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

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Empirical evidence on distributional preferences shows that people do not judge inequality as problematic per se but that they take into account the fairness or unfairness of the outcome. This article conceptualizes a view of unfair inequality and introduces a new measure of inequality based on two widely held fairness principles: equality of opportunity and freedom from poverty. It develops a method for decomposing inequality and its trends into an unfair and a fair component. We provide two empirical applications of our measure. First, we analyse the development of inequality in the US from 1969 to 2014 from a fairness perspective. Second, we conduct a corresponding international comparison between the US and 31 European countries in 2010. Our results document that unfair inequality matches the well-documented inequality growth in the US since 1980. This trend is driven by decreases in social mobility, i.e., increasing importance of parental education and occupation for the income of their children. Among the 32 countries of our international comparison, the land of opportunity ranks among the most unfair societies in 2010.

Key words: Inequality, Equality of opportunity, Poverty, Fairness, Measurement.

JEL Codes: D31, D63, I32

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 inequality is (1) necessary to incentivize individuals and (2) may reflect just deserts in a market economy. However, standard measures of inequality are inappropriate to inform the fairness

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debate because they neither correspond to standard principles of distributive justice, nor to the distributional preferences upheld by the larger public. In this article, we propose a new measure of (unfair) inequality based on two widely held normative principles, namely equality of opportunity and freedom from poverty. 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, based on the slogan "*We are the 99%*" the Occupy Wall Street 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. More redistribution would disincentivize 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 equity is adequately represented by inequality measures that invoke 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 zero, represents the most equitable distribution when people exert different levels of effort?

Most theories of distributive justice argue that we should not be concerned by inequality per se, but that we should focus on the sources and structure of inequality. In general, these theories differentiate between fair (justifiable) and unfair (unjustifiable) 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, Hole, Sørensen, and Tungodden, 2007; Alesina and Giuliano, 2011; Alesina, Stantcheva, and Teso, 2018).[4] Yet, in spite of its wide acceptance, the notion of individual responsibility 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, Ferreira, and Walton, 2006).[5] Hence, while outcome differences based

1. Among others: Atkinson and Piketty (2007), Leigh (2007), Roine and Waldenström (2015), Guvenen and Kaplan (2017), Piketty, Saez, and Zucman (2018).

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

3. This distinction is emphasized in Rawls (1971), Sen (1980), Dworkin (1981*a*), Dworkin (1981*b*), Arneson (1989), Cohen (1989), Roemer (1993), Roemer (1998), Lippert-Rasmussen (2001), and Lippert-Rasmussen (2011).

4. Moreover, the literature branches on intergenerational mobility (e.g. Solon, 1992; Björklund and Jäntti, 1997; Black and Devereux, 2011; Corak, 2013; Chetty, Hendren, Kline, and Saez, 2014a), the gender pay gap (e.g. Blau and Kahn, 2017; Kleven, Landais, Søgaard, and Egholt, 2018) and also on racial disparities (e.g. Lang and Lehmann, 2012; Kreisman and Rangel, 2015) are concerned with inequalities that are 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 in one case a new piece of information

on exogenous circumstances imply violations of fairness, the reverse statement does not hold true. 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 article, 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 take seriously the idea that equity is not represented by equality 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).

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 the principles of EOp and FfP.[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 equality of opportunity and poverty.

Our article 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, while treating the second principle as a mere weighting factor (Brunori, Ferreira, Lugo, and Peragine, 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, we provide two empirical applications of our measure yielding important insights for the inequality debate and the design of appropriate policy responses. First, we analyse the development of inequality in disposable household income in the US over the time period 1969–2014. Our results show that the US trend in unfair inequality has mirrored the marked increase of total inequality since 1980. While total inequality in the US has more than doubled in the time period 1980–2014, so has unfair inequality. The underlying relative share of unfair inequality has increased from 15.2% to 18.9%. This trend is especially driven by increasing inequality across individuals with different socio-economic background characteristics as described by their parental education and occupation. Hence, increasing unfairness in the US results from increased violations of the EOp principle; and decreases in social mobility across generations in particular. Second, we compare inequality in disposable household income between the US and 31 European countries in 2010. In absolute terms, the US have the second highest level of unfair inequality after Greece. Furthermore, we show that unfairness in the US has a remarkably different structure than in European societies with comparable levels of unfairness. While unfair inequality in these European countries is especially driven by violations of the FfP principle in the aftermath of

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.

the 2008 financial crisis, unfairness in the US is predominantly driven by violations of the EOp principle.

We emphasize that these empirical findings are contingent on normative choices and hence open to debate. Our measurement approach provides a blueprint for how to decompose total inequality into its *fair* and *unfair* components based on the principles of EOp and FfP. To implement these measures one must take a stance on the following questions: What are the individual (non-)responsibility characteristics that warrant compensation (EOp)? What is the minimal basic income necessary to make ends meet (FfP)? We do not attempt to settle these questions in this article. Instead, in the spirit of Foster (1998), we provide extensive sensitivity analysis based on (1) different circumstance sets, (2) different treatments of the correlation between individual circumstances and efforts, and (3) different basic income thresholds. We therefore provide a menu of different normative assumptions based on which the reader may draw her own conclusion about the development of unfairness in the US over time and differences in unfairness across countries.

The remainder of this article 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 two empirical applications describing unfair inequality in the US from 1969 to 2014, as well as an international comparison in 2010. Sensitivity analyses with respect to alternative normative assumptions are provided in Section 5. Lastly, Section 6 concludes.

2. NORMATIVE PRINCIPLES

2.1. *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 and 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 biological sex, race, or the socio-economic status of parents. If individual responsibility factors were the sole determinants of the outcome distribution, EOp would be realized to its full extent.

To operationalize the opportunity-egalitarian idea, the literature draws on the concepts of *circumstances* and *efforts*. Circumstances are those outcome determinants for which individuals shall not be held responsible whereas efforts belong to the realm of personal responsibility. To the extent that the former rather than the latter are stronger (weaker) determinants of the 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 different circumstances. The principle is *ex ante* because opportunity sets are evaluated prospectively without regard for 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 with the same circumstances. It entails that outcome

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

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 circumstance characteristics.[8] The precise cut between circumstances and efforts is normatively contentious. For example, some argue in favour of including genetic endowments into the set of circumstances (Lefranc, Pistolesi, and Trannoy, 2009) while others deny that natural endowments provide ground for compensation (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 favour 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 empirical baseline, 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.[9] 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 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.

2.2. *Freedom from poverty*

Poverty is an important focal point in public debates about the 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 rights we have in virtue of being humans (Fleurbaey, 2007).[10] Akin to the literature on EOp, the normative concern for poverty operates on a principle of compensation: poor 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 multi-dimensionality of poverty (Aaberge and Brandolini, 2015), much of the empirical poverty literature focuses on income. In general, poverty measurement follows a two-step process. First, set a threshold that partitions

8. See Fleurbaey and Peragine (2013) and Ramos and Van de gaer (2016) for a comprehensive discussion of different compensation and reward principles.

9. A more nuanced distinction separates factors beyond individual control into "brute luck," i.e., lotteries that cannot be avoided, and "option luck," i.e., lotteries with voluntary participation. Existing literature agrees that people have a strong tendency to compensate brute luck, while there is more heterogeneity in the treatment of option luck (e.g. Cappelen, Konow, Sørensen, and Tungodden, 2013*a*). Additionally, Mollerstrom, Reme, and Sørensen (2015) provide evidence that compensation for brute luck may be influenced by people's tendency to expose themselves to option luck. Lefranc *et al.* (2009) and Lefranc and Trannoy (2017) discuss the treatment of luck within the EOp framework.

10. 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 article, we use the term "unfair" in a colloquial sense to indicate that a distribution of some good is unfair if it raises moral objection. This practice is also consistent with a *generic* instead of a *specific* interpretation of justice. See Konow (2001) for a thorough discussion of this distinction.

the population into its deprived and non-deprived factions. All else equal, the more lenient the definition of the poverty line, the larger the group to which compensation is owed. Second, choose a function to aggregate the gaps between observed incomes and the poverty line 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 widely debated in the literature (among others Foster, 1998; Decerf, 2017). In our baseline empirical application, we draw on an internationally comparable absolute poverty line. However, we provide sensitivity analyses for different thresholds 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, Moene, Srensen, and Tungodden (2013*b*) use an international dictator game to show that transfers increase if the recipient comes from a poorer country. Fisman, Kuziemko, and Vannutelli (2020) show that inequality aversion goes hand in hand with a preference for increasing the incomes of the worst-off in society.

2.3. *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 EOp and FfP are individually insufficient to characterize what a fair distribution of resources requires (Anderson, 1999; da Vita, 2007). These theoretical insights are bolstered by empirical evidence that distributional preferences are sensitive to (1) *ex ante* inequalities that are determined by exogenous circumstances and (2) *ex post* inequalities that are insensitive to responsibility considerations. For example, Cappelen *et al.* (2013*a*) show that people endorse an *ex ante* equal-opportunity ethic, however, they also correct for *ex post* inequalities that are the result of luck. Andreoni, Aydin, Barton, Bernheim, and Naecker (2020) 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 Supplementary Figure S.5, we furthermore show survey evidence on public support for different 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 individual. However, since EOp serves as a mere weighting factor in the evaluation of incomes below the poverty line, 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 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 poverty line. Effectively, they apply standard poverty measures to circumstance types instead of individuals.

As a consequence, this 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 income distribution.

3. MEASURING UNFAIR INEQUALITY

In this section, we describe the construction of unfair inequality measures that treat EOp and FfP as co-equal grounds for compensation.

3.1. *Notation*

Consider the society $\mathcal{N}=\{1,2,..,N\}$ and an associated vector of non-negative incomes $y=(y_1,y_2,...,y_N)$. y corresponds to the observed income distribution. Let us furthermore define a basic income $y_{\min}$. It is a fixed income threshold defining what is required to make ends meet in a given society at a given time. Based on y and $y_{\min}$, we can partition the population into a poor and a non-poor faction:

$$\mathcal{P}=\{i\in\mathcal{N} \mid y_i \le y_{\min}\};\ \mathcal{R}=\mathcal{N}\setminus\mathcal{P}. \tag{3.1}$$

Individual incomes are a function of two sets of factors: first, *circumstances* beyond individual control $\Omega\subseteq\mathbb{R}^C$. Second, 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 (S) *circumstance types* (*effort tranches*) that are defined as follows:

$$\mathcal{T}(\omega)=\{i\in\mathcal{N}:\ \omega_i=\omega\};\ \mathcal{S}(\theta)=\{i\in\mathcal{N}:\ \theta_i=\theta\}. \tag{3.2}$$

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

Next to the empirical income distribution y, consider a fair norm distribution $y^*=(y_1^*,y_2^*,...,y_N^*)$. It is the normative bliss distribution for which society should strive in absence of incentive constraints and behavioural responses to redistribution. While y is given in the data, y^* must be constructed based on explicit normative principles.[11]

3.2. *Measuring divergence*

Endowed with y and y^* 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, Cappelen, Lind, Sørensen, and Tungodden (2011), each of which generalizes standard measures of inequality. While Cowell (1985) and Magdalou and Nock (2011) build on the entropy class of inequality measures, Almås *et al.* (2011) generalize the Gini index. In contrast to standard measures of inequality, these generalized measures do not decrease (increase) with progressive

11. Standard measures of inequality such as the Gini coefficient or top income shares adhere to the norm of outcome egalitarianism, i.e., the norm distribution corresponds to the perfect equality distribution where each individual is assigned the mean income of the empirical distribution: $y_i^*=\mu,\ \forall\ i\in\mathcal{N}$.

(regressive) transfers from rich (poor) to poor (rich) but rather with transfers that reduce (increase) the distance between y and y^*. This requirement is equivalent to the standard Pigou-Dalton principle of transfers if and only if $y^* = \mu$. Otherwise, transfers from poor to rich can be desirable if the income of the poor exceeds its norm value, while the income of the rich falls short of it.

In our baseline, we use the measure proposed by Magdalou and Nock (2011) yielding the following aggregator for the divergence between y and y^*:[12]

$$D(y||y^*) = \sum_{i \in \mathcal{N}} \left[\phi(y_i) - \phi(y_i^*) - (y_i - y_i^*)\phi'(y_i^*)\right],$$

$$\text{where } \phi(z) = \begin{cases} -\ln z, & \text{if } \alpha = 0, \\ z \ln z, & \text{if } \alpha = 1, \\ \frac{1}{\alpha(\alpha-1)} z^{\alpha}, & \text{otherwise.} \end{cases} \tag{3.3}$$

α is indicative of different value judgments: the higher α, the more weight is attached to positive divergences of empirical income y_i from its respective norm income y_i^*. The lower α, the more weight is attached to shortfalls from y_i^*. 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 $y_i^* = \mu$, $\forall\, i \in \mathcal{N}$. As such we ensure close proximity to the empirical literature on EOp, in which the MLD is prevalent (among others Ferreira and Gignoux, 2011; Hufe, Peichl, Roemer, and Ungerer, 2017). Furthermore, attaching higher weight to shortfalls from y_i^* is consistent with experimental evidence showing a preference for overcompensating the undeserving instead of failing to compensate the deserving (Cappelen, Cappelen, and Tungodden, 2018).[13] Thus, our baseline measure of unfair inequality aggregates divergences between y and y^* as follows:

$$D(y||y^*) = \frac{1}{N} \sum_{i \in \mathcal{N}} \left[\ln \frac{y_i^*}{y_i} - \frac{y_i^* - y_i}{y_i^*}\right].[14] \tag{3.4}$$

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

3.3. *Baseline measure*

3.3.1. Norm vector. Let $\mathcal{D} \subseteq \mathbb{R}_+^N$ be the set containing all possible norm distributions y^*. In the following, we will define subsets of eligible distributions $\mathcal{D}^h \in \mathcal{D}$ that are consistent with the normative intuitions of EOp and FfP.

First, we characterize EOp by reference to the principles of *ex ante* compensation and utilitarian reward (Fleurbaey and Peragine, 2013; Ramos and Van de gaer, 2016). These principles state that the expected income of an individual should not correlate with her circumstance type. Thus, we are infinitely inequality averse with respect to inequalities *between* circumstance types. The ideal

12. 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 directly carry 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.

13. Robustness checks using alternative specifications of α are provided in Section 5.4.

14. We can scale the measure by $1/N$ to satisfy the *principle of population* without further adjustment since we will constrain y^* such that $\mu^* = \mu$ (Magdalou and Nock, 2011).

of an equal-opportunity society is realized if there is equality in average incomes across types. $\mathcal{D}^1$ is the subset of distributions for which this criterion is satisfied:

$$\mathcal{D}^1 = \left\{ y^* \in \mathcal{D} \;\middle|\; \mu^*_{\mathcal{T}(\omega)} = \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{T}(\omega)} y^*_i = \frac{1}{N} \sum_{j \in \mathcal{N}} y_j = \mu, \; \forall\, \omega \in \Omega \right\}. \tag{3.5}$$

Note that $\mathcal{D}^1$ implies $\mu^* = \mu$. By fixing the volume of resources, we let the distribution of resources be the only margin of difference between y and y^*.[15] Furthermore, by invoking $\mathcal{D}^1$ we 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 5.1.

Second, according to FfP people have a claim for basic income $y_{\min}$ even if their low income follows from factors within their control. Therefore, we want to identify those who are poor due to a lack of effort exertion instead of exogenous circumstances and compensate them such that they are able to make ends meet. We follow extant literature and let effort tranches $\mathcal{S}(\theta)$ be represented by relative incomes within $\mathcal{T}(\omega)$. Within their types, we hold individuals fully responsible for their income y_i, i.e., within $\mathcal{T}(\omega)$ relative differences in y are proportional to relative differences in θ.[16] Hence, we define a partition according to which people are labelled (non-)poor after considering their counterfactual gains from opportunity equalization while maintaining relative income (effort) differences within types:

$$\mathcal{P}(\omega) = \left\{ i \in \mathcal{T}(\omega) \;\middle|\; y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} \leq y_{\min} \right\}; \; \mathcal{R}(\omega) = \mathcal{T}(\omega) \setminus \mathcal{P}(\omega), \; \forall\, \omega \in \Omega. \tag{3.6}$$

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

$$\mathcal{D}^2 = \left\{ y^* \in \mathcal{D} \;\middle|\; y^*_i = y_{\min}, \; \forall\, i \in \mathcal{P}(\omega), \; \forall\, \omega \in \Omega \right\}. \tag{3.7}$$

The FfP requirement consists of two components: $y^*_i = \frac{1}{N_{\mathcal{P}(\omega)}} \sum_{j \in \mathcal{P}(\omega)} y^*_j = \mu^*_{\mathcal{P}(\omega)}$ and $\mu^*_{\mathcal{P}(\omega)} = y_{\min}$. 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—they all have an equal claim to nothing less (but also nothing more) than the *basic income* $y_{\min}$.

15. Cappelen and Tungodden (2017) call this restriction the "no-waste-condition." It is standard in the literature on inequality measurement which abstracts from the efficiency costs to reach a norm distribution. Even in (optimal) policy analysis abstracting from behavioural responses often is a useful benchmark (see the discussion in Bierbrauer, Boyer, and Peichl, 2021). 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 such a framework, the planner seeks to realize a specific notion of fairness while taking behavioural responses to taxation into account. See Fleurbaey and Maniquet (2018) for a recent overview.

16. In our baseline, we rely on a relative conception of effort where absolute effort exertion of individuals is evaluated relative to the average behaviour within their circumstance type; i.e., while the propensity to study or to work long hours may vary across circumstance types, one does not hold individuals responsible average differences in these behaviours. An alternative to this identification approach is presented in Roemer (1998) who identifies effort tranches by the quantiles of type-specific income distributions. This identification approach also relies on a relative conception of effort. However, it is stronger since the type-specific distribution of efforts (and not just their average) is effectively treated as a circumstance worthy of compensation. Robustness checks using this alternative specification are provided in Section 5.3. See Appendix B for further theoretical details.

Third, there is no inequality aversion with respect to the share of income that exceeds $y_{\min}$. Therefore, we impose a proportionality requirement.[17] $\mathcal{D}^3$ denotes the subset of distributions that respect relative income differences in excess income above $y_{\min}$ after accounting for opportunity equalization:

$$\mathcal{D}^3 = \left\{ y^* \in \mathcal{D} \;\middle|\; \frac{y_i^* - y_{\min}}{y_j^* - y_{\min}} = \frac{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}},\ \forall\, i,j \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega \right\}. \tag{3.8}$$

The intersection $\cap_{h=1}^{3} \mathcal{D}^h$ characterizes our baseline norm distribution:

Proposition 1. Suppose $\mu > y_{\min}$. Then, the intersection $\cap_{h=1}^{3} \mathcal{D}^h$ yields a singleton which defines the norm distribution y^*:

$$y_i^* = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P}(\omega),\ \forall\, \omega \in \Omega, \\ y_{\min} + \tilde{y}_i \times \delta_{\mathcal{T}(\omega)}, & \forall\, i \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega, \end{cases} \tag{3.9}$$

where $\tilde{y}_i = y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}$ and $\delta_{\mathcal{T}(\omega)} = \frac{\mu - y_{\min}}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} \left(\frac{\mu_{\mathcal{R}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - y_{\min} \right)}$.

While the formal proof for Proposition 1 is disclosed in Appendix A, we describe its intuition in the following.[18] Norm incomes of individuals in $\mathcal{P}(\omega)$ are pinned down by basic income $y_{\min}$. This prescription follows from the FfP requirement (3.7): those who are poor due to factors other than exogenous circumstances are owed compensation to make ends meet but nothing more.

Norm incomes of individuals in $\mathcal{R}(\omega)$ are pinned down by basic income $y_{\min}$ plus a type-specific proportional transfer rate $\delta_{\mathcal{T}(\omega)}$ that is applied to $\tilde{y}_i$, i.e., individual income in excess of $y_{\min}$. The focus on $\tilde{y}_i$ follows from the proportionality requirement (3.8): above $y_{\min}$ fair incomes must remain proportional to the counterfactual equal-opportunity distribution.

The type-specific transfer rate $\delta_{\mathcal{T}(\omega)}$ is chosen to ensure the satisfaction of the EOp requirement (3.5) while accounting for income gains of those who are lifted to $y_{\min}$ through the FfP requirement (3.7). To understand its mechanics, let us reformulate $\delta_{\mathcal{T}(\omega)}$ as follows:

$$\delta_{\mathcal{T}(\omega)} = \frac{\mu - y_{\min}}{\mu - \frac{N_{\mathcal{P}(\omega)}}{N_{\mathcal{T}(\omega)}} \frac{\mu_{\mathcal{P}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - \frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} y_{\min}}. \tag{3.10}$$

Note $\frac{\mu_{\mathcal{P}(\omega)}}{\mu_{\mathcal{T}(\omega)}} = \frac{y_{\min}}{\mu} \implies \delta_{\mathcal{T}(\omega)} = 1$: there is no tax/subsidy on $\tilde{y}_i$ in type $\mathcal{T}(\omega)$ if the ratio of average incomes of the poor and average incomes of the type correspond to the ratio of the target situation where both FfP and EOp are satisfied. Similarly, $\frac{\mu_{\mathcal{P}(\omega)}}{\mu_{\mathcal{T}(\omega)}} < (>) \frac{y_{\min}}{\mu} \implies \delta_{\mathcal{T}(\omega)} < (>) 1$: there is a tax (subsidy) on $\tilde{y}_i$ in type $\mathcal{T}(\omega)$ if the relative average incomes of the poor fall short of (exceed) their

17. Instead of a "flat tax" that preserves relative income differences one could also formulate the measure in terms of a "lump-sum tax" preserving absolute income differences (e.g. Bossert and Fleurbaey, 1995). However, such an absolute version can only be calculated under stronger feasibility conditions that are rarely satisfied in our empirical application. In cases where it is satisfied, the results are very close to our baseline measure. As a consequence, we forego a detailed analysis of such an absolute norm in this article.

18. We derive norm distributions from axioms that describe normative principles. Alternatively, one may understand the derivation as an optimization under constraints. For example, we could minimize inequality of opportunity ($\mathcal{D}^1$) while considering freedom from poverty ($\mathcal{D}^2$) and the proportionality requirement ($\mathcal{D}^3$) as optimization constraints. Such alternative derivation, however, would not change the substantial result. See also Appendix A for further detail.

relative average income in the target situation. Hence, if $\mathcal{P}(\omega)$ receive too little of the type-specific resources, $\mathcal{R}(\omega)$ are urged to compensate and vice versa.

The fair income distribution y^* is a function of simple summary statistics of the empirical income distribution y. Some may argue that y^* should be independent of y. First, we note that the underlying principles that inform the construction of y^* are always independent of y. Second, we note that the dependence of y^* on y in the implementation of these principles is not particular to our measurement approach. To the contrary, such dependence characterizes many standard measures of inequality, poverty and inequality of opportunity.[19] In fact, whether and to what extent an insulation of y^* from y is desirable, depends on the normative intuitions one strives to capture. For example, $y_{\min}$ can be set in absolute terms, or in relative terms as some functional of y. The former is preferable if one thinks that the poverty concept applies to basic human needs. The latter is preferable if one aims to capture aspects of social deprivation as well (Foster, 1998). Within our measurement approach, the extent of such dependence can be strengthened or loosened in several ways. First, in the baseline analysis, we choose an absolute poverty threshold and therefore insulate $y_{\min}$ from changes in y. However, we provide sensitivity analyses based on relative poverty thresholds in Section 5.2.[20] Second, in the baseline analysis y^* is dependent on changes in the intra-type variance of incomes. Such dependence follows from the proportionality requirement (3.8) that proposes to honour relative income differences within types by interpreting them as indicators of differential effort exertion. However, in Section 3.4, we introduce an alternative norm distribution that insulates y^* from such dependence by harmonizing intra-type variances across circumstance types.

3.3.2. Measure and comparative statics. Substituting the norm distribution given in (3.9) into the divergence measure given in (3.4), we obtain our baseline measure of unfair inequality:

$$\begin{aligned} D(y||y^*) = & \frac{1}{N} \sum_{i \in \mathcal{P}(\omega)} \left\{ \ln \frac{y_{\min}}{y_i} - \left(\frac{y_{\min} - y_i}{y_{\min}} \right) \right\} \\ & + \frac{1}{N} \sum_{i \in \mathcal{R}(\omega)} \left\{ \ln \left(\frac{y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)}}{y_i} \right) - \left(\frac{y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)} - y_i}{y_{\min} + \tilde{y}_i \delta_{\mathcal{T}(\omega)}} \right) \right\}, \end{aligned} \tag{3.11}$$

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 comparative statics in the following.

Assume $y_{\min} \to 0$. The limiting case of $y_{\min} = 0$ is equivalent to abstracting from the concern for FfP altogether. EOp remains the only normative foundation for inequality aversion. At the limit, $\mathcal{P}(\omega) = \emptyset$, $\mu_{\mathcal{R}(\omega)} = \mu_{\mathcal{T}(\omega)}$, 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 and the measure of unfair inequality read as follows:

$$y_i^* = y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}},\ \forall\, i \in \mathcal{T}(\omega),\ \forall\, \omega \in \Omega, \tag{3.12}$$

19. For example, the standard approach to inequality measurement can be characterized as finding a suitable distance measure between y and a norm vector where every individual has the mean of the distribution, i.e., $y_i^* = \mu,\ \forall\, i \in \mathcal{N}$. The properties of the distance measure can be further specified (e.g. the Pigou-Dalton property, scale independence, decomposability, etc.). But as the empirical vector changes, the norm vector changes as well.

20. Such poverty lines are relative in that they appeal to the concept of relative deprivation by calculating $y_{\min}$ as a function of the observed distribution y. Once these relative thresholds are determined we hold them fixed for our calculations—i.e., they are not relative to any counterfactual distribution in which either EOp or FfP is satisfied.

$$D(y||y^*) = \frac{1}{N}\sum_{i\in\mathcal{N}} \ln\frac{\mu}{\mu_{\mathcal{T}(\omega)}}. \tag{3.13}$$

With $y_{\min}=0$, unfair inequality collapses to inequality in the distribution of average outcomes among 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.

Assume $N_{\mathcal{P}(\omega)}\to 0$, $\forall\, \omega\in\Omega$. Note the difference to our previous thought experiment where 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 $y_{\min}$ but happens to be in the fortunate position of having zero poverty incidence once incomes are corrected for unequal opportunities. At the limit, $\mathcal{P}(\omega)=\emptyset$, $\mu_{\mathcal{R}(\omega)}=\mu_{\mathcal{T}(\omega)}$, 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 and the measure of unfair inequality read as follows:

$$y_i^* = y_i\frac{\mu}{\mu_{\mathcal{T}(\omega)}},\ \forall\, i\in\mathcal{T}(\omega),\ \forall\, \omega\in\Omega, \tag{3.14}$$

$$D(y||y^*) = \frac{1}{N}\sum_{i\in\mathcal{N}} \ln\frac{\mu}{\mu_{\mathcal{T}(\omega)}}. \tag{3.15}$$

With $N_{\mathcal{P}(\omega)}=0$, $\forall\, \omega\in\Omega$, opportunity equalization is sufficient to satisfy the criteria of both EOp and FfP . Hence, as $N_{\mathcal{P}(\omega)}\to 0$, $\forall\, \omega\in\Omega$, 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 our measure continues to detect unfairness through violations of EOp even if FfP is perfectly satisfied.

Assume we reduce the set of non-responsibility characteristics that constitute unfair outcome determinants from an opportunity-egalitarian perspective. This reduction can be represented by letting the number of circumstance types travel to one, i.e. $T\to 1$. At the limit, the entire population would be considered a single circumstance type. 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, $N_{\mathcal{P}(\omega)}=N_{\mathcal{P}}$, $\mu_{\mathcal{T}(\omega)}=\mu$, and $\mu_{\mathcal{P}(\omega)}=\mu_{\mathcal{P}}$. As a consequence, $\tilde{y}_i=y_i-y_{\min}$ and $\delta_{\mathcal{T}(\omega)}=\delta=\left(1-\frac{PG}{RG}\right)$, where PG (RG) denotes the poverty (richness) gap.[21] The resulting norm vector and the measure of unfair inequality read as follows:

$$y_i^* = \begin{cases} y_{\min}, & \forall\, i\in\mathcal{P}, \\ y_{\min}+(y_i-y_{\min})\left(1-\frac{PG}{RG}\right), & \forall\, i\in\mathcal{R}, \end{cases} \tag{3.16}$$

$$D(y||y^*) = \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}}\ln\left(\frac{y_{\min}}{y_i}\right)}_{\text{Watts Index}} - \underbrace{\frac{1}{N}\sum_{i\in\mathcal{P}}\left(\frac{y_{\min}-y_i}{y_{\min}}\right)}_{\text{Poverty Gap Ratio}}$$
$$+\frac{1}{N}\sum_{i\in\mathcal{R}}\left\{\ln\left(\frac{y_{\min}+(y_i-y_{\min})\delta}{y_i}\right)-\left(\frac{(y_i-y_{\min})(\delta-1)}{y_{\min}+(y_i-y_{\min})\delta}\right)\right\}. \tag{3.17}$$

21. Following existing literature we define the poverty (richness) gap as $PG=N_{\mathcal{P}}/N(y_{\min}-\mu_{\mathcal{P}})$ and $RG=N_{\mathcal{R}}/N(\mu_{\mathcal{R}}-y_{\min})$, respectively (Peichl, Schaefer, and Scheicher, 2010).

$T=1$ 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 and the total volume of excess income above $y_{\min}$. The decomposability property of the MN-measures allows us evaluate unfairness in the truncated distribution $y_{\mathcal{P}}=(y_1, y_2, \ldots, y_{\min})$. 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 to the headcount ratio), the *principle of transfers* (as opposed 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 the proportionality condition (3.8). Therefore, it is not indifferent to transfers between individuals with incomes above $y_{\min}$.

Assume $\mu_{\mathcal{T}(\omega)} \rightarrow \mu, \ \forall \ \omega \in \Omega$. Note the difference to our previous thought experiment where we 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 $\mu_{\mathcal{T}(\omega)} \rightarrow \mu, \forall \ \omega \in \Omega$. The limiting case corresponds to an equal-opportunity society without disparities in average outcomes across circumstance types. At the limit, $\tilde{y}_i = y_i - y_{\min}$, $\delta_{\mathcal{T}(\omega)} = \left(1-\frac{PG(\omega)}{RG(\omega)}\right)$, where $PG(\omega)$ $(RG(\omega))$ denotes the type-specific poverty (richness) gap. The resulting norm vector and the measure of unfair inequality read as follows:

$$y_i^* = \begin{cases} y_{\min}, & \forall \ i \in \mathcal{P}, \ \forall \ \omega \in \Omega, \\ y_{\min} + (y_i - y_{\min})\left(1-\frac{PG(\omega)}{RG(\omega)}\right), & \forall \ i \in \mathcal{R}, \ \forall \ \omega \in \Omega, \end{cases} \tag{3.18}$$

$$D(y||y^*) = \underbrace{\frac{1}{N}\sum_{i \in \mathcal{P}} \ln\left(\frac{y_{\min}}{y_i}\right)}_{\text{Watts Index}} - \underbrace{\frac{1}{N}\sum_{i \in \mathcal{P}} \left(\frac{y_{\min}-y_i}{y_{\min}}\right)}_{\text{Poverty Gap Ratio}}$$

$$+\frac{1}{N}\sum_{i \in \mathcal{R}} \left\{ \ln\left(\frac{y_{\min}+(y_i-y_{\min})\delta_{\mathcal{T}(\omega)}}{y_i}\right) - \left(\frac{(y_i-y_{\min})(\delta_{\mathcal{T}(\omega)}-1)}{y_{\min}+(y_i-y_{\min})\delta_{\mathcal{T}(\omega)}}\right) \right\}. \tag{3.19}$$

With $\mu_{\mathcal{T}(\omega)} = \mu, \ \forall \ \omega \in \Omega$, 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 shows that our measure continues to detect unfairness through violations of FfP even if EOp is perfectly satisfied.

The previous comparative statics illustrate the 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. 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 ($\mu_{\mathcal{T}(\omega)} = \mu, \ \forall \ \omega \in \Omega$), 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*

There are different ways of conceptualizing EOp (Roemer and Trannoy, 2016). In this section, we briefly discuss two alternations to the EOp concept.[22]

First, the baseline norm applies a criterion of *weak equality of opportunity*. It only requires the expectation of outcomes to be identically distributed across circumstance types (Lefranc *et al.*, 2009). To the contrary, *strong equality of opportunity* would require equality of outcomes conditional on exerting similar levels of effort.

Second, the baseline norm treats EOp and FfP as *non-separable* in their scope of application. For example, it evaluates type-specific opportunity sets by reference to $\mu_{\mathcal{T}(\omega)}$—the average incomes of all $i \in \mathcal{T}(\omega)$. To the contrary, under a *separability assumption*, EOp and FfP would operate on disjunct supports of the income distribution y. While FfP characterizes the normative requirement for $\mathcal{P}$, the distributional ideal of EOp only applies to $\mathcal{R}$.

In Appendix B, we derive alternative versions of our measure that are based on *strong equality of opportunity*, and *separability*, respectively. The empirical implications of these alternations are discussed in Section 5.3.

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 analyse 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.[23]

We re-iterate that the implementation of our measurement approach affords normative assumptions that are open to debate. In our baseline analysis, we choose circumstances Ω and basic income $y_{\min}$ based on standard choices in the empirical literature on equality of opportunity and poverty. These choices may not find unanimous support. Therefore, we interpret the empirical results presented in this section as one plausible description of unfair inequality in the US and Europe. Differences based on alternating normative assumptions are presented in Section 5.

4.1. *Unfair inequality in the US over time*

4.1.1. Data source. The PSID is a main resource for the study of inequality, poverty and intergenerational transmission processes in the US (see Johnson, McGonagle, Freedman, and Sastry, 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

22. In addition, we provide the following extensions: In Supplementary material F.1, we illustrate how additional inequality aversion may be introduced into our framework. In Supplementary material F.2, we illustrate how heterogeneity in individual needs may be integrated based on individual-specific deprivation thresholds.

23. 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 are 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.

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.[24] 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).[25] We will now briefly outline the construction of the inputs to our inequality measure: y, Ω, Θ, and $y_{\min}$. Further detail on the construction of all relevant variables, as well as descriptive statistics are disclosed in Supplementary materials B and D.

4.1.2. 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 labour, asset flows, windfall gains, private transfers, public transfers, private retirement income, and social security pensions.[26] 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 Mok, 2019; Mittag, 2019). Furthermore, it has been shown that households with extremely low reported incomes tend to misreport their income from earnings (Brewer, Etheridge, and O'Dea, 2017; Meyer, Wu, Mooers, and Medalia, 2021). To mitigate distortions from benefit under-reporting, we use the time series provided in Meyer, Mok, and Sullivan (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 labour incomes we identify individuals that report zero earnings but non-zero working hours. We replace their reported earnings level by a prediction from a Mincer wage regression and adjust household labour 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.[27] For the sake of inter-period and between-country comparisons, we deflate all income figures with the purchasing power

24. 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.

25. 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.

26. In Supplementary Table S.1, we provide a detailed breakdown of these income aggregates into their single components. We note that public transfers mostly include non-medical cash assistance. Of the most important in-kind transfers it includes food stamps but not housing subsidies.

27. The modified OECD equivalence scale assigns a value of 1 to the household head, of 0.5 to each additional adult member, and of 0.3 to each child below age 14. Throughout the article, we deflate observed incomes by this household-specific factor in order to acknowledge differences in needs across households of different size and age structure while accounting for economies of scale in consumption.

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.

4.1.3. 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. 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 (1) dropped out of secondary education, (2) attained a secondary school degree, or (3) acquired at least some tertiary education. Lastly, we proxy the occupational status of parents by grouping them in (1) elementary occupations, (2) semi-skilled occupations, or (3) 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 5.1.

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 Supplementary 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.

4.1.4. Basic income 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 that reflects three times the cost of a well-balanced diet. Since then it has been updated only by 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, takes us beyond the focus on basic needs, since such lines may react to changes in the upper percentiles of the distribution irrespective of income changes for those in need (Foster, 1998).

For our baseline estimates we rely on a revised set of international absolute 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

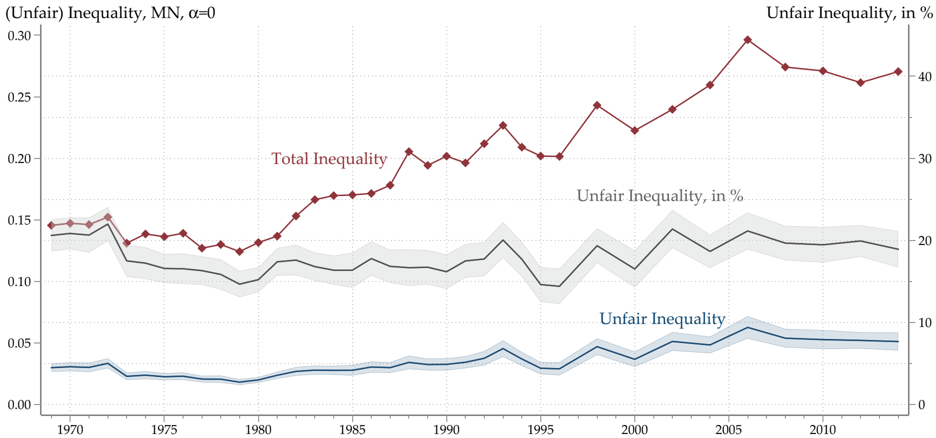

FIGURE 1

Unfair inequality in the US, 1969–2014

Baseline results

Data: PSID.
Notes: 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 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 5.2.

4.1.5. 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 $y^* = \mu, \ \forall\, i \in \mathcal{N}$. The time series replicates the well-documented pattern of inequality development in the US (among others Heathcote, Perri, and Violante, 2010*a*; 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.

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 3.11). Unfair inequality remains at a 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 follows 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 20.6% in 1969, unfair inequality drops to a share of

15.2% in 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 50% inequality growth 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, unfair inequality follows a slightly steeper growth curve than total inequality. Starting at a level 16.2% in 1990, the unfair share of inequality climbs to 21.2% in 2006 and stalls at a level of 18.9% 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. Therefore, they evaluate remaining unfairness after taking transfers through existing welfare state institutions and redistribution within households into account.[28]

4.1.6. Decomposition. To develop a better understanding for the observed inequality trends, we conduct a Shapley value decomposition to identify the contributions of 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 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.

In 1969, approximately half of unfair inequality, that is 9.7% of total inequality, was associated with violations of the FfP principle. The previously described attenuation of relative unfairness in the 1970s is almost fully explained by 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 0.013 points (9.0%) in 1970 to 0.006 points (5.0%) in 1979. Following the decrease of the 1970s, the contribution of FfP bounces back to its initial levels in the 1980s and subsequently follows a flat time trend that persists until the present day.[29] In 2014, violations of FfP contribute 0.014 points to our measure of unfairness and explain 5.1% 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

28. 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).

29. While the absolute contribution of FfP is rather stable between 1969 and 2014, its relative contribution is halved from 9.7% to 5.1%. This decrease in the relative contribution follows mechanically from the increase in total inequality. For further illustration, see also Supplementary Figure S.6 in which we fit locally smoothed time trends for the relative contributions of both EOp and FfP.

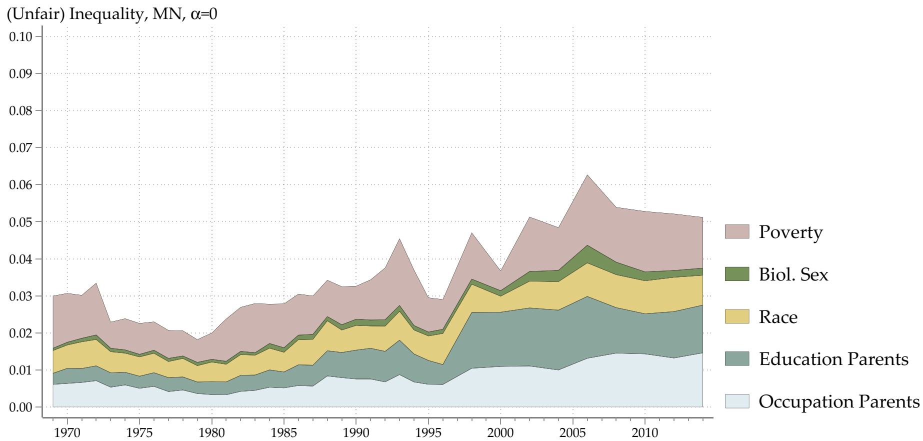

FIGURE 2
Unfair inequality in the US, 1969–2014
Decomposition

Data: PSID.
Notes: 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).

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 (Supplementary Figure S.7 and Supplementary Table S.5).[30] 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 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 0.013 points (9.8%) in 1980, over 0.024 points (11.7%) and 0.031 points (14.1%) in 1990 and 2000, to 0.037 points (13.9%) in the latest period of observation.

Analysing 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 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 Supplementary 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 increasing for both males and females. While

30. See Wimer, Fox, Garfinkel, Kaushal, and Waldfogel (2016) for similar results.

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.[31]

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 decreases slightly from 4.2% to 3.0%, 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, 2021).[32]

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 (6.3%) in 1969, their importance has tripled to 0.028 points (10.2%) 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 to 2014. This finding is in line with Aaronson and Mazumder (2008); Davis and Mazumder (2019) who find that the intergenerational elasticity of income has declined for cohorts entering the labour 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, Hendren, Kline, Saez, and Turner (2014b), and Song, Massey, Rolf, Ferrie, Rothbaum, and Xie (2020) conclude that inter-generational 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.[33]

To summarize, unfair inequality in the US by-and-large replicates the development of total inequality. In the 1970s, unfairness decreased due to decreases in poverty. To the contrary, the growth of unfair inequality since the 1980s is almost exclusively attributable to increased violations of the EOp principle, and the growing importance of parental education and education for the income of their offspring in particular.

31. See also Lundberg, Pollak, and Stearns (2016) on the interaction between changing gender gaps, family structures, and the intergenerational transmission of advantages.

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

33. Mobility measures can be decomposed into (1) the copula of parental background characteristics and child outcomes and (2) 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 (1) while holding (2) constant. To the contrary, mobility measures like the intergenerational elasticity (IGE) allow for changes in (2). 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. (1) We model child income as a function of parental education and occupation instead of parental income. (2) We summarize persistence by calculating inequality in a predicted distribution instead of interpreting regression parameters. (3) Child outcomes refer to annual incomes at various points of the life-cycle instead of modelling 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 Supplementary 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.

4.2. *Cross-country differences in unfair inequality*

4.2.1. 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 inequality, poverty and social exclusion in the EU and covers a total of 31 countries (see e.g. Atkinson, Guio, and Marlier (2017) and the references cited therein). 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.[34] 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 variable construction, as well as descriptive statistics are provided in Supplementary materials B and D.

4.2.2. Outcome variable. We construct disposable household income as the sum of total household income from labour, 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.[35] In analogy to the PSID, we scale reported public transfers by a country-specific under-reporting factor and adjust labour incomes by imputing individual labour incomes of respondents with zero labour 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.

4.2.3. Circumstance types and effort tranches. For each country we partition the population based on the following circumstance characteristics: (1) biological sex, (2) migration background, (3) educational achievement of the highest educated parent, and (4) the highest occupation category of either parent. While circumstances (1), (3), and (4) mirror the PSID specification, we replace the binary race variable of the PSID with a binary indicator 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 Supplementary Figure S.3, this transformation is innocuous with respect to cross-country comparisons of inequality and poverty statistics.

4.2.4. Basic income threshold. Internationally comparable absolute poverty thresholds are again constructed based on the procedure suggested by Jolliffe and Prydz (2016). Twenty-one out of the 31 European countries belong to the highest quintile of countries in terms of PPP-adjusted household final consumption expenditures per capita. Hence, they are characterized by the same poverty threshold as the US: \$12,874 per annum (PPP-adj.). Ten 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.).

4.2.5. Baseline results. Figure 3 replicates Figure 1 for the cross-country comparison. The red diamonds indicate total inequality, the blue squares unfair inequality. The

34. 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.

35. In Supplementary Table S.2, we provide a detailed breakdown of these income aggregates into their single components.

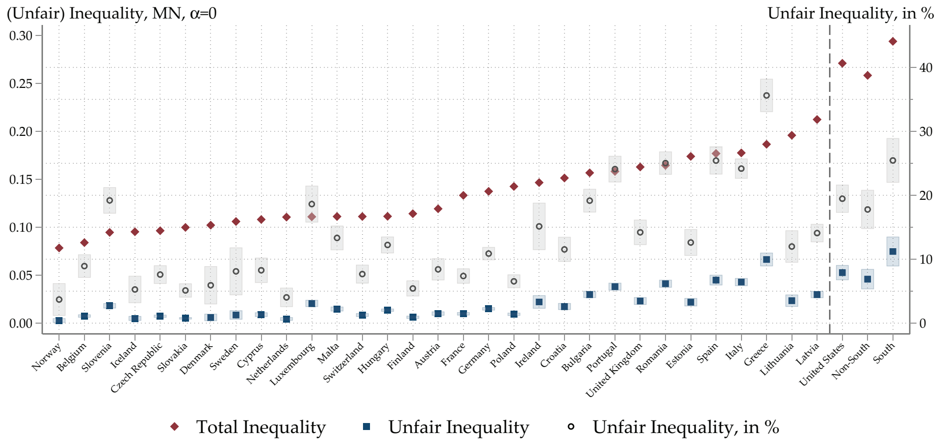

FIGURE 3

Unfair inequality across countries, 2010

Baseline results

Data: PSID and EU-SILC.

Notes: 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.

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, Davis, Mazumder, Nybom, Schnitzlein, and Vaage, 2017) and poverty prevalence (Ziliak, 2006), we also provide results separating the South of the US from the rest of the country 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, Belgium and Slovenia. 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 on average 26.6% of total inequality in the European countries of this group. The US attains an unfair share of 19.5%. 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 Nordic countries plus the Netherlands. Country rankings differ depending on whether we analyse total inequality or unfairness. While for example the Netherlands ranks 10th in terms of total inequality, it ranks second in terms of least unfair inequality.

4.2.6. 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

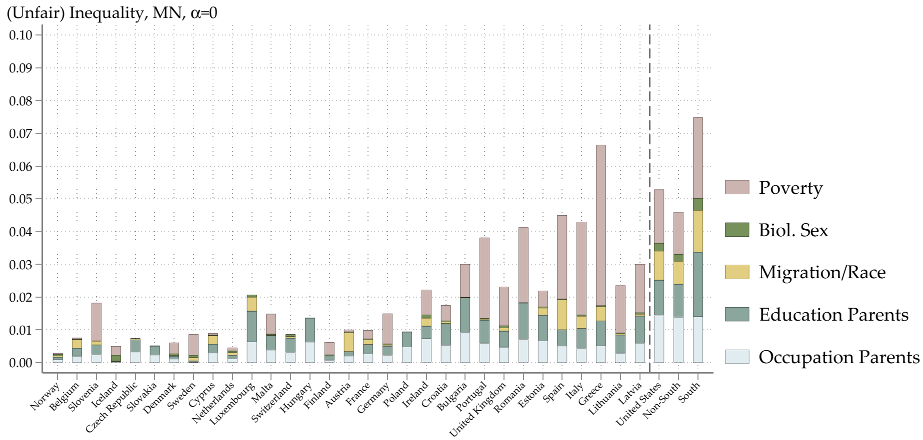

FIGURE 4

Unfair inequality across countries, 2010

Decomposition

Data: PSID and EU-SILC.

Notes: 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).

differential impact of the economic crisis on unfairness in Europe 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, and 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 Supplementary 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 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 cannot be explained by 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.

5. SENSITIVITY ANALYSIS

In this section, we investigate the sensitivity of our baseline results to alternative normative assumptions. For brevity, we only present results 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 Supplementary Figures S.12–S.15 and Supplementary Table S.7.

First, 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 basic income $y_{\min}$. We acknowledge that these choices may be normatively contentious. It is not our ambition to resolve such disagreement. Instead we provide results for alternative choices of Ω, Θ, and $y_{\min}$ in Sections 5.1 and 5.2, respectively.

Second, our baseline measures is based on a weak conceptualization of EOp and treats EOp and FfP as non-separable in their scope of application. We provide empirical results for unfair inequality based on strong equality of opportunity and separability in Section 5.3.[36]

Third, differences between y and y^* 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.

5.1. *Alternative responsibility cuts*

Any measurement of responsibility-sensitive 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 (1) their biological sex, (2) their race, (3) the occupation of their parents, and (4) the education of their parents. However, there may be further characteristics beyond individual control that evoke normative concern. Examples could be the quality of neighbourhoods in which people grew up (Chetty, Hendren, and Katz, 2016), parenting practices (Doepke, Sorrenti, and Zilibotti, 2019), or genetic endowments (Papageorge and Thom, 2020).

To be sure, the PSID puts strong constraints on testing the influence of different circumstance characteristics.[37] We therefore proceed as follows: first, we extract two additional circumstances that are consistently measured across the period of our analysis: (1) the census region in which respondents grew up and (2) 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).[38] Hence, we repeat our analysis for 210 different specifications of Ω. The results are presented in Figure 5. The upper line again marks the development of total inequality. The lower crosses mark unfair inequality under each of the different specifications of Ω in any

36. See discussion in Section 3.4 and Appendix B for a formal derivation.

37. 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.

38. 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.

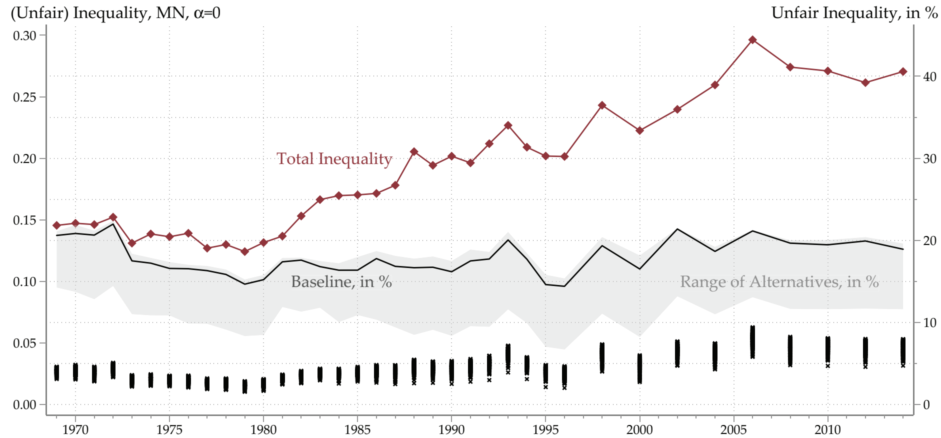

FIGURE 5

Unfair inequality in the US, 1969–2014

Alternative circumstance sets

Data: PSID.

Notes: 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 grey area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

given year. The black line marks the relative share of unfair inequality from our baseline estimate. The grey 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 remain unaffected by the specification of Ω. However, we 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 11.6% of total inequality in 2014. The upper bound is 19.6%. 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 that are consistently elicited across all sample countries. These include (1) the relationship status of parents, (2) the number of siblings, (3) the financial situation of the parental household, as well as (4) 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. Supplementary Figure S.12 reveals that in spite of level differences the 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 which itself is at least partially under the control of individuals (Gelbach, 2016). 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

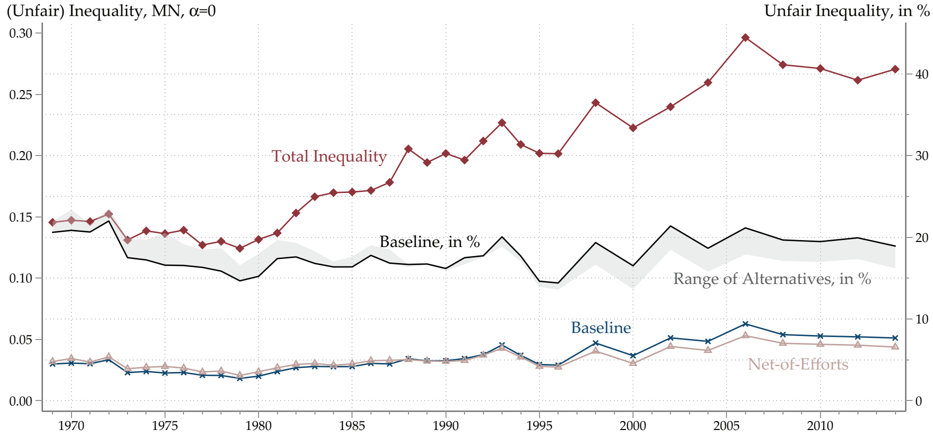

FIGURE 6

Unfair inequality in the US, 1969-2014

Accounting for preferences

Data: PSID.

Notes: 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 grey area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

two variables that are partially under the control of individuals and highly predictive of incomes—(1) educational attainment and (2) annual working hours—and clean circumstances from their correlation with these effort variables before repeating our analysis.[39] 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 6 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 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 attains 16.2% in 2014. The differential development of our baseline and the alternative measure is consistent with evidence on the increasing stratification of college completion by parental background characteristics (Davis and Mazumder, 2019; Hilger, 2019), increasing college wage premia (Heathcote, Storesletten, and Violante, 2010*b*), and longer working hours among the highly educated (Fuentes and Leamer, 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.

5.2. *Alternative basic income thresholds*

There is no clear consensus on how to set a basic income threshold $y_{\min}$ that captures the material requirements 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 $y_{\min}$

39. We describe the exact steps of this procedure in Supplementary material E.

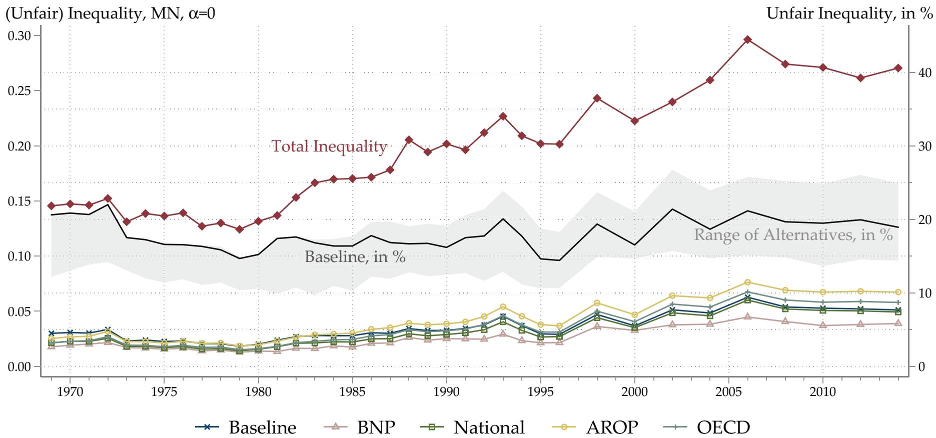

FIGURE 7

Unfair inequality in the US, 1969–2014

Alternative minimum thresholds

Data: PSID.

Notes: 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 grey 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 B.

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 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.[40] The results for these different poverty thresholds are shown in Figure 7.

Our general conclusions with respect to the trend of unfairness in the US are insensitive to the specification of $y_{\min}$. If anything, the relative poverty thresholds of the OECD and AROP tend to magnify the relative increase of unfairness since the 1990s. However, we observe sharp level differences in unfair inequality depending on the stringency of $y_{\min}$. Proponents of the AROP threshold (\$18,737) would conclude that unfairness explained 24.9% of total inequality in 2014, while proponents of the BNP (\$1,445) threshold would detect a relative share of 14.4%.

40. 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 article.

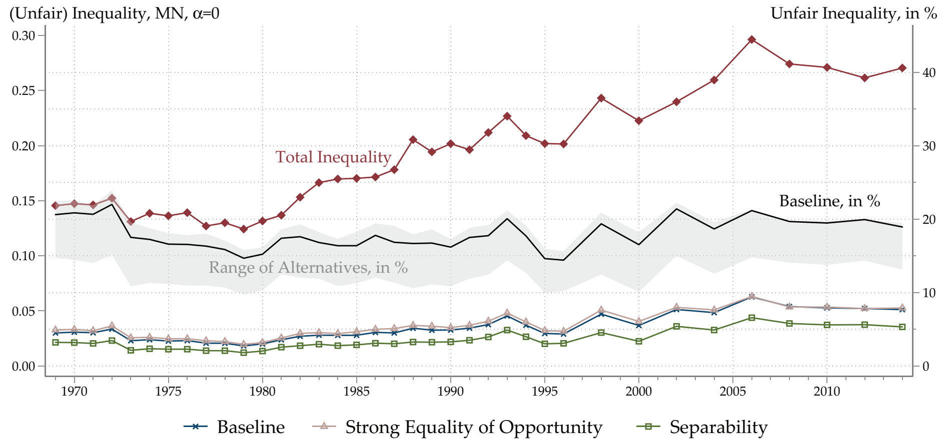

FIGURE 8

Unfair inequality in the US, 1969–2014

Alternative norm distributions

Data: PSID.

Notes: 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 Section 3.4. (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 grey area shows the range of unfair inequality in percent (in %) of total inequality depending on the alternative measurement specifications.

5.3. *Alternative norm distributions*

Our baseline estimates of unfair inequality are based on weak EOp and reconcile EOp and FfP in a non-separable way. In Section 3.4, we have presented alternative norm distributions that divert from the baseline by operating on a strong notion of EOp, or assume separability between EOp and FfP. Figure 8 presents the development of (unfair) inequality in the US under each of these different conceptualizations. The black line marks the relative share of unfair inequality from our baseline estimate. The grey 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 are 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. Invoking strong equality of opportunity yields results that are congruent to our baseline. Invoking separability consistently leads to lower levels of unfair inequality. Separability entails that (1) opportunity sets of circumstance types are evaluated by excess incomes above $y_{\min}$ only and (2) empirically poor individuals are excluded from compensation through opportunity-equalizing transfers beyond $y_{\min}$. Both features make the distribution of type-specific advantages more homogeneous and therefore require less transfers across types to attain the normative bliss distribution y^*. If one prefers the separability assumption over our baseline measure, one would conclude that unfairness amounts to 13.1% instead of 18.9% of total inequality in 2014.

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 present results based on the measures of Cowell (1985) and Almås *et al.* (2011). The

TABLE 1
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.
Notes: 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).

Cowell-family 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 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 1 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, our conclusions are robust to using alternative divergence measures.

6. CONCLUSION

In this article, we propose a novel measure of unfair inequality that reconciles the ideals of EOp and 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 analyse the development of inequality in the US over the time period 1969–2014 through the lens 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 insights for current debates on inequality. First, the US trend in unfair inequality has traced the marked increase of total inequality since 1980. Second, this trend is mainly driven by a less equal distribution of opportunities across people with different parental education and occupation characteristics. Third, unfairness in the US shows a remarkably different structure than in comparable European societies. In 2010, unfairness in Europe is largely driven by the consequences of the 2008 financial crisis; unfairness in the US is driven by the intergenerational transmission of disadvantages. The underlying determinants of the latter are arguably more persistent than income shortfalls due to economic downturns illustrating the 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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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

Data Availability Statement

The data and code underlying this research is available on Zenodo at https://doi.org/10.5281/zenodo.5772718.

APPENDIX

A. PROOF OF PROPOSITION 1

Proof of Proposition 1. The proof proceeds in two steps. First, we show that $y^* \in \cap_{h=1}^3 \mathcal{D}^h$. Second, we show that $\cap_{h=1}^3 \mathcal{D}^h$ is a singleton. The second step is established by contradiction.

Step 1. Define y^* as in equation (3.9):

$$y_i^* = \begin{cases} y_{\min}, & \forall\, i \in \mathcal{P}(\omega),\ \forall\, \omega \in \Omega, \\ y_{\min} + (y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}) \times \frac{\mu - y_{\min}}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\frac{\mu_{\mathcal{R}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - y_{\min})}, & \forall\, i \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega. \end{cases}$$

We reshape the second term of equation (3.9) as follows:

$$\begin{aligned} \mu &= y_{\min} + \frac{y_i^* - y_{\min}}{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} \times \frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} (\frac{\mu_{\mathcal{R}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - y_{\min}) \\ &= y_{\min} + \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{j \in \mathcal{R}(\omega)} (y_i^* - y_{\min}) \frac{\mu_{\mathcal{R}(\omega)} \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} \\ &= \frac{1}{N_{\mathcal{T}(\omega)}} \Bigg[\sum_{j \in \mathcal{P}(\omega)} \underbrace{\qquad y_{\min} \qquad}_{= y_j^*,\ \forall\, j \in \mathcal{P}(\omega)} + \sum_{j \in \mathcal{R}(\omega)} \underbrace{y_{\min} + (y_i^* - y_{\min}) \frac{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}}_{= y_j^*,\ \forall\, j \in \mathcal{R}(\omega)} \Bigg]. \end{aligned}$$

The first term corresponds to the norm income of any $j \in \mathcal{P}(\omega)$ as prescribed by $\mathcal{D}^2$; the second term corresponds to the norm income of any $j \in \mathcal{R}(\omega)$ as prescribed by $\mathcal{D}^3$. Simplifying the previous equation we obtain the EOp requirement $\mathcal{D}^1$:

$$\mu = \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{j \in \mathcal{T}(\omega)} y_j^* = \mu^*_{\mathcal{T}(\omega)}.$$

We conclude $y^* \in \cap_{h=1}^3 \mathcal{D}^h$.

Step 2. Now let's assume there is $\hat{y}^* \neq y^*$ such that $\hat{y}^* \in \cap_{h=1}^{3} \mathcal{D}^h$.
By $\mathcal{D}^2$ we know that for any $j \in \mathcal{P}(\omega)$:

$$\hat{y}_i^* = y_{\min}.$$

By $\mathcal{D}^3$, we know that for any $j \in \mathcal{R}(\omega)$:

$$\hat{y}_i^* = y_{\min} + \frac{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} (\hat{y}_j^* - y_{\min}).$$

Using both requirements in $\mathcal{D}^1$ and simplifying, we get:

$$\begin{aligned}
\mu &= \frac{1}{N_{\mathcal{T}(\omega)}} \left[\sum_{i \in \mathcal{P}(\omega)} y_{\min} + \sum_{i \in \mathcal{R}(\omega)} \left(y_{\min} + \frac{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} (\hat{y}_j^* - y_{\min}) \right) \right] \\
&= y_{\min} + \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{R}(\omega)} \frac{\hat{y}_j^* - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} \left(y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min} \right) \\
&= y_{\min} + \frac{\hat{y}_j^* - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} \times \frac{1}{N_{\mathcal{T}(\omega)}} \sum_{i \in \mathcal{R}(\omega)} \left(y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min} \right) \\
&= y_{\min} + \frac{\hat{y}_j^* - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}} \times \frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} \left(\frac{\mu_{\mathcal{R}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - y_{\min} \right).
\end{aligned}$$

Solving for $\hat{y}_j^*$ we obtain:

$$\hat{y}_j^* = \begin{cases} y_{\min}, & \forall\, j \in \mathcal{P}(\omega),\ \forall\, \omega \in \Omega, \\ y_{\min} + \left(y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min} \right) \times \frac{\mu - y_{\min}}{\frac{N_{\mathcal{R}(\omega)}}{N_{\mathcal{T}(\omega)}} \left(\frac{\mu_{\mathcal{R}(\omega)}}{\mu_{\mathcal{T}(\omega)}} \mu - y_{\min} \right)}, & \forall\, j \in \mathcal{R}(\omega),\ \forall\, \omega \in \Omega. \end{cases}$$

Hence, in contrast to the initial assumption of $\hat{y}^* \neq y^*$, we obtain $\hat{y}^* = y^*$ which is a contradiction. We conclude $\cap_{h=1}^{3} \mathcal{D}^h$ is a singleton.[41] □

B. ALTERNATIVE CONCEPTUALIZATIONS

In this appendix, we provide formal derivations of the alternative norm distributions discussed in Section 3.4. Proofs for the propositions proceed analogously to the proof of Proposition 1 and are collected in Supplementary material A.

B.1. *Strong equality of opportunity.*

We divert from the baseline by replacing *weak equality of opportunity* with *strong equality of opportunity*. The satisfaction of strong EOp requires the equalization of all moments of the type-specific income distribution. We therefore reformulate (3.5) as follows:

$$\mathcal{D}^{1a} = \left\{ y^* \in \mathcal{D} \;\middle|\; y_i^* = \frac{1}{N_{\mathcal{S}(\theta)}} \sum_{j \in \mathcal{S}(\theta)} y_j^* = \mu^*_{\mathcal{S}(\theta)},\ \forall\, i \in \mathcal{S}(\theta),\ \forall\, \theta \in \Theta \right\}. \tag{B.1}$$

Note that $\mathcal{D}^{1a}$ implies $\mu^* = \mu$. Invoking strong EOp requires a subsequent redefinition of the poor and the non-poor fraction of the population, as well as of the FfP and the proportionality requirement:

$$\mathcal{P}(\theta) = \left\{ i \in \mathcal{S}(\theta) \;\middle|\; y_i \frac{\mu_{\mathcal{S}(\theta)}}{y_i} \leq y_{\min} \right\};\ \mathcal{R}(\theta) = \mathcal{S}(\theta) \setminus \mathcal{P}(\theta),\ \forall\, \theta \in \Theta \tag{B.2}$$

41. In footnote 18, we highlight the possibility to derive the same norm distribution from an optimization under constraints. The formal set-up for such an optimization problem could look as follows:

$$\min \sum_{T} (\mu^*_{\mathcal{T}(\omega)} - \mu) \text{ subject to}$$

$$y_i^* = y_{\min},\ \forall\, i \in \mathcal{P}(\omega),\ \frac{y_i^* - y_{\min}}{y_j^* - y_{\min}} = \frac{y_i \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}}{y_j \frac{\mu}{\mu_{\mathcal{T}(\omega)}} - y_{\min}},\ \forall\, i,j \in \mathcal{R}(\omega).$$

$$\mathcal{D}^{2a}=\left\{y^*\in\mathcal{D}\;\middle|\;y_i^*=y_{\min},\;\forall\,i\in\mathcal{P}(\theta),\;\forall\,\theta\in\Theta\right\},\tag{B.3}$$

$$\mathcal{D}^{3a}=\left\{y^*\in\mathcal{D}\;\middle|\;\frac{y_i^*-y_{\min}}{y_j^*-y_{\min}}=\frac{\mu_{\mathcal{S}(\theta)}-y_{\min}}{\mu_{\mathcal{S}(\theta')}-y_{\min}},\;\forall\,i\in\mathcal{R}(\theta),\;\forall\,j\in\mathcal{R}(\theta'),\;\forall\,\theta\in\Theta\right\}.\tag{B.4}$$

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

$$y_i^*=\begin{cases}y_{\min}, & \forall\,i\in\mathcal{P}(\theta),\;\forall\,\theta\in\Theta,\\ y_{\min}+(\mu_{\mathcal{S}(\theta)}-y_{\min})\,\frac{\mu-y_{\min}}{\frac{N_{\mathcal{R}(\Theta)}}{N}(\mu_{\mathcal{R}(\Theta)}-y_{\min})}, & \forall\,i\in\mathcal{R}(\theta),\;\forall\,\theta\in\Theta,\end{cases}\tag{B.5}$$

where $\mathcal{R}(\Theta)=\cup\mathcal{R}(\theta)$.

B.2. *Separability.*

We divert from the baseline by replacing *non-separability* with *separability*. According to separability FfP applies for any $i\in\mathcal{P}$, whereas EOp applies for any $i\in\mathcal{R}$. We therefore reformulate (3.5) as follows:

$$\mathcal{D}^{1b}=\left\{y^*\in\mathcal{D}\;\middle|\;\mu^*_{\mathcal{T}(\omega)\cap\mathcal{R}}=\frac{1}{N_{\mathcal{T}(\omega)\cap\mathcal{R}}}\sum_{i\in\mathcal{T}(\omega)\cap\mathcal{R}}y_i^*=\mu^*_{\mathcal{R}},\;\forall\,\omega\in\Omega\right\}.\tag{B.6}$$

Invoking separability requires a subsequent redefinition of FfP and the proportionality requirement:

$$\mathcal{D}^{2b}=\left\{y^*\in\mathcal{D}\;\middle|\;y_i^*=y_{\min},\;\forall\,i\in\mathcal{P}\right\},\tag{B.7}$$

$$\mathcal{D}^{3b}=\left\{y^*\in\mathcal{D}\;\middle|\;\frac{y_i^*-y_{\min}}{y_j^*-y_{\min}}=\frac{y_i-y_{\min}}{y_j-y_{\min}},\;\forall\,i,j\in\mathcal{T}(\omega)\cap\mathcal{R},\;\forall\,\omega\in\Omega\right\}.\tag{B.8}$$

Note that $\mathcal{D}^{1b}\cap\mathcal{D}^{2b}\cap\mathcal{D}^{3b}$ does not imply the satisfaction of constant resources. Therefore, we additionally impose:

$$\mathcal{D}^{4b}=\left\{y^*\in\mathcal{D}\;\middle|\;\mu=\frac{1}{N}\sum_{i\in\mathcal{N}}y_i=\frac{1}{N}\sum_{i\in\mathcal{N}}y_i^*=\mu^*\right\}.\tag{B.9}$$

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

$$y_i^*=\begin{cases}y_{\min}, & \forall\,i\in\mathcal{T}(\omega)\cap\mathcal{P},\;\forall\,\omega\in\Omega,\\ y_{\min}+(y_i-y_{\min})\times\frac{(\mu-y_{\min})}{\frac{N_{\mathcal{R}}}{N}(\mu_{\mathcal{T}(\omega)\cap\mathcal{R}}-y_{\min})}, & \forall\,i\in\mathcal{T}(\omega)\cap\mathcal{R},\;\forall\,\omega\in\Omega.\end{cases}\tag{B.10}$$

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