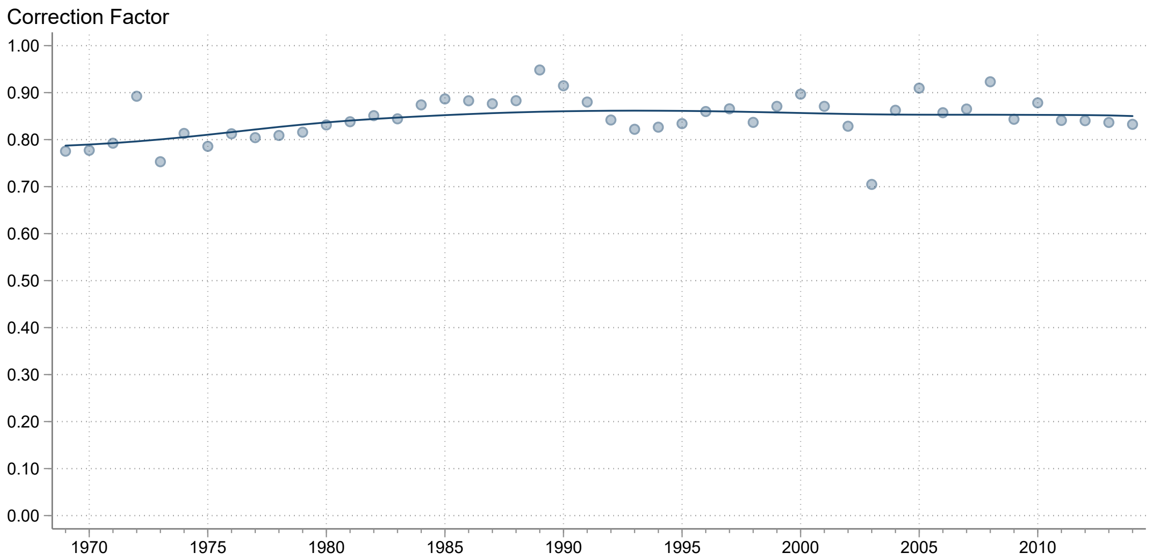
We account for the under-reporting of government transfer income by scaling up household public cash assistance of each recipient household in year t by the inverse of the following adjustment factor:

$$UR_t = \frac{V_{pt}}{\sum_p V_{pt}} * UR_{pt}^{PSID}, \tag{63}$$

where UR_{pt}^{PSID} is the share of transfer income from government program p in year t reported by PSID households when comparing their cumulated reports to government statistics on annual spending in the respective program. V_{pt} indicates the total volume of government spending on program p in year t. UR_{pt}^{PSID} and V_{pt} are taken from the time series provided in Meyer et al. (2015). The government programs p include Unemployment Insurance (UI), Workers' Compensation (WC), Social Security Retirement and Survivors Insurance (OASI), Social Security Disability Insurance (SSDI), Supplemental Security Income (SSI), the Food Stamp Program (SNAP), and Aid to Families with Dependent Children/Temporary Assistance for Needy Families (AFDC/TANF). Since their time series end in 2010 we fit UR_{pt}^{PSID} to a second-order polynomial of the year-variable and impute UR_{pt}^{PSID} for 2012 and 2014 with the predicted values. The time series for

UR_t^{PSID} is displayed in Figure S.1.

Figure S.1 – Correction Factor for Under-reporting of Transfer Income (US), 1969-2014



Data: Meyer et al. (2015).
Note: Own calculations. This figure displays the correction factor for under-reported transfer incomes in the PSID over the time period 1969-2014. The correction factor is calculated based on equation (63) and the time series presented in Meyer et al. (2015). The solid lines display Lowess smoothed time trends where each data point is constructed using 80% of all data points (Bandwidth 0.8).

We account for the under-reporting of labor income by imputing individual labor incomes according to the following procedure. First, we identify individuals with zero or missing labor income information but non-zero working hours. Second we run the following Mincer regression on the pooled PSID sample:[2]

$$\begin{aligned} \ln y_{ict} = \beta_0 + \beta_1 Hours_{ict} + \beta_2 Hours_{ict}^2 + \beta_3 Age_{ict} + \beta_4 Age_{ict}^2 \\ + \beta_5 Race_{ict} + \beta_6 Male_{ict} + \beta_7 Education_{ict} + \gamma_t + \epsilon_{ict}. \end{aligned} \tag{64}$$

Third, we impute individual labor incomes of the identified individuals with the income predictions from the Mincer regression. Fourth, we aggregate the volume of imputed incomes across all members of a household and add the imputed incomes to the household labor income provided by PSID CNEF.

[2]The underlying variables are constructed according to the details provided in this Data Appendix. Regression results are available upon request.

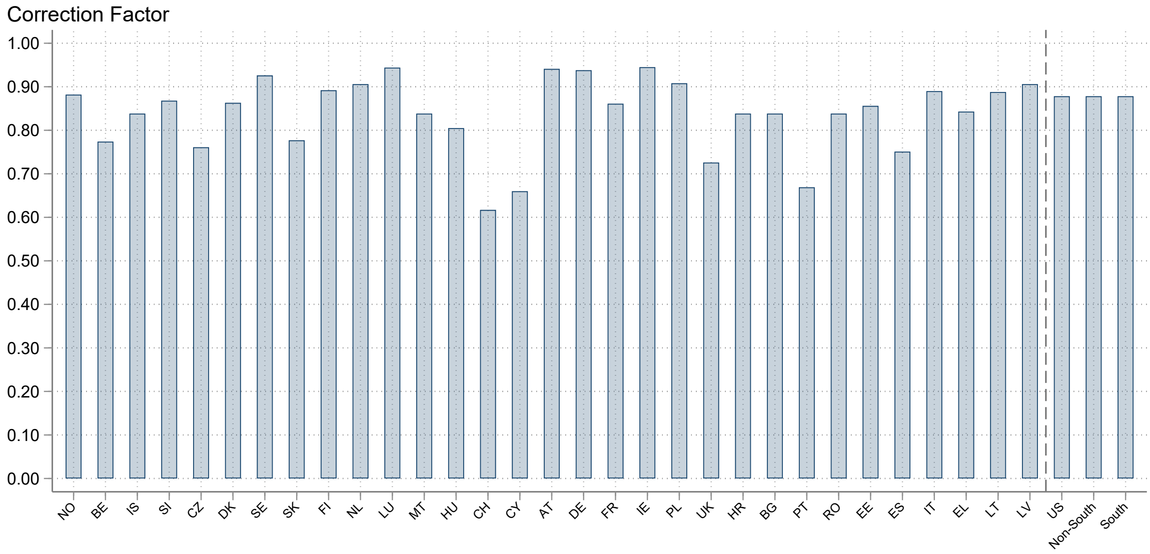
The resulting variable for disposable household income is converted to equivalized disposable household income using the modified OECD equivalence scale, winsorized at the 1st and 99.5th percentiles, and converted into PPP-adjusted US Dollar using the conversion factors provided by the Penn World Tables (Feenstra et al. 2015).

EU-SILC. We construct household disposable income as the sum of household labor income, household asset income, household private transfers, household private pensions, other household income, household public pensions, household public cash assistance minus total household taxes.

For consistency with the PSID, we set household asset income and household private transfers to zero if they are negative or missing. We account for the under-reporting of government transfer income by scaling up household public cash assistance of each recipient household in country c by the inverse of the adjustment factor UR_c^{SILC}. UR_c^{SILC} is extracted from EUROSTAT (2013) – a report in which EUROSTAT compares various income sources from EU-SILC with the corresponding national accounts aggregates. Specifically, UR_c^{SILC} contains family/children-related allowances, unemployment benefits, old-age benefits, survivors' benefits, sickness benefits, disability benefits, education-related allowances, and social exclusion benefits not elsewhere classified. This exercise is conducted for the income reference period 2008 and we write the calculated values forward to 2010. Furthermore, five of our sample countries were excluded from the analysis due to a lack of information from either of the two data sources (Bulgaria, Malta, Romania, Iceland and Croatia). For these countries we impute UR_c^{SILC} with the European cross-country sample mean. The values for UR_c^{SILC} are displayed in Figure S.2.

We account for the under-reporting of labor income by imputing individual labor incomes in the same way as in the PSID. To this end we construct a EU-SILC country-panel spanning the time period 2006-2014. In contrast to the PSID we run the underlying Mincer regression separately for each country in the EU-SILC sample and replace the race

Figure S.2 – Correction Factor for Under-reporting of Transfer Income (Cross-Country Sample), 2010



Data: EUROSTAT (2013) and Meyer et al. (2015).
Note: Own calculations. This figure displays the correction factor for under-reported transfer incomes in the the cross-country sample in 2010. The correction factor is calculated based on equation (63) and the time series presented in Meyer et al. (2015) as well as the under-reporting factors reported in EUROSTAT (2013). Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions.

indicator with the migration background indicator:[3]

$$\begin{aligned} \ln y_{ict} = \beta_0 + \beta_1 Hours_{ict} + \beta_2 Hours^2_{ict} + \beta_3 Age_{ict} + \beta_4 Age^2_{ict} \\ + \beta_5 Mig.\ Background_{ict} + \beta_6 Male_{ict} + \beta_7 Education_{ict} + \gamma_t + \epsilon_{ict}. \end{aligned} \quad (65)$$

Again, the resulting variable for disposable household income is converted to equivalized disposable household income using the modified OECD equivalence scale, winsorized at the 1st and 99.5th percentiles, and converted into PPP-adjusted US Dollar using the conversion factors provided by the Penn World Tables (Feenstra et al. 2015).

C.2 Biological Sex

PSID. We use the binary biological sex variable provided by PSID CNEF. Using the panel dimension of the PSID we replace the few missing values with the mode of all records for the respective individual.

[3] The underlying variables are constructed according to the details provided in this Data Appendix. Regression results are available upon request.

EU-SILC. We use the binary biological sex variable provided by EU-SILC. Respondents with missing information are dropped through list-wise deletion.

C.3 Race/Migration Background

PSID. We use the 6-category race indicator (White, Black, Am. Indian-Inuit, Asian-Pacific Islander, Black, Hispanic, Other) provided by PSID CNEF and transform it into a binary indicator for non-Hispanic whites and others. Using the panel dimension of the PSID we replace missing values with the mode of all records for the respective individual.

EU-SILC. We use the 3-category migration background indicator (born in country of residence, born in other European country, born elsewhere) provided by EU-SILC and transform it into a binary indicator for whether the respondent was born in her current country of residence or not. Respondents with missing information are dropped through list-wise deletion.

C.4 Parental Education

PSID. We use the 9-category indicator for paternal and maternal education provided by the PSID and transform them into a 3-category indicator for high, medium, and low education according to the classification scheme outlined in Table S.2. We retain the highest information of either parent. We replace missing information by the highest recorded education level from previous years. Since educational attainment cannot be downgraded we also replace lower educational attainments by the highest recorded education level from previous years.

EU-SILC. We use the 5-category indicator for paternal and maternal education provided by EU-SILC and transform them into a 3-category indicator for high, medium, and low education according to the classification scheme outlined in Table S.2. We then retain the highest information of either parent. Respondents with missing information are dropped through list-wise deletion.

Table S.2 – Harmonization of Education Codes

	PSID	EU-SILC
High	(1) College BA and no advanced degree mentioned	(1) At least first stage of tertiary education
	(2) College and advanced or professional degree	(2) –
	(3) College but no degree	(3) –
Middle	(4) 12 grades	(4) Upper secondary education
	(5) 12 grades plus non-academic training	(5) –
Low	(6) 0-5 grades	(6) Pre-primary, primary education, lower secondary education
	(7) 6-8 grades	(7) Father (mother) could neither read nor write
	(8) 9-11 grades	(8) Don't know
	(9) Could not read or write	(9) –

C.5 Parental Occupation

PSID. In the PSID, waves 1970-2001 report occupation codes with reference to 1970 census codes. Waves 2003-2015 report occupation codes with reference to 2000 census codes. If available on 3-digit level, we use the cross-walk routine provided by Autor and Dorn (2013) to standardize codes based on the 1990 census classification. 1 (28) of the 1970 (2000) 3-digit occupational codes available in the PSID are not included in the cross-walks provided by Autor and Dorn (2013). These categories are matched to their 1990 census classification analogues by the authors of this paper. This classification is available on request. We then aggregate all codes to the 1-digit level and apply the classification scheme outlined in Table S.3.

Additionally, wives of household heads report parental occupation codes in terms of 1970 codes at the 2-digit level in the 1976 wave. We aggregate them to the 1-digit level and apply the classification scheme outlined in Table S.3. Using the panel dimension of the PSID we replace missing values with the mode of all records for the respective individual.

EU-SILC. In EU-SILC, the 2011 wave reports occupation codes with reference to the ISCO-08 classification. We aggregate all codes to the 1-digit level and apply the classification scheme outlined in Table S.3. Respondents with missing information are dropped through list-wise deletion.

Table S.3 – Harmonization of Occupation Codes

	Census 1970	Census 1990	ISCO-08
High	(1) Professional, Technical and Kindred workers	(1) Managerial and Professional Specialty Occ.	(1) Managers
	(2) Managers, Officials and Proprietors	(2) Technical and Sales Op.	(2) Professionals
	(3) Self-Employed Businessmen	–	(3) Technicians and Associate Professionals
Middle	(4) Clerical and Sales Workers	(3) Administrative Support Occ., Including Clerical	(4) Clerical Support Workers
	(5) Craftsmen, Foremen and Kindred Workers	(5) Precision Production, Craft, and Repair Occ.	(5) Service and Sales workers
	(6) Operatives and Kindred Workers	(7) Machine Op., Assemblers, and Inspectors	(7) Craft and Related Trade Workers
	–	(6) Extractive and Precision Production Occ.	(8) Plant and Machine Op.s and Assemblers
Low	(7) Laborers, Service Workers and Farm Laborers	(4) Service, Farming, Forestry, and Fishing Occ.	(6) Skilled Agric., Forestry and Fishery Workers
	(8) Farmers and Farm Managers	(8) Transportation and Material Moving Occ., Handlers, Equipment Cleaners, Helpers, and Laborers	(9) Elementary Occ.
	(9) Miscellaneous (incl. Armed Services, Protective Workers etc.)	(9) Military Occ.	(0) Armed Forces Occ.
	(-) Not in Labor Force	(-) Not in Labor Force	(-) Not in Labor Force

C.6 Other Circumstances

PSID. For the robustness checks presented in section 5 we construct two additional circumstance variables. First, the PSID collects the census region of upbringing for all individuals. Furthermore, we transform the resulting 4-category variable into three binary indicators. Second, the PSID reports the state of upbringing of both mother and father of individual respondents. We transform this variable into a binary variable indicating whether either the mother or the father had been raised in a foreign country. Using the panel dimension of the PSID we replace missing values in both variables with the mode of all records for the respective individual.

EU-SILC. For the robustness checks presented in section 5 we construct four additional circumstance variables. First, EU-SILC provides a 5-category variable indicating whether respondents at the age of 14 lived with i) both parents (or persons considered as parents), ii) father only (or person considered as a father), iii) mother only (or person considered as a mother), iv) in a private household without any parent, or v) in a collective household or institution. We transform this variable into a binary variable indicating whether individuals lived with both parents at the age of 14. Second, EU-SILC provides a categorical variable indicating the number of children in the household in which they lived at age 14. We transform this variable into a binary variable indicating whether individuals lived with less than 3 siblings at age 14. Third, EU-SILC provides a 6-category variable indicating whether the financial situation of the household in which respondents lived at the age of 14 was i) very bad, ii) bad, iii) moderately bad, iv) moderately good, v) good or vi) very good. We transform this variable into a binary variable indicating whether individuals lived in a household in which the situation was at least moderately good. Fourth, EU-SILC provides a 3-category variable indicating whether respondents at the age of 14 lived in i) owner-occupied housing, ii) as tenants or iii) in a household to which accommodation was provided for free. We transform this variable into a binary variable indicating whether individuals lived in owner-occupied housing. Respondents with missing information in any of these variables are dropped through list-wise deletion.

C.7 Individual Working Hours

PSID. PSID CNEF reports the total annual working hours of individuals. We replace missing hours information with zero if the respondent reports to be unemployed. In each year, we winsorize the resulting distribution from above at the 99th percentile.

EU-SILC. EU-SILC reports weekly working hours of individuals in their main and side jobs. We set hours to zero if the respondent reports to be unemployed, retired or otherwise inactive in the labor market. We add hours in the main and the side jobs to obtain total weekly working hours and multiply by 52 to obtain total annual working hours. In each year, we winsorize the resulting distribution from above at the 99th percentile.

C.8 Individual Education

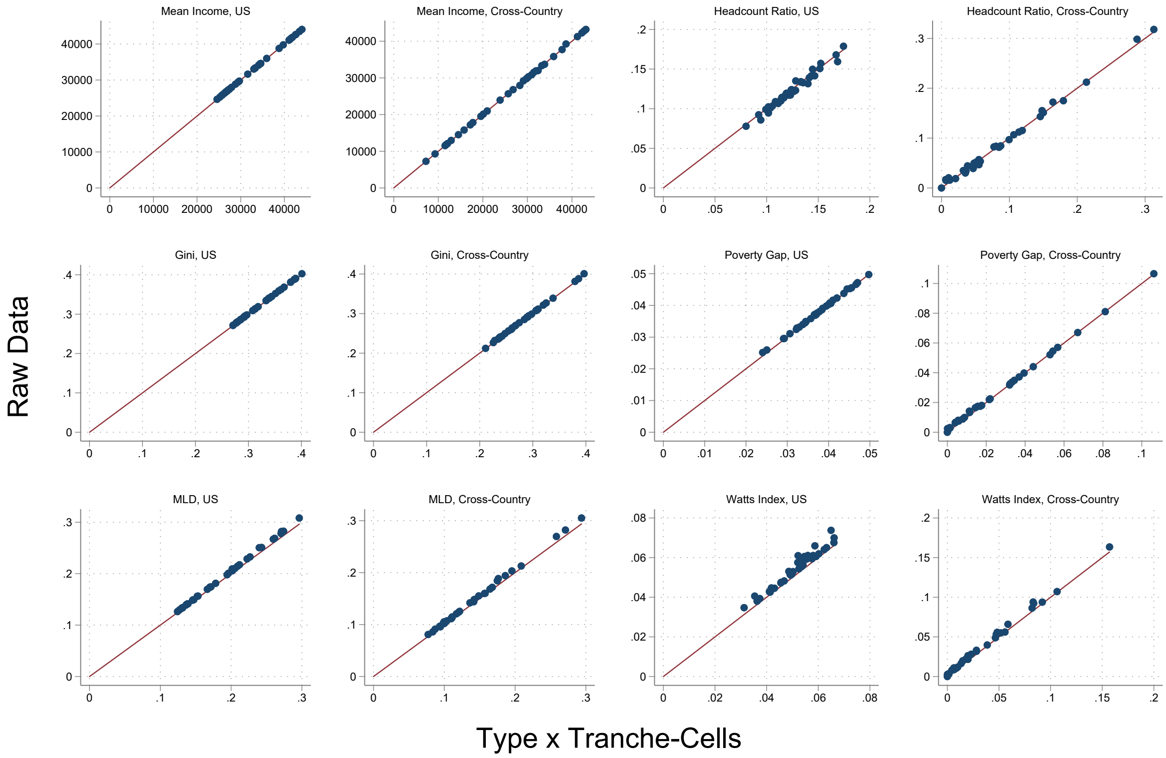
PSID. PSID CNEF reports individual educational attainment by total years of education. We map years of education into a 5-point categorical variable that corresponds to the ISCED-11 classification: (Pre-)Primary (1-6 years), Lower Secondary (7-11 years), Upper Secondary (12 years), Post-Secondary Non-Tertiary (13-14 years), Tertiary (>14 years). We replace missing information by the highest recorded education level from previous years. Since educational attainment cannot be downgraded we also replace lower educational attainments by the highest recorded education level from previous years.

EU-SILC. EU-SILC reports individual educational attainment in terms of the ISCED-11 classification. In view of small cell sizes we reduce the scale from 7 categories to 5 categories by merging Pre-Primary and Primary Education and First Stage Tertiary and Second Stage Tertiary Education. This merger corresponds to the 5-point categorical variable that we have coded for the PSID. Respondents with missing information are dropped through list-wise deletion.

C.9 Transformation to Type-Tranche Cells

In each country-year cell of our data we partition the population into a maximum of 36 circumstance types. These types are divided into 20 quantiles ordered by increasing incomes that identify Roemerian effort tranches. Since we use population weights, individual observations with high weights may span more than one effort tranche. To assure the existence of all effort tranches in every type, we duplicate the respective individual observations and divide their weight by two. We repeat this procedure until all type-effort cells are populated. We then collapse the data to the type-tranche level by replacing individual incomes and effort variables (individual education, individual working hours) by their respective cell average. Hence, each country-year cell of our data contains a maximum of 36 x 20 observations. In Figure S.3 we plot summary statistics of the raw distribution of our outcome variable against the same statistics calculated on the collapsed data. These statistics include the mean, the Gini coefficient, the mean log deviation, the poverty headcount ratio, the poverty gap ratio, as well as the Watts index. Results are presented separately for the US sample over time and the cross-country comparison sample. The closer the data points align to the 45 degree line, the smaller the information loss from collapsing the raw data to the type-tranche level.

Figure S.3 – Raw Data vs. Type x Tranche-Cells



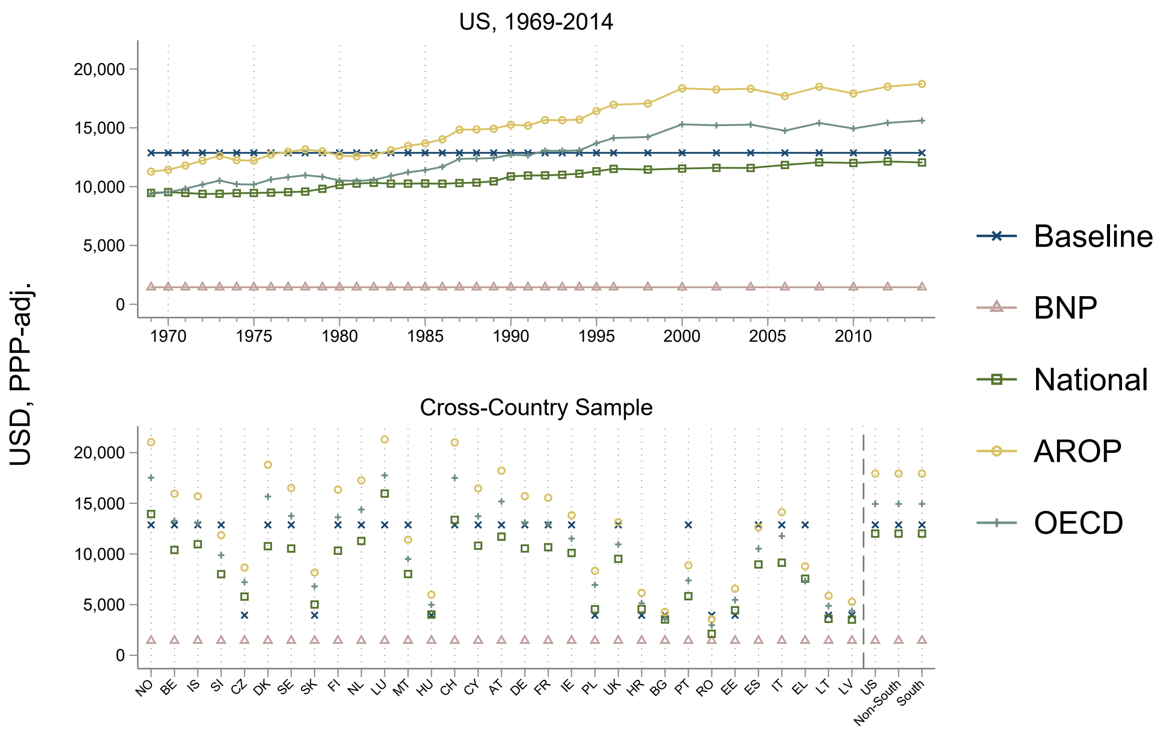
Data: PSID and EU-SILC.
Note: Own calculations. This figure plots standard measures of inequality and poverty estimated on the raw data against the corresponding estimates on data that is collapsed to type-tranche cells. The maroon line displays the 45 degree line. If inequality and poverty estimates on the raw data and the collapsed data were perfectly identical, all data points would align on the 45 degree line.

C.10 Poverty Lines

The PPP-adjusted US Dollar values of all poverty lines are displayed in Figure S.4.

Baseline. Jolliffe and Prydz (2016) provide national poverty lines and average consumption expenditures per capita in PPP-adjusted US Dollar per day for a sample of 126 countries. With the exception of Malta and Cyprus all countries of our sample are covered in their data base. Based on average per capita consumption expenditures we divide the data sample into quintiles. We assign the median poverty line of each consumption expenditure quintile to the respective countries. The resulting five poverty lines are

Figure S.4 – Alternative Poverty Lines



Data: PSID, EU-SILC, EUROSTAT, US Census Bureau, and Allen (2017).
Note: Own calculations. This figure displays the value of alternative poverty thresholds $y_{\min}$ for each country-year cell in our data samples. The upper panel refers to the longitudinal US sample. The lower panel refers to the cross-country sample. All poverty lines are expressed in PPP-adjusted US Dollar (USD). Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions.

multiplied by 365 to obtain national poverty lines in terms of PPP-adjusted US Dollar per capita and year. Following the suggestion of van den Boom et al. (2015) we divide each poverty line by 0.7 to convert the poverty lines from per capita into adult-equivalent terms. In view of their high-income status we assign Malta and Cyprus the same poverty line as the countries from the highest consumption expenditure quintile.

National Poverty Line. For the US we retrieve the time series of the official poverty line for unrelated individuals under the age of 65 from the US Census Bureau and convert it into PPP-adjusted US Dollar using the conversion factors provided by the Penn World Tables (Feenstra et al. 2015). Similarly, we retrieve the official poverty lines for all European countries in 2010 from EUROSTAT. The poverty lines are provided in PPP-adjusted units already, requiring no further adjustment.

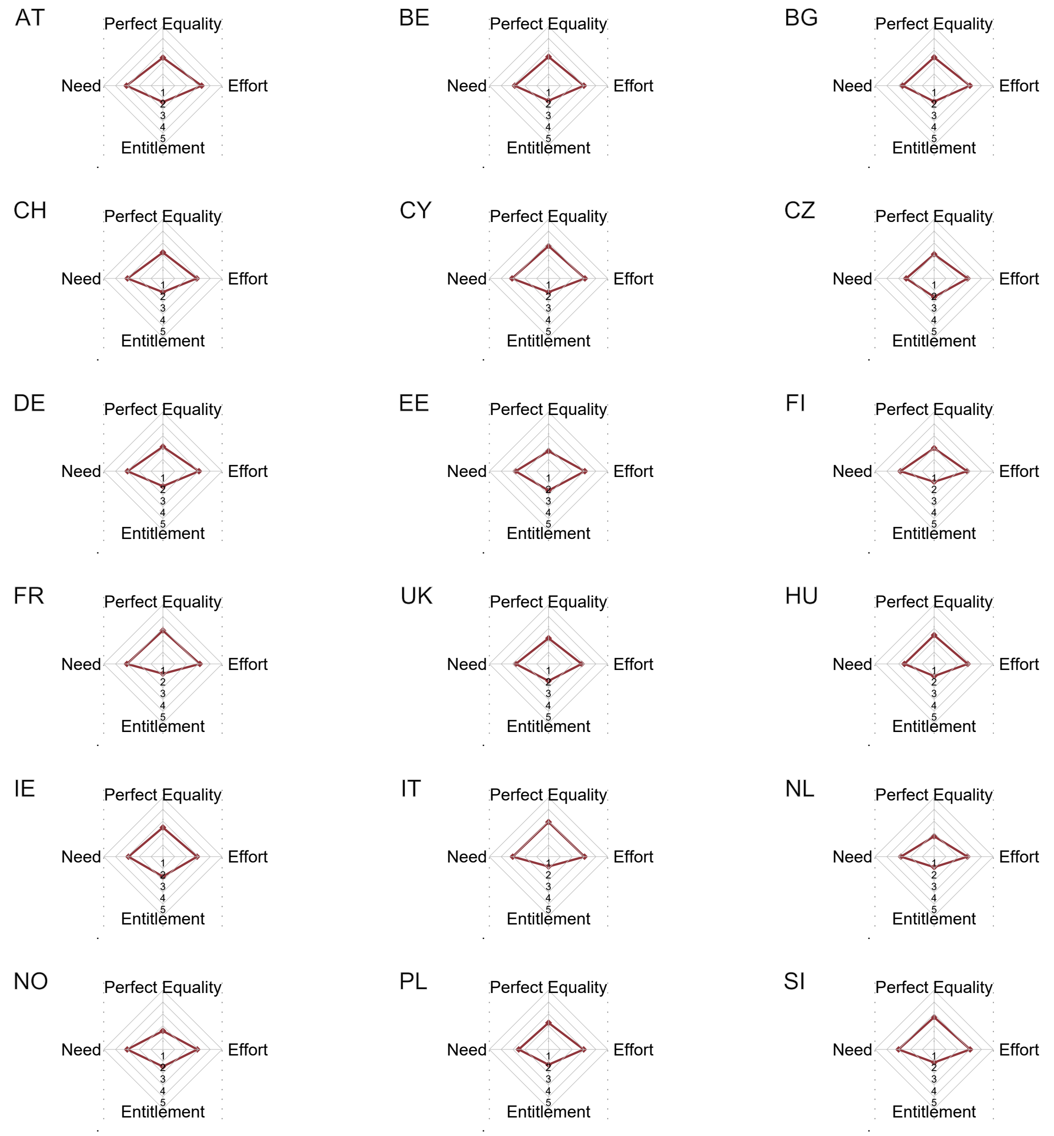
Basic Needs Poverty (BNP) Line. Allen (2017) provides basic needs adjusted poverty lines in PPP-adjusted US Dollar per day for four countries in our sample: Lithuania (\$4.62), United Kingdom (\$3.49), United States (\$3.72) and France (\$4.02). Taking the unweighted average across these poverty lines yields a value of \$3.96 which we multiply by 365 to obtain the annual BNP line. We apply this BNP line to all countries and years in our sample.

At-Risk-of-Poverty (AROP) Line. In each country-year cell we calculate the median of the distribution of disposable household income (see above). The AROP line is then drawn at 60% of the respective country-year-specific median.

OECD Poverty Line. The OECD poverty line is calculated as the AROP line. However, the OECD line is drawn at 50% of the respective country-year-specific median.

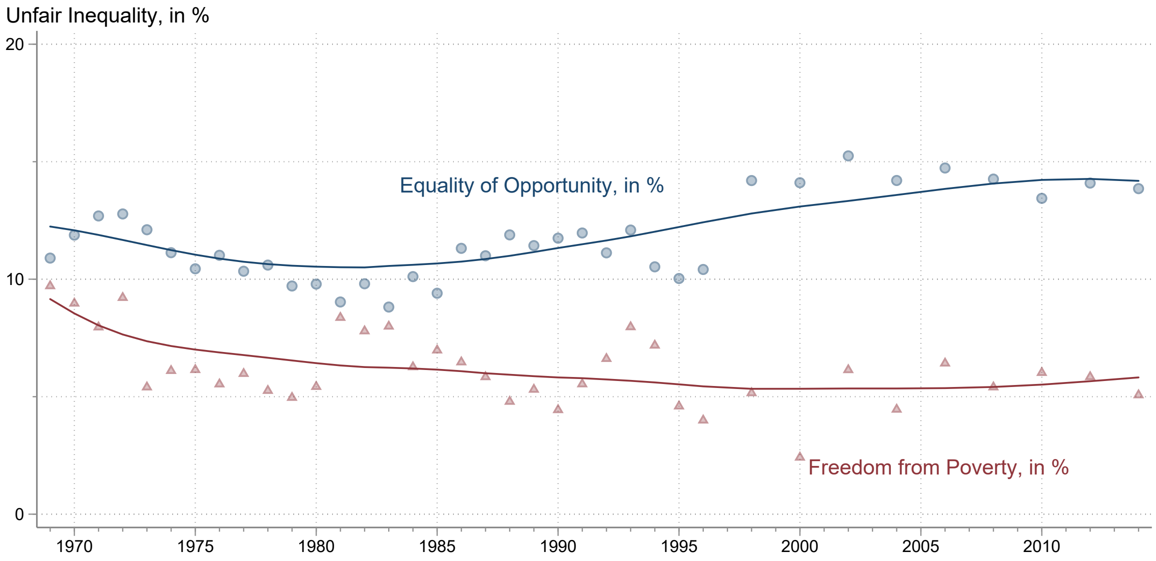
D SUPPLEMENTARY FIGURES

Figure S.5 – Normative Preferences



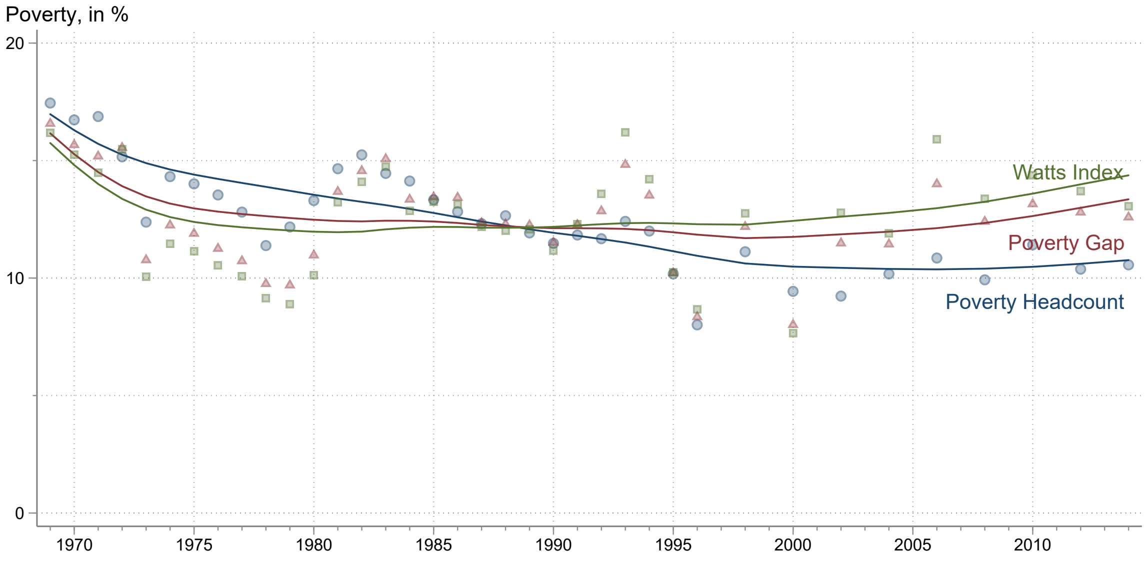
Data: European Social Survey (2018).
Note: Own calculations. This figure displays the average support for four different principles of justice in 18 of our sample countries. Answers are given on a 5-point Likert scale ranging from 1 (Agree Strongly) to 5 (Disagree Strongly). We invert the scale such that higher values indicate stronger support. The questions for the different dimensions are based on Hülle et al. (2018) and read as as follows. i) Perfect Equality: A society is fair when income and wealth are equally distributed among all people. ii) Effort: A society is fair when hard-working people earn more than others. iii) Need: A society is fair when it takes care of those who are poor and in need regardless of what they give back to society. iv) Entitlement: A society is fair when people from families with high social status enjoy privileges in their lives.

Figure S.6 – Decomposition by Principle (US), 1969-2014



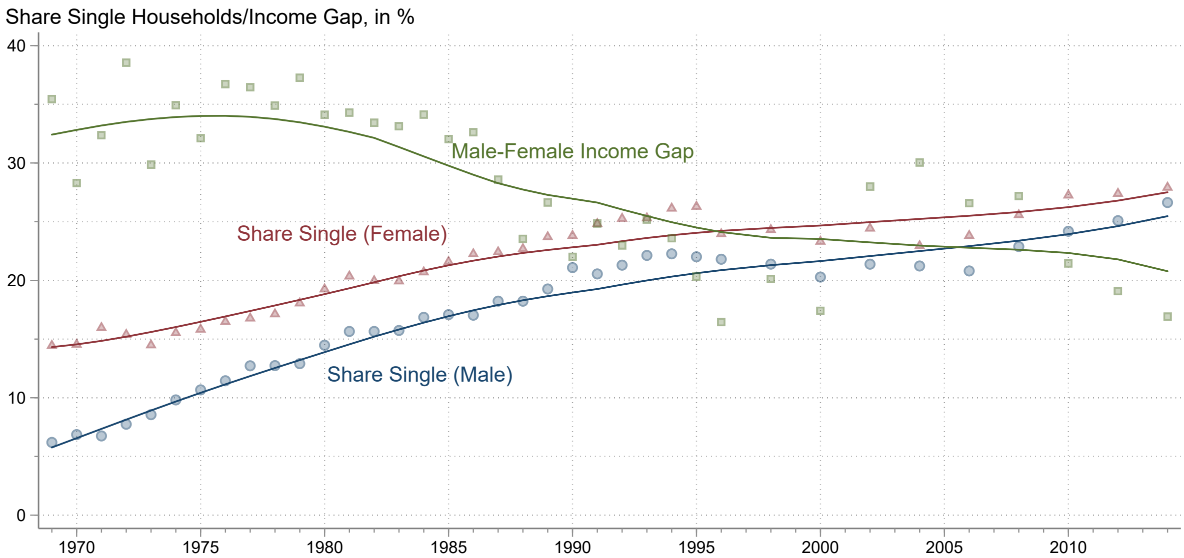
Data: PSID.
Note: Own calculations. This figure displays the contribution of EOp and FfP to total inequality in the US over the period 1969-2014. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The decomposition is based on the Shapley value procedure proposed in Shorrocks (2012). The solid lines display Lowess smoothed time trends where each data point is constructed using 80% of all data points (Bandwidth 0.8).

Figure S.7 – Poverty in the US, 1969-2014



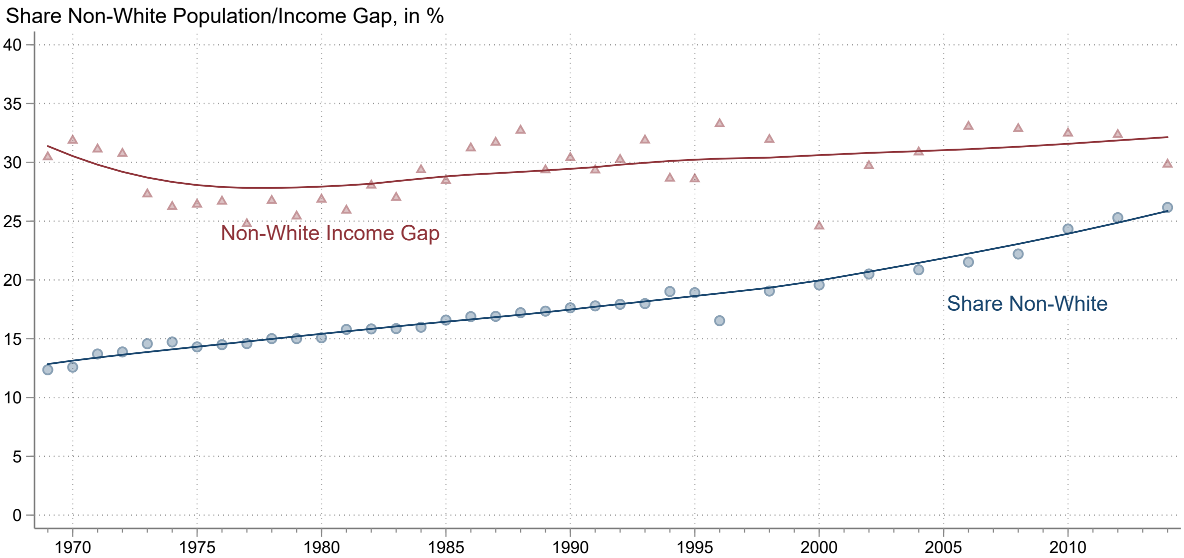
Data: PSID.
Note: Own calculations. This figure displays the development of poverty in the US over the period 1969-2014 according to different poverty measures. Poverty statistics are displayed in units of the poverty headcount ratio (in %): All data points are rescaled by multiplying with the cross-year mean of the poverty headcount ratio and dividing by the cross-year mean of the respective poverty measure. The solid lines display Lowess smoothed time trends where each data point is constructed using 80% of all data points (Bandwidth 0.8).

Figure S.8 – Income Gaps and Population Shares of Single Households in the US, 1969-2014



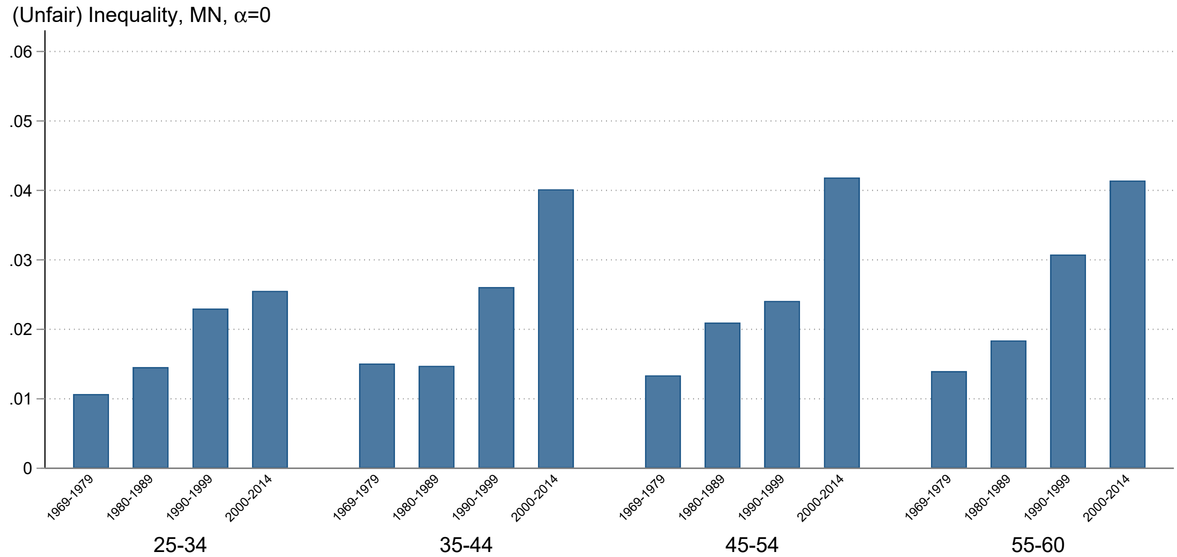
Data: PSID.
Note: Own calculations. This figure displays the share of females (males) living in households with only one adult present (in %) and the female-male income gap among those households. The female-male income gap is calculated as $\left(1 - \frac{\mu_{ft}}{\mu_{mt}}\right) * 100$ where μ_{ft} (μ_{mt}) is the average disposable household income of females (males) living in households with only one adult present in year t. The solid lines display Lowess smoothed time trends where each data point is constructed using 80% of all data points (Bandwidth 0.8).

Figure S.9 – (Non-)White Income Gaps and Population Shares in the US, 1969-2014



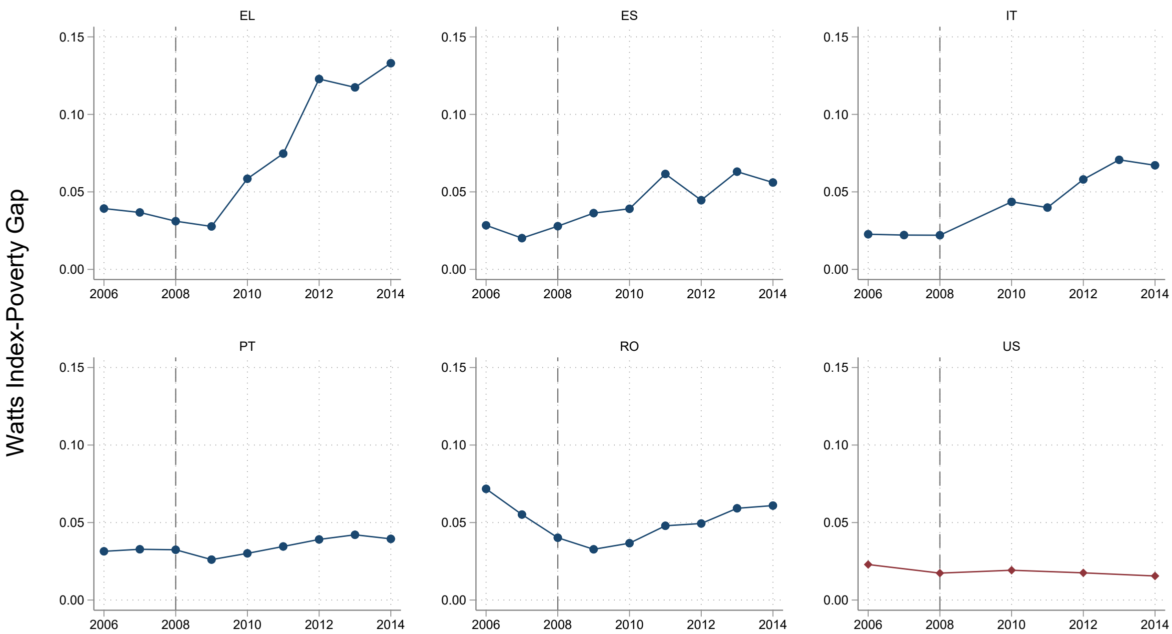
Data: PSID.
Note: Own calculations. This figure displays the share of individuals classified as non-white/Hispanic (in %) and the average income gap in comparison to individuals classified as white/non-Hispanic. The income gap is calculated as $\left(1 - \frac{\mu_{nt}}{\mu_{wt}}\right) * 100$ where μ_{nt} (μ_{wt}) is the average disposable household income of the non-white/Hispanic (white/non-Hispanic) population in year t. The solid lines display Lowess smoothed time trends where each data point is constructed using 80% of all data points (Bandwidth 0.8).

Figure S.10 – Social Mobility in the US, 1969-2014



Data: PSID.
Note: Own calculations. This figure displays estimates of unfair inequality considering parental education and parental occupation as the only relevant circumstance characteristics while abstracting from the concern for FfP. The calculation is conducted for each age bin-year-cell and then aggregated to the indicated year bins by taking unweighted averages. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality.

Figure S.11 – Poverty, 2006-2014



Data: PSID and EU-SILC.
Note: Own calculations. This figure displays the development of FfP as measured by the difference between the Watts index and the poverty gap ratio over the period 2006-2014. The selected countries represent the six most unfair societies of our cross-country sample in 2010. The vertical dashed line marks the starting year of the global financial crisis.

E SUPPLEMENTARY TABLES

Table S.4 – Descriptive Statistics US, 1969-2014

	Income	Circumstances				Efforts		Poverty
		Male	Race	Educ.	Occ.	Hours	Educ.	
1969	24,636	0.53	0.88	1.37	1.73	1,575	2.98	0.18
1970	25,254	0.53	0.87	1.39	1.74	1,551	3.01	0.17
1971	25,718	0.52	0.86	1.40	1.75	1,537	3.03	0.16
1972	26,597	0.52	0.86	1.42	1.75	1,557	3.06	0.15
1973	27,110	0.48	0.85	1.61	1.77	1,519	3.10	0.12
1974	26,689	0.48	0.85	1.64	1.78	1,485	3.26	0.14
1975	26,342	0.48	0.86	1.70	1.79	1,459	3.30	0.13
1976	27,392	0.48	0.86	1.72	1.80	1,478	3.33	0.13
1977	27,093	0.48	0.85	1.74	1.81	1,507	3.36	0.12
1978	27,481	0.48	0.85	1.75	1.82	1,548	3.37	0.11
1979	27,105	0.48	0.85	1.77	1.83	1,552	3.39	0.12
1980	26,668	0.48	0.85	1.78	1.83	1,553	3.41	0.13
1981	25,934	0.48	0.84	1.81	1.85	1,553	3.43	0.14
1982	26,854	0.48	0.84	1.83	1.86	1,531	3.45	0.16
1983	27,968	0.48	0.84	1.85	1.87	1,551	3.47	0.15
1984	28,854	0.48	0.84	1.90	1.89	1,642	3.62	0.14
1985	29,413	0.48	0.83	1.92	1.91	1,647	3.65	0.13
1986	29,704	0.47	0.83	1.94	1.92	1,647	3.66	0.14
1987	31,644	0.48	0.83	1.96	1.93	1,669	3.68	0.12
1988	33,380	0.48	0.83	1.99	1.94	1,689	3.70	0.12
1989	33,061	0.48	0.83	2.00	1.95	1,704	3.71	0.12
1990	34,134	0.48	0.82	2.02	1.96	1,719	3.72	0.11
1991	33,301	0.48	0.82	2.03	1.97	1,693	3.73	0.12
1992	34,607	0.48	0.82	2.06	1.98	1,662	3.74	0.11
1993	34,567	0.48	0.82	2.08	2.00	1,671	3.75	0.12
1994	34,478	0.49	0.81	2.10	2.02	1,699	3.73	0.12
1995	36,012	0.49	0.81	2.12	2.03	1,748	3.75	0.09
1996	38,791	0.49	0.83	2.25	2.09	1,780	3.80	0.08
1998	39,776	0.49	0.81	2.21	2.11	1,808	3.76	0.11
2000	41,579	0.49	0.80	2.23	2.13	1,791	3.75	0.09
2002	41,104	0.49	0.79	2.23	2.15	1,755	3.75	0.09
2004	42,586	0.49	0.79	2.22	2.14	1,750	3.82	0.10
2006	44,061	0.48	0.78	2.23	2.16	1,735	3.83	0.11
2008	43,496	0.48	0.78	2.24	2.17	1,681	3.86	0.10
2010	41,268	0.48	0.76	2.25	2.19	1,606	4.00	0.11
2012	41,874	0.48	0.75	2.27	2.21	1,659	4.03	0.10
2014	42,675	0.48	0.74	2.29	2.22	1,703	4.05	0.10

Data: PSID.
Note: Own calculations. This table displays descriptive statistics for the longitudinal US sample. *Male* displays the share of males. *Race* displays the share of white/non-Hispanics. The circumstance variables *Educ.* (*Occ.*) show the average education (occupation) level of the parent with the highest education (occupation) status measured on a 3-point scale. *Hours* show the average working hours per year. The effort variable *Educ.* shows the average education level measured on a 6-point scale. *Poverty* shows the share of people below the baseline poverty line. Further detail on the construction of all variables is disclosed in Supplementary Material C.

Table S.5 – Descriptive Statistics Cross-Country Sample, 2010

	Income	Circumstances				Efforts		Poverty
		Male	Mig./ Race	Educ.	Occ.	Hours	Educ.	
AT	35,829	0.50	0.79	1.80	1.94	1,599	3.37	0.03
BE	31,917	0.50	0.84	1.79	2.29	1,574	3.65	0.03
BG	9,295	0.50	1.00	1.70	1.94	1,631	3.27	0.12
CH	42,784	0.49	0.69	1.89	2.27	1,710	3.60	0.02
CY	33,336	0.48	0.78	1.49	1.92	1,671	3.38	0.04
CZ	17,836	0.44	0.96	1.56	2.24	1,695	3.32	0.00
DE	30,311	0.50	0.87	2.05	2.22	1,597	3.50	0.08
DK	33,699	0.52	0.94	2.04	2.31	1,623	3.66	0.04
EE	14,526	0.48	0.87	2.03	2.30	1,596	3.69	0.05
EL	19,526	0.50	0.89	1.38	1.81	1,311	3.26	0.32
ES	25,679	0.51	0.84	1.32	1.92	1,392	3.13	0.17
FI	30,887	0.52	0.97	1.85	1.85	1,549	3.76	0.05
FR	31,520	0.49	0.90	1.40	2.01	1,616	3.40	0.05
HR	12,952	0.50	0.89	1.61	1.95	1,299	3.15	0.05
HU	12,098	0.48	0.99	1.55	2.00	1,425	3.30	0.02
IE	29,921	0.42	0.79	1.74	1.97	1,167	3.70	0.08
IS	27,941	0.51	0.89	1.90	2.26	1,828	3.53	0.05
IT	26,813	0.50	0.88	1.32	1.99	1,435	2.91	0.16
LT	11,848	0.48	0.94	1.66	1.94	1,528	3.83	0.08
LU	43,214	0.50	0.49	1.66	2.18	1,595	3.07	0.02
LV	11,545	0.47	0.88	1.83	2.14	1,480	3.51	0.11
MT	23,952	0.50	0.95	1.37	1.99	1,420	2.68	0.15
NL	32,002	0.50	0.88	1.91	2.34	1,450	3.61	0.03
NO	37,728	0.54	0.93	2.15	2.38	1,718	3.62	0.02
PL	17,200	0.47	1.00	1.70	1.90	1,622	3.35	0.02
PT	20,140	0.48	0.91	1.15	1.93	1,574	2.31	0.30
RO	7,264	0.50	1.00	1.25	1.57	1,602	3.22	0.21
SE	29,750	0.55	0.91	1.99	1.00	1,526	3.73	0.06
SI	20,999	0.51	0.88	1.54	2.05	1,598	3.37	0.17
SK	15,795	0.49	0.99	1.78	2.13	1,667	3.42	0.02
UK	29,198	0.47	0.87	1.71	2.34	1,596	3.81	0.08
US	41,268	0.48	0.76	2.25	2.19	1,606	4.00	0.11
US (Non-South)	42,268	0.48	0.80	2.28	2.20	1,615	4.00	0.10
US (South)	39,261	0.48	0.68	2.21	2.16	1,589	4.00	0.14

Data: PSID and EU-SILC.
Note: Own calculations. This table displays descriptive statistics for the cross-country sample. *Male* displays the share of males. *Mig./Race* displays the share of people born in their current country of residence (white/non-Hispanics) in the European (US) sample. The circumstance variables *Educ.* (*Occ.*) show the average education (occupation) level of the parent with the highest education (occupation) status measured on a 3-point scale. *Hours* show the average working hours per year. The effort variable *Educ.* shows the average education level measured on a 6-point scale. *Poverty* shows the share of people below the baseline poverty line. Further detail on the construction of all variables is disclosed in Supplementary Material C.

F DECORRELATING Ω AND Θ

First, we regress the outcome of interest (y_i^e) on a vector of type fixed effects ($\delta_{\mathcal{T}(\omega)}$), a categorical variable for educational attainment (educ_i) and annual working hours (hours_i):

$$y_i^e = \delta_{\mathcal{T}(\omega)} + \beta_1 \text{hours}_i + \beta_2 \text{educ}_i + \epsilon_i. \tag{66}$$

Second, we construct a counterfactual distribution $\tilde{Y}^e$ by adding residuals to the estimated type averages net of their correlation with the considered effort variables:

$$\tilde{y}_i^e = \hat{\delta}_{\mathcal{T}(\omega)} + \hat{\epsilon}_i. \tag{67}$$

Third, we use $\tilde{Y}^e$ as an input to the construction of the reference distribution Y^r (see equation 15) and repeat our analysis according to the usual steps.

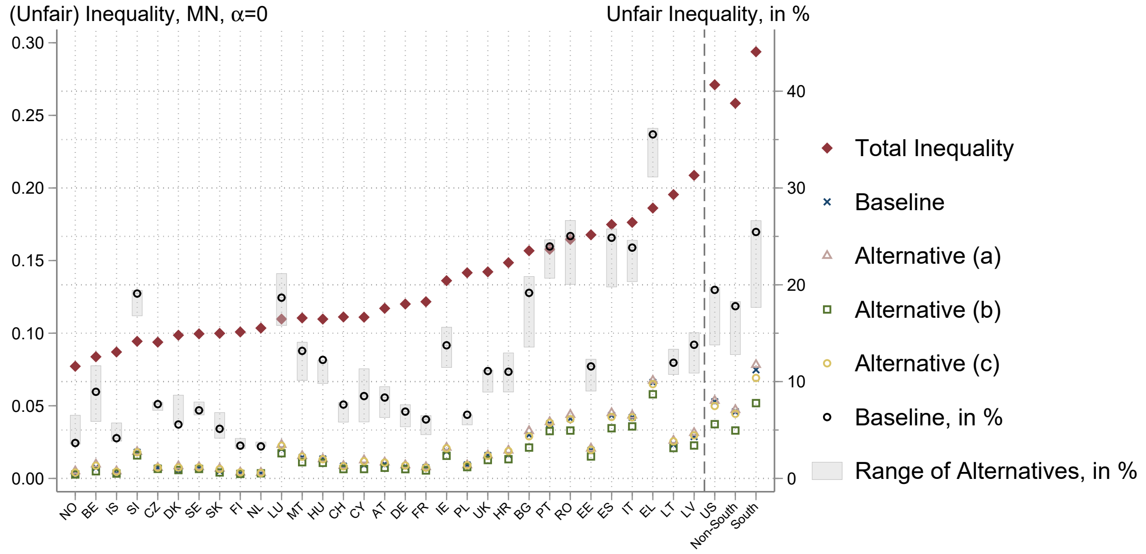
To develop an intuition for this procedure consider the polar case in which circumstances influenced outcomes only indirectly through their impact on education and working hours. Then $\hat{\delta}_{\mathcal{T}(\omega)} = \mu^e$, $\forall\ \omega \in \Omega$ and our measure of unfairness collapses to the case in which we abstracted from the concern for EOp altogether (see equations (21) and (22)). This is precisely what the normative stance of Barry (2005) requires.

Reversely, consider the polar case in which there is zero correlation between circumstances on the one hand, and education and working hours on the other hand. In this case circumstances influence outcomes only directly without affecting intermediate outcomes that are partially under the control of individuals. Then $\hat{\delta}_{\mathcal{T}(\omega)} = \mu^e_{\mathcal{T}(\omega)}$, $\forall\ \omega \in \Omega$, and we would recover exactly our baseline measure of unfair inequality (see equations (15) and (16)).[4]

[4] Another way to think about this procedure is that the alternative normative stance of Barry (2005) does not require perfect equalization of type means tout court, but perfect equalization of type means once they are cleaned from effort influence.

G SENSITIVITY ANALYSIS CROSS-COUNTRY COMPARISON

Figure S.12 – Unfair Inequality across Countries, 2010
Alternative Norm Distributions

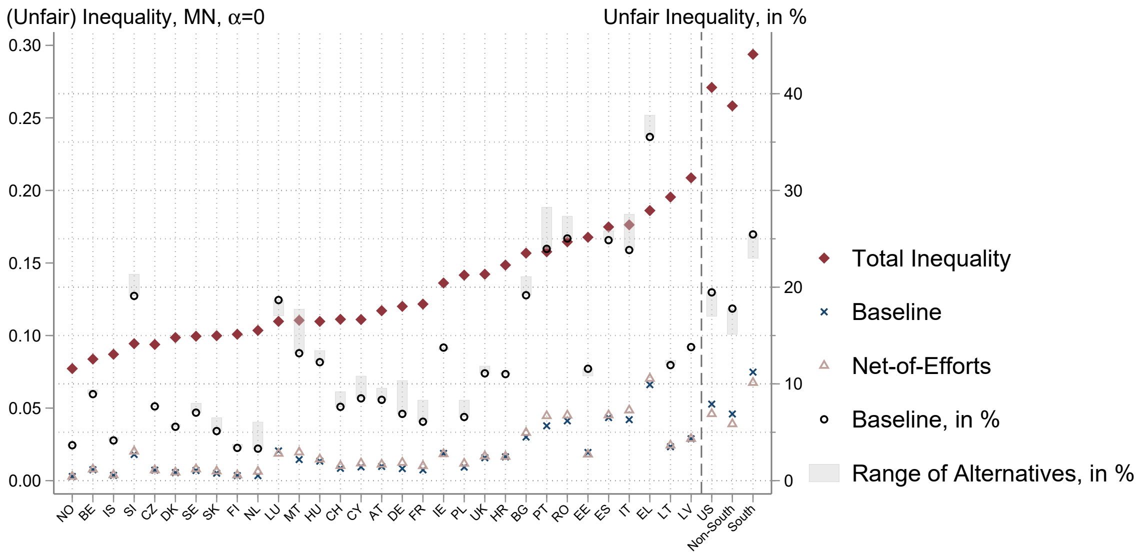


Data: PSID and EU-SILC.
Note: Own calculations. This figure displays cross-country differences in (unfair) inequality in 2010 according to the alternative norm distributions outlined in Table 1. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

Figure S.13 – Unfair Inequality across Countries, 2010
Alternative Circumstance Sets

Data: PSID and EU-SILC.
Note: Own calculations. This figure displays cross-country differences in (unfair) inequality in 2010 according to alternative specifications of the circumstance set Ω. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

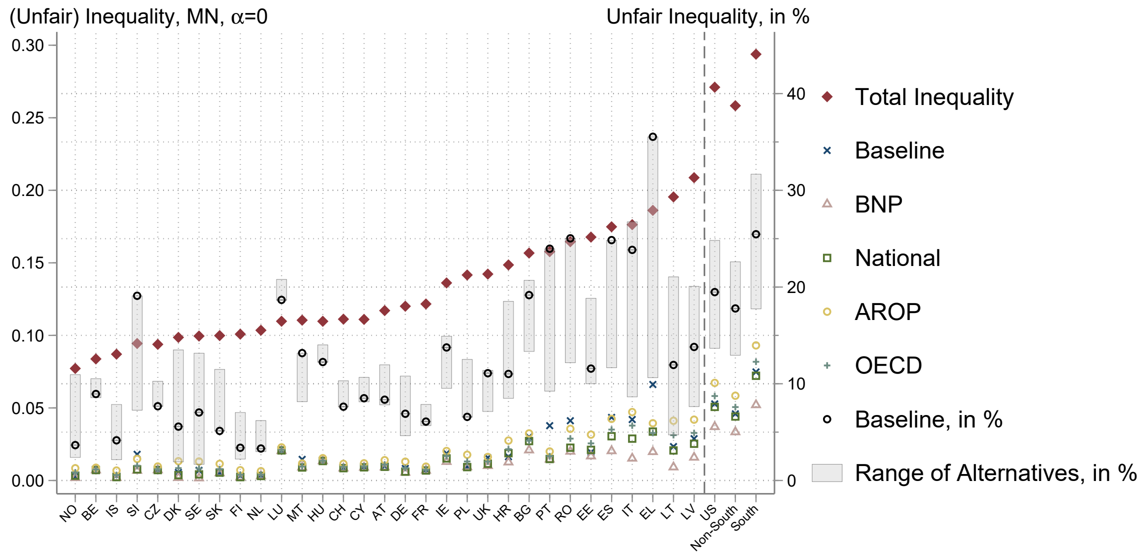
Figure S.14 – Unfair Inequality across Countries, 2010
Accounting for Preferences



Data: PSID and EU-SILC.
Note: Own calculations. This figure displays cross-country differences in (unfair) inequality in 2010 according to alternative treatments of the correlation between the effort set Θ and the circumstance set Ω. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

Figure S.15 – Unfair Inequality across Countries, 2010

Alternative Minimum Thresholds



Data: PSID and EU-SILC.
Note: Own calculations. This figure displays cross-country differences in (unfair) inequality in 2010 according to alternative specifications of the poverty threshold $y_{\min}$. Data points to the left of the vertical dashed line refer to the European country sample. Data points to the right of the vertical dashed line refer to the US and its census regions. (Unfair) inequality is calculated based on the divergence measure proposed by Magdalou and Nock (2011) with $\alpha = 0$ (MN, $\alpha = 0$) which corresponds to the MLD for total inequality. Relative measures of unfair inequality are expressed in percent (in %) of total inequality. The gray area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications. The construction of the alternative minimum thresholds is discussed in Supplementary Material C.

Table S.6 – Rank Correlation across Countries, 2010

	Magdalou and Nock			Cowell			Almås et al.
	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$	
Magdalou and Nock							
$\alpha = 0$	1.00	.	.	.	.	.	.
$\alpha = 1$	0.98	1.00	.	.	.	.	.
$\alpha = 2$	0.95	0.99	1.00	.	.	.	.
Cowell							
$\alpha = 0$	0.99	0.99	0.98	1.00	.	.	.
$\alpha = 1$	0.98	1.00	0.99	0.99	1.00	.	.
$\alpha = 2$	0.97	1.00	0.99	0.99	1.00	1.00	.
Almås et al.							
	0.95	0.98	0.98	0.97	0.98	0.98	1.00

Data: PSID and EU-SILC.
Note: Own calculations. This table displays rank correlations for unfair inequality across countries based on different divergence measures. Unfair inequality is calculated based on the divergence measures proposed by Magdalou and Nock (2011), Cowell (1985), and Almås et al. (2011).

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