Upper and Lower Bounds of Inequality of Opportunity: Theory and Evidence for Germany and the US

Judith Niehues and Andreas Peichl

This version: 15th April 2011*

Preliminary version, do not quote without permission

Abstract

Theories of distributive justice distinguish between ethically acceptable inequalities – due to differences in effort – and unfair inequalities – due to circumstances beyond the sphere of individual responsibility. In this paper, we suggest a new estimator of inequality of opportunity (IOp) which allows identifying an upper bound for unfair inequalities in addition to the well-known lower bound estimator. We illustrate our approach by comparing IOp estimates for Germany and the US based on harmonized micro data. Our lower bound estimates yield IOp shares of 30% for annual earnings in Germany. The upper bound of IOp, in contrast, accounts for around 70% of the observed inequality. Results for the US are significantly lower with shares of 16 and 40% respectively. Hence, equality of opportunity is higher in the "land of opportunities". Our results further suggest that lower bound estimates of IOp might demand for too little redistribution in order to equalize unfair inequalities. A policy simulation reveals that the abolishment of joint taxation in favor of individual taxation significantly reduces IOp.

JEL Codes: D31, D63, H24, J62

Keywords: Equality of opportunity, Fairness, Inequality, Redistribution, Taxation of couples

* Judith Niehues (`judith.niehues@uni-koeln.de`) is affiliated to SOCLIFE, University of Cologne and IZA Andreas Peichl (`peichl@iza.org`) is affiliated to IZA, the University of Cologne, ISER and CESifo. We would like to thank Dan Hamermesh and John Roemer as well as seminar and conference participants in Bonn, Cologne and Milan for helpful comments and suggestions. Corresponding author: Andreas Peichl, IZA Bonn, P.O. Box 7240, 53072 Bonn, Germany.

1 Introduction

Empirical evidence suggests that preferences for redistribution are systematically correlated with beliefs about the relative importance of effort and luck in the determination of income (see Konow (2003), Alesina and Giuliano (2010) and Gaertner and Schokkaert (2011) for overviews). Individuals are more willing to accept income differences which are due to individual effort (or laziness) rather than exogenous circumstances (Fong (2001)). Theories of distributive justice distinguish ethically acceptable inequalities on the one hand and unfair inequalities on the other hand.[1] In empirical applications, the main problem is the identification of the latter, that is the amount of inequality which is due to circumstances beyond the sphere of individual responsibility. It has been recognized that previous estimates of such inequality of opportunity (IOp henceforth) yield lower bounds only (Bourguignon et al. (2007), Ferreira and Gignoux (2010)). In this paper, we suggest a new estimator of IOp which additionally allows identifying an upper bound for unfair inequalities. We illustrate our approach by comparing IOp estimates for Germany and the US – two countries with different welfare state regimes, attitudes towards inequality and redistribution (see Figure 3 in the appendix) and social mobility.[2]

The concept of equality of opportunity (EOp) in contrast to equality of outcomes (EO) has received considerable attention since the seminal contributions of John Roemer (1993, 1998), Van der gaer (1993) and Fleurbaey (1995).[3] The traditional notion of EO refers to an equal distribution of economic outcomes (e.g. well-being, consumption or income) across the population. The EOp theory, in contrast, separates the influences on the outcomes of an individual into circumstances and effort. Circumstances are defined as all factors beyond the sphere of individual control, for which society deems individuals should not be held responsible, such as parental education, gender, age, place of birth or ethnic origin. Effort, on the other hand, comprises all actions and choices within individual responsibility for which society holds the individual accountable, e.g. schooling choices or labor supply decisions.

[1] See, e.g. Sen (1980, 1985, 1992), Dworkin (1981a,b), Arneson (1989), Cohen (1989) and Roemer (1993, 1998).

[2] For instance, Alesina and Glaeser (2004) show that Americans believe that social mobility is important and high in the US, whereas Europeans perceive lower chances to climb the social ladder in their countries.

[3] See e.g. Roemer et al. (2003), Dardanoni et al. (2005), Betts and Roemer (2006), Lefranc et al. (2008), Checchi et al. (2010), Checchi and Peragine (forthcoming) as well as Aaberge et al. (2011) Almas et al. (2011), Björklund et al. (2011), Dunnzlaff et al. (2010).

In empirical estimations of EOp it is impossible to observe all characteristics that constitute individual's circumstances (think e.g. of innate talent or ability). Hence, in practice, all existing estimates of IOp are only lower bound estimates of the true share of unfair inequalities due to circumstances. This has important implications for the design of redistributive policies. As most theories of distributive justice are based on ethical principles which only defend compensation for inequalities due to circumstances, underestimating the true amount of this IOp might lead to too little redistribution when designing a fair tax benefit system (Luongo and Peragine (2010)) – or to too much if the implicit assumption is that the upper bound is 100%. In addition, especially when comparing countries or over time, the observed and unobserved circumstances might behave differently which can lead to different conclusions when looking only at a(n observed) subset of all potential circumstances.

In order to tackle the lower-bound problem, we suggest a new estimator for IOp which takes into account the maximum value of (observed and unobserved) circumstances. Our method is based on a two-step approach. First, we estimate a fixed effects model using panel data. We argue that the time-constant unobserved heterogeneity is the maximum amount of circumstance variables which an individual should not be held responsible for – as, by definition it comprises all exogenous circumstances as well as some not changing effort variables. Second, we use this estimated unit effect to estimate the maximum extent of inequality which can be attributed to IOp, i.e. inequality due to circumstances. This two-stage estimator allows us to quantify an upper bound of IOp. Together with the well-known lower bound we thus provide a range for the extent of IOp which allows to better compare income distributions and to give guidelines for the design of redistribution policies.

In order to empirically illustrate our new estimator, we apply the method to a rich set of micro level panel data. We rely on the Cross-National Equivalent Files (CNEF) for Germany and the US. The CNEF contains harmonized data from the national panel surveys which cover a long time period and include a comprehensive set of income, circumstance and effort variables. The German SOEP data has been widely used for income inequality analyses (see, e.g. Fuchs-Schuendeln et al. (2010), Peichl, Pestel and Schneider (2010)). However, so far it has not been used to analyze IOp. We compare our estimates to US data taken from the PSID which has been used by Pistolesi (2009) to analyze "IOp in the land of opportunities". Comparing Germany and the US is interesting in itself, as both countries have different welfare states and people have different believes about redistribution and social mobility.[4]

Our lower bound estimates yield IOp shares of up to one-third for annual earnings in Germany, which is comparable to previous findings. The upper bound of IOp, in contrast, accounts for around 70% of the observed inequality. Results for the US are significantly lower with shares of 16 and 40% respectively. Hence, EOp is higher in the "land of opportunities". Our results further suggest that lower bound estimates of IOp might demand for too little redistribution in order to equalize unfair inequalities. Furthermore, we identify gender as an important source of IOp which is mainly driven by the indirect effect of gender on earning outcomes through the selection into part-time employment. A policy simulation reveals that the abolishment of joint taxation in favor of individual taxation significantly reduces IOp in Germany.

The setup of the paper is as follows: In Section 2, we introduce the conceptual framework of EOp and outline the methodology we apply to estimate the upper bounds of IOp. Section 3 describes the data and income concepts used. Section 4 presents the results of our empirical analysis and Section 5 the results of the policy simulation. Section 6 concludes.

2 Conceptual Framework and Methodology

2.1 Measuring IOp

In order to compare our new estimators with previous results, we follow standard literature. In accordance with Roemer (1998), we distinguish between two generic determinants of individual outcome y: circumstances C, which are characteristics outside individual control, and effort E, representing all factors affecting earnings that are assumed to be the result of personal responsibility. We follow the ex ante approach of equality of opportunity and partition the population of discrete agents $i \in \{1, ...N\}$ into a set of types $\Pi = \{T_1, T_2, ...T_k\}$, i.e. subgroups of the population that are homogeneous in terms of their circumstances. We focus on annual labor earnings w of individual i at time point s as our economic advantage variable which depends both on individual circumstances and personal effort:

[4] There is a number of studies investigating social and economic mobility (see, e.g., Corak and Heisz (1999), Bjoerklund, and Jaentti (1997, 2009), Björklund et al. (2010). While these studies only implicitly measure IOp, we can directly estimate it in our approach.

$$w_{is} = f(C_i, E_{is}) \tag{1}$$

The approach we take to empirically identify EOp is based on Ferreira and Gignoux (2010) who rely on a parametric approach that allows estimating the impact of various circumstances even in the presence of small sample / cell sizes. EOp is achieved if the mean advantage levels μ are identical across types. If $\mu^k(w) = \int_0^\infty w dF^k(w)$, this criterion for EOp can be written as[5]

$$\mu^k(w) = \mu^l(w), \forall l, k | T_k \in \Pi, T_l \in \Pi \tag{2}$$

Measuring inequality of opportunity thus means capturing the extent to which $\mu^k(w) \neq \mu^l(w)$, for $k \neq l$. Hence, the IOp index is computed on the *smoothed* distribution $\{\mu_i^k\}$, which is obtained when each individual outcome w_i^k is replaced by the group-specific mean, $\mu^k(w)$.

In order to respect the axioms of anonymity, Pigou-Dalton transfer principle, normalization, population replication, scale invariance and subgroup decomposability, we choose a member of the Generalized Entropy class as inequality measure.[6] By introducing the further requirement of *path-independent decomposability* (see Foster and Shneyerov (2000)), the set of eligible indices reduces to the *mean logarithmic deviation*, denoted by I_0. Ferreira and Gignoux (2010) define two scalar measures of inequality of opportunity based on I_0:

$$\theta_a = I_0(\{\mu_i^k\}) \tag{3}$$

$$\theta_r = \frac{I_0(\{\mu_i^k\})}{I_0(w)} \tag{4}$$

θ_a is a measure of the absolute level of opportunity inequality (IOL), whereas θ_r is an inequality of opportunity ratio since it measures the relation of inequality of opportunity to total inequality (IOR).

[5] For a more detailed discussion on this criterion and its relation to Roemer´s original definition, see Ferreira and Gignoux (2010), pp 9-10.

[6] Cf. Shorrocks (1980), Foster (1985), or Ferreira and Gignoux (2010).

2.2 Empirical strategy to estimate IOp

Lower bound of IOp In our empirical estimation approach we follow Bourguignon et al. (2007) and Ferreira and Gignoux (2010) who use a parametric specification to estimate *lower bounds* of IOp. Relying on a parametric approach allows us to estimate the impact of numerous circumstance variables even in the presence of small sample sizes. Noting that circumstance variables are exogenous by definition, whereas effort variables can also be affected by circumstances, equation (1) can be re-written as

$$w_{is} = f(C_{i,}E(C_i)_{is}, u_{is}) \tag{5}$$

Note, that w_{is} here denote annual individuals labor earnings of time point s. By log-linearization this yields the following empirical specifications

$$\ln(w_{is}) = \alpha C_i + \beta E_{is} + u_{is} \tag{6}$$

$$E_{is} = HC_i + v_{is} \tag{7}$$

Equation (6) represents the direct effect of circumstances, equation (7) the indirect effect of circumstances on effort. Since it is unlikely that we will observe all relevant circumstance and effort variables that constitute individuals outcomes, estimating this structural model will likely yield biased estimates. However, in order to compute inequality of opportunity shares, it is not necessary to estimate the structural model and to derive causal relationships. By substituting the effort equation (7) into the earnings equation (6), we get the following reduced form relationship:

$$\ln(w_{is}) = (\alpha + \beta H)C_i + \beta v_{is} + u_{is} \tag{8}$$

This reduced form equation can then be simply estimated by OLS to derive the fraction of variance which is explained by circumstances.

If we then include all available k observed circumstances C^K in equation (17), the estimates $\widehat{\psi}$ measure the overall effect of circumstances on labor earnings, combining both, the direct and indirect effects.

$$\ln(w_{is}) = \sum \psi^K C_i^K + v_{is} \tag{9}$$

Note that the resulting measures should be interpreted as lower bounds since including any additional circumstance variables would necessarily increase the share of inequality explained by circumstances.[7] Following Ferreira and Gignoux (2010), we can then construct a parametric estimate of the smoothed distribution:

$$\widetilde{\mu} = \exp[\widehat{\psi}^{K} C_i^K + \sigma^2/2] \tag{10}$$

where the tilde indicates the counterfactual advantage level and the hat the parameter estimate from the OLS regression. As we replace earnings outcomes by their predictions, all individuals with the same circumstances necessarily have the same advantage levels. Thus, in case of absolute EOp, all predicted earning levels would be identical. Consequently, IOp can then be measured as the inequality of these counterfactual earnings levels, where differences are only due to differences in circumstances.

Our measure of the absolute level of inequality of opportunity (IOL) thus equals

$$\theta_a^{LB} = I_0(\widetilde{\mu}) \tag{11}$$

where I_0 represents the mean logarithmic deviation. And

$$\theta_r^{LB} = \frac{I_0(\widetilde{\mu})}{I_0(w_i)} \tag{12}$$

as the relation of inequality of opportunity to total inequality (IOR). So far, the approach is in line with the existing literature such as Bourguignon et al. (2007) and Ferreira and Gignoux (2010).

Upper bound of IOp To also derive upper bound of IOp, we apply our setting to a longitudinal data structure. This implies that individual earnings at time point t (with $t \neq s$) might be influenced by time-constant observable circumstances C_i (economically exogenous by definition), by time-varying observable effort variables E_{it} as well as time-constant unobserved factors u_i, time-specific unobserved factors u_t and an independent error term ε_{it}:

$$w_{it} = f(C_i, E_{it}, u_i, u_t, \varepsilon_{it}) \tag{13}$$

[7] See Ferreira and Gignoux (2010) for a detailed explanation, why these measures can only be interpreted as lower bounds.

Log-linearization yields the empirical specification

$$\ln(w_{it}) = \alpha C_i + \beta E_{it} + u_i + u_t + \varepsilon_{it} \tag{14}$$

which corresponds to the data generating process of a fixed effects model with time-specific effects. Thus u_t takes up serial effects such as inflation and other time-specific earnings shocks which are common for all individuals and ε_{it} comprise unsystematic factors which influence wage such as luck.[8] Using this longitudinal design enables us to derive consistent estimates for the effort variables despite their endogeneity with respect to the unobserved circumstances. As opposed to other studies which assess the impact of effort variables in EOp settings, we can also estimate the effect independently of unobserved circumstances.

If one argues that all effort variables are not exogenous in the sense that they vary over time (at least to some extent), then - given the time period is long enough - all time-constant unobserved heterogeneity might be attributable to exogenous circumstances. Furthermore, assuming that no circumstance variables were observable, all circumstances were accounted for by the individual specific unit-effect $c_{i.}$:

$$\ln(w_{it}) = \beta E_{it} + c_i + u_t + \varepsilon_{it} \tag{15}$$

As data limitations do not allow us to look at the whole earnings history of individuals, of course, we cannot be sure that there are no unobserved effects in c_i, which might be rather attributed to effort, such as long-term motivation and actual work effort. Although this cannot be ruled out, we argue that the time-constant unobserved heterogeneity c_i is the maximum amount of circumstance variables which an individual might not be held responsible for.[9] Estimating equation (15) by a simple FE model with period dummies then yields estimates for $\hat{c}_i$:

$$\hat{c}_i = \bar{w}_i - \sum \hat{\beta}_k^{FE} \bar{x}_{ik} - \bar{\varepsilon}_i \tag{16}$$

We use this estimate as an indicator for the maximum value of time-constant circumstances of an individual $\hat{c}_i$. Thus, this regression can be regarded as a pre-stage for estimating our final model of interest, where we use $\hat{c}_i$ as a circumstance variable

[8] Cf. Lefranc et al. (2009) for an explicit consideration of luck in the EOp framework.

[9] Note that omitting any effort variables that interact with circumstances biases our results upwards, emphasizing that we should interpret our results as upper bounds of IOp.

which includes all unobservable and observable (which we treat as unobserved) time-constant circumstances of an individual.

When estimating our model of interest we go back to a cross-sectional setting and use the annual earnings $\ln(w_{is})$ of time point s (with $s \neq t$) as dependent variable (identical with the lower bound estimation) and simply estimate the reduced-form (bivariate) model:

$$\ln(w_{is}) = \psi \hat{c}_i + \upsilon_{is} \tag{17}$$

Again, we can construct a parametric estimate of the smoothed distribution by replacing individual earnings by their predictions:

$$\widetilde{\mu} = \exp[\widehat{\psi} c_i] \tag{18}$$

Based on these predicted counterfactual levels we can then derive upper bound measures of IOp. Our measure of the absolute level of the upper bound of inequality of opportunity (IOL) thus equals

$$\theta_a^{UB} = I_0(\widetilde{\mu}) \tag{19}$$

and upper bound of the shares of IOp in total inequality of outcomes (IOR)

$$\theta_r^{UB} = \frac{I_0(\widetilde{\mu})}{I_0(w)}, \tag{20}$$

respectively. As our estimated circumstance variable includes all unobserved and observed time-constant characteristics of an individual which might have an influence on earnings, our measure of IOL can be interpreted as *upper-bound* (^{UB}) estimate of inequality of opportunity. Thus, by accounting for unobserved circumstances and observed circumstances, we are able to estimate lower and upper bounds of IOL and can identify a reasonable range for the true values of IOp.

3 Data

As a basis for all estimations we rely on the Cross-National Equivalent Files (CNEF) of the SOEP for Germany and the PSID for the US. The CNEF contains ex-post equivalized and harmonized data from the national panel surveys. Specifically most of our time-varying effort variables and all income variables are derived from the

CNEF. However, further circumstance variables are added from the original SOEP and PSID, respectively. The SOEP is a panel survey of households and individuals in Germany that has been conducted annually since 1984. Population weights allow to make respondents' data to be representative for the German population as a whole.[10] We use information from all available waves from the SOEP from 1984 until 2009 (since 1991 also including East-Germany). The PSID began in 1968 and the most current wave is from 2007. First, the panel was run on an annual basis, from 1997 onwards individuals were surveyed in one out of two years. In our analysis we only use information from the PSID from 1981 onwards, since specific information on the occupation and industry of the individual is not available in the previous waves.[11]

In line with the previous literature, the units of our analysis are individuals aged 25-55 who are either in part-time or in full-time employment. The dependent variable of the regression analyses are logarithmic real annual labor earnings, adjusted by consumer prices indices. Inequality measures are based on the corresponding absolute levels of earnings. To derive satisfying estimates of the constant unobserved heterogeneity $\hat{u}_i$ (the unit-effect) a long time period is needed. Consequently, we base our analysis only on those individuals who report positive earnings for at least five subsequent points in time.[12] We further restrict our sample to individuals with data on parental educational background.

We first estimate lower bounds of IOp by using annual log earnings of the most current wave of each of the surveys (2009 for Germany, 2007 for the US) and by relying on a cross-sectional design. We also rely on a number of *circumstance variables.* We include gender, a dummy whether the individual was born in a foreign country, categorical variables of the occupation and education of the father, the degree of urbanization of the place where the individual was born as well as the height and year of birth of the individual. In the case of Germany, we include a dummy if the individual was born in East-Germany and for the US we include a corresponding dummy whether the individual was born in the South of the US. Additionally, for the US we include a variable which indicates the race of the individual. Summary

[10] A detailed overview of the GSOEP is provided by Haisken De-New and Frick (2003) or Wagner et al. (2007). Issues concerning sampling and weighting methods or the imputation of information in case of item or unit non-response is well documented by the GSOEP Service Group.

[11] Note that the income reference period in both surveys is the year before the interview. Hence, we actually cover the period 1983 until 2008 for Germany and 1981 until 2006 for the US.

[12] This is a rather arbitrary restriction. However, expanding the number of time points does not qualitatively change the results but substantially reduces the number of observations.

statistics on the mean annual earnings and all employed circumstance variables are illustrated in table 4 and 5, respectively.

We include as *effort variables* in our longitudinal fixed effects earnings regressions weekly working hours, age-standardized experience, individual's education in years and an industry dummy with twelve categories. We term these variables effort variables since they can be affected by individual choices and can vary over time. Summary statistics of these variables are illustrated in table 6 for Germany and in table 7 for the US. Note that in either case we do not include the most current wave when deriving the unit effects from the FE regression.

4 Lower and Upper bounds of IOp

Lower bound of IOp The first step of our analysis is the estimation of the log earnings equation (9) of the most current survey wave on all observable circumstances which are expected to have an impact on individual labor earnings. The results of these reduced form OLS regressions are illustrated in table 1 for Germany and in table 2 for the US. The results for Germany base on the SOEP 2009 wave, for the US on wave 2007 from the PSID. The specifications in the first column are based on the whole sample, in column (2) and (3) the sample is restricted to male and female individuals, respectively. The first set of regression is based on part-time and full-time employed individuals, the specifications (4) - (6) only base on individuals in full-time employment.

As column (1) of both tables shows, women have annual labor earnings which are around 50 percent smaller than those of men. The effect is highly significant. When only looking at individuals in full-time employment in column (4), the effect size decreases substantially in both countries. This indicates that a large fraction of the earnings difference is due to the fact that women are more likely to be employed in part-time employment. However, the effect is still negative and significant when only looking at full-time employed, implying that there are further negative opportunities for women. The effect of being born in a foreign country is negative and significant in most specifications for Germany. In the US, the effect of being born in a foreign country is rather unclear. It should be noted, though, that in the US sample there is only a small fraction of individuals who are born in a foreign country (see table 5). Being born in a disadvantaged region is related to significantly lower earnings in both countries. In Germany the effect is more pronounced in the male subsample, whereas in the US in the female subsample. Furthermore, in the US being 'non-white' reveals an earnings decreasing effect in the male subsample. In the sample of female full-time employed indivduals, surprsingly, the effect is positive and significant. However, the estimation is only based on 201 individuals. The regressions also reveal that the education of the father matters for the acquisition of individual earnings. If the father has an upper secondary (college) education, the children's wages are significantly higher in both countries. Accordingly, the occupational status of the father also matters in both countries. If the father was occupied as a white-collar worker or as a professional rather than in blue-collar professions, this is associated with significantly higher earnings in Germany. In the US a self-employed father (includes managers) seems to be particularly favourable for the earnings aqcuistion of their children. The degree of urbanisation of the place where the individuals were born also plays a role for future labor earnings. Individuals who were born in large city have on average considerably larger earnings than individuals who grew up in the countryside. The impact is more robust in the US as compared to Germany. As expected, later born individuals reveal smaller earnings. Here the effect is more robust in Germany. The same is true for body height, which has a substantial positive impact in all specifications in Germany. Interestingly, in the US this effect is only evident in the male subsample. Overall, the observed circumstances can explain up to 26.4 percent of the overall variation in log earnings in Germany, and up to 20.4 % in the US. In a world of equal opportunities these exogenous circumstances should actually have no effect on earnings - hinting at some degree of inequality of opportunity in both countries.

In the next step, the coefficients of the reduced form OLS regression are used to predict counterfactual advantage levels $\widetilde{\mu}$ in annual earnings which are only due to differences in circumstances. Thus, if there was absolute EOp, all predicted advantage levels $\widetilde{\mu}$ would be exactly the same. The inequality measures based on these counterfactual advantage levels $\widetilde{\mu}^{LB}$ are represented in table 3.

We first focus on the left-hand side of the table which includes both, part-time and full-time employed individuals. The inequality of observed annual labor earnings is equal to a mean log deviation of 0.249 in Germany and 0.358 in the US. In fact, the inequality of outcomes is substantialler larger in the US than in Germany in all samples, which is in line with previous findings. In Germany, the inequality in earnings is substantially smaller if we look at the male sample separately. This indicates that men are more likely employed in full-time jobs and thus earnings are distributed more homogenously than across women. In the US, the outcome inequality level remains at a similar level in the male subsample and decreases in the female subsample.

With respect to IOp, we reveal a lower bound of 0.071 for the whole sample in Germany, which corresponds to an IOp share of 28.7 percent. Therefore, according to our estimates, in Germany up to one third of the inequality of outcomes can be explained by the observed circumstances. This lower bound of IOp is substantially smaller when we look at the female and male sample separately. When we only look at men (women), the IOp share only accounts for around 17.3 (10.2) percent of the inequality in earnings. The decrease again hints at gender as an important source of IOp. In the US, we find a lower bound of 0.058 in the whole sample. Even in absolute terms this is smaller than in Germany. Given the higher outcome inequality in the US, the difference is even more evident when we look at the IOp share, which equals 16.3 percent in the US. Thus, there seems to be substantially less IOp in the US as compared to Germany. Again, we find smaller lower bounds in the male and female subsamples, which also highlights the role of gender in the US. If we focus on full-time employed individuals only, we do not observe this drop in the lower bound IOp share. In contrast, IOp shares only vary between 19.7 and 15.0 percent across the full and separate samples in Germany, and between 16.7 and 15.4 percent in the US. Note that in the full-time employed sample the difference in IOp shares between Germany and the US is less pronounced. For the female subsample the IOp share in the US is even larger than in Germany. Also, here the absolute IOp levels in the US exceed the IOLs in Germany. This is mainly due to the fact that in the US earnings inequality in the full-time employed sample is similar to the inequality in the whole sample, which also includes part-time employed individuals. In Germany, by contrast, inequality of outcomes decreases substantially when only looking at full-time employed.

Table 1: Germany: Real earnings and observed circumstances - Lower Bound of IOp

.

Dependent variable: Log real earnings

VARIABLES	(1) All	(2) Males	(3) Females	(4) All	(5) Males	(6) Females
Female	-0.515***			-0.093**		
	(0.036)			(0.037)		
Non-german origin	-0.110*	-0.172**	-0.062	-0.115*	-0.115	-0.136
	(0.065)	(0.070)	(0.113)	(0.066)	(0.079)	(0.124)
East-german origin	-0.150***	-0.408***	0.097**	-0.356***	-0.427***	-0.211***
	(0.030)	(0.035)	(0.048)	(0.029)	(0.036)	(0.051)
Secondary	0.006	0.004	0.019	0.093	0.046	0.256
	(0.090)	(0.101)	(0.150)	(0.099)	(0.112)	(0.216)
Intermediate	0.153	0.175	0.173	0.253**	0.244**	0.339
	(0.096)	(0.107)	(0.159)	(0.103)	(0.117)	(0.222)
Upper Secondary	0.247**	0.256**	0.263	0.320***	0.326***	0.365
	(0.100)	(0.111)	(0.166)	(0.107)	(0.121)	(0.227)
Farmer	0.080	-0.108	0.285*	0.036	0.003	0.163
	(0.079)	(0.080)	(0.153)	(0.075)	(0.084)	(0.168)
White-collar	0.127***	0.082*	0.168***	0.077**	0.059	0.113*
	(0.038)	(0.042)	(0.062)	(0.036)	(0.044)	(0.065)
Professional	0.239***	0.214***	0.271***	0.219***	0.201***	0.260***
	(0.045)	(0.050)	(0.075)	(0.042)	(0.051)	(0.077)
Self-employed	0.041	-0.006	0.070	0.060	0.009	0.230**
	(0.054)	(0.058)	(0.093)	(0.052)	(0.059)	(0.112)
Civil servant	0.098*	-0.038	0.254***	0.018	-0.031	0.148
	(0.051)	(0.055)	(0.089)	(0.048)	(0.056)	(0.093)
Small City	0.052*	0.015	0.078	0.029	0.027	0.032
	(0.029)	(0.033)	(0.048)	(0.029)	(0.034)	(0.054)
Large City	0.101***	0.025	0.150**	0.036	0.056	-0.003
	(0.036)	(0.040)	(0.059)	(0.034)	(0.041)	(0.063)
Year of birth	-0.012***	-0.016***	-0.007**	-0.016***	-0.016***	-0.014***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Height	0.885***	0.753***	0.974***	0.744***	0.686***	1.005***
	(0.198)	(0.214)	(0.344)	(0.190)	(0.221)	(0.372)
Constant	32.749***	41.373***	22.052***	40.494***	41.478***	36.028***
	(3.960)	(4.489)	(6.500)	(3.872)	(4.770)	(6.686)
Observations	2575	1345	1230	1588	1132	456
R^2	0.264	0.187	0.085	0.218	0.212	0.149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on SOEP. Specifications (1)-(3) include individuals in part-time and full-time employment, specifications (4)-(6) only full-time employed individuals.

Table 2: US: Real earnings and observed circumstances - Lower Bound of IOp

.

Dependent variable: Log real earnings

VARIABLES	(1) All	(2) Males	(3) Females	(4) All	(5) Males	(6) Females
Female	-0.469***			-0.266***		
	(0.052)			(0.071)		
Born outside US	0.047	-0.148	0.414	-0.378	-0.330	-0.647
	(0.312)	(0.381)	(0.536)	(0.297)	(0.333)	(0.622)
Born in the south	-0.125***	-0.101*	-0.155**	-0.162***	-0.111*	-0.346***
	(0.043)	(0.056)	(0.066)	(0.053)	(0.061)	(0.106)
non-white	-0.079	-0.245***	0.089	-0.129**	-0.244***	0.224*
	(0.048)	(0.064)	(0.073)	(0.061)	(0.072)	(0.114)
High school	0.132	0.059	0.197	-0.023	-0.120	0.038
	(0.117)	(0.173)	(0.156)	(0.162)	(0.232)	(0.212)
Intermediate	0.179	0.250	0.057	0.079	0.064	-0.211
	(0.129)	(0.187)	(0.177)	(0.175)	(0.243)	(0.255)
College	0.444***	0.485***	0.234	0.350**	0.310	0.110
	(0.129)	(0.186)	(0.183)	(0.175)	(0.242)	(0.287)
Farmer	0.061	0.190*	-0.098	0.168*	0.076	0.469**
	(0.084)	(0.108)	(0.133)	(0.101)	(0.115)	(0.205)
White-collar	0.176**	0.197**	0.192*	0.221**	0.229**	0.253
	(0.071)	(0.097)	(0.101)	(0.089)	(0.103)	(0.172)
Professional	0.088	0.062	0.299***	0.081	0.085	0.167
	(0.055)	(0.065)	(0.107)	(0.064)	(0.070)	(0.197)
Self-employed	0.162***	0.150*	0.228***	0.277***	0.198**	0.450***
	(0.062)	(0.087)	(0.087)	(0.078)	(0.094)	(0.138)
Small City	0.126*	0.143*	0.094	0.208***	0.178**	0.342**
	(0.065)	(0.082)	(0.103)	(0.079)	(0.089)	(0.158)
Large City	0.161**	0.165*	0.099	0.284***	0.273***	0.299*
	(0.068)	(0.088)	(0.108)	(0.083)	(0.095)	(0.164)
Year of Birth	-0.006*	-0.012***	0.002	-0.008**	-0.017***	0.015*
	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)	(0.008)
Height	0.331	0.769**	-0.255	0.591*	0.778**	-0.393
	(0.252)	(0.330)	(0.384)	(0.309)	(0.353)	(0.636)
Constant	21.380***	32.612***	6.029	26.401***	42.212***	-18.338
	(6.178)	(8.226)	(9.620)	(8.005)	(9.302)	(15.406)
Observations	1802	1049	753	876	675	201
R^2	0.172	0.123	0.054	0.204	0.187	0.173

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on PSID. Specifications (1)-(3) include individuals in part-time and full-time employment, specifications (4)-(6) only full-time employed individuals.

Table 3: Indices of Inequality of Opportunity

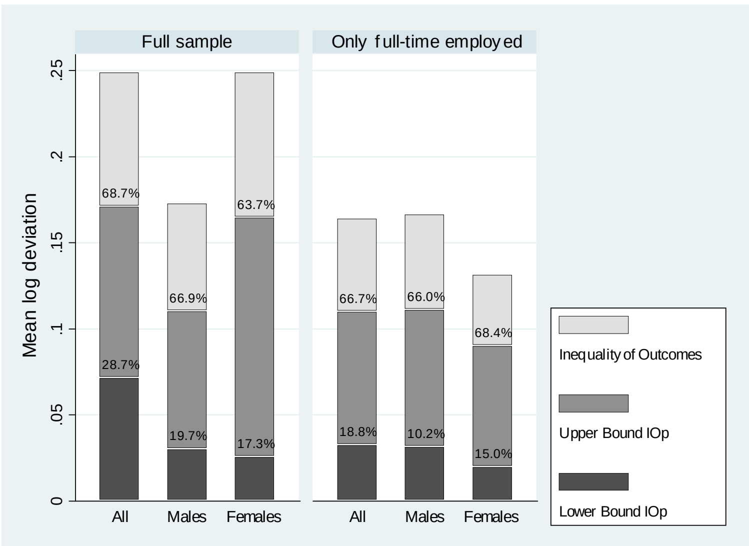
	Part-time & full-time employment			Only full-time employment		
	All	Male	Female	All	Male	Female
	Germany					
Inequality of Outcomes $I_0(w)$	0.249	0.173	0.249	0.164	0.166	0.131
Lower Bound						
IOL $\theta_a^{LB} = I_0(\widetilde{\mu})$	0.071	0.030	0.025	0.032	0.031	0.020
IOR $\theta_r^{LB} = \frac{I_0(\widetilde{\mu})}{I_0(w)}$	28.73	17.31	10.24	19.72	18.77	15.03
Upper Bound						
IOL $\theta_a^{UB} = I_0(\widetilde{\mu})$	0.171	0.110	0.164	0.110	0.111	0.090
IOR $\theta_r^{UB} = \frac{I_0(\widetilde{\mu})}{I_0(w)}$	68.70	63.66	66.03	66.91	66.69	68.44
	United States					
Inequality of Outcomes $I_0(w)$	0.358	0.346	0.263	0.319	0.320	0.212
Lower Bound						
IOL $\theta_a^{LB} = I_0(\widetilde{\mu})$	0.058	0.040	0.016	0.053	0.049	0.035
IOR $\theta_r^{LB} = \frac{I_0(\widetilde{\mu})}{I_0(w)}$	16.28	11.54	6.06	16.65	15.40	16.65
Upper Bound						
IOL $\theta_a^{UB} = I_0(\widetilde{\mu})$	0.134	0.115	0.097	0.148	0.132	0.133
IOR $\theta_r^{UB} = \frac{I_0(\widetilde{\mu})}{I_0(w)}$	37.48	33.28	36.83	46.28	41.12	62.53

Source: Own calculations based on SOEP and PSID data.

Upper bound of IOp To derive upper bounds of IOp, the first step is the estimation of the annual earnings equation (15) on the observable time-varying effort variables. Tables 8 and 9 in the appendix present the results of the FE model for Germany and the US. Again, we run separate regressions for full-time employed individuals as well as males and females. In Germany we find a clear non-linear relationship between age-standardized experience and earnings in almost all specifications. In the US this non-linear relationship is only evident in the female subsample and in general, work experience seems to have less impact. Working hours have a significant positive impact on earnings in both countries and the effect is robust across all specifications. The same is basically true for education, only for full-time employed women in Germany the effect is reversed. With regard to the industry dummy, in both countries, an occupation in the energy & mining, manufacturing, construction, transportation, financial (only in the US) and health sector is associated with higher earnings than if you are employed in the agriculture sector (reference). Only in the case of female full-time employed, all industry categories reveal negative effects. Overall, the models explain up to 22.5 percent of the within-variation of real earnings in Germany and up to 34.5 percent in the US. The explanatory power of the models is substantially lower in the full-time employed samples. Based on these first-stage FE wage regressions we then predict unit-effects for all individuals, as suggested by equation (16). In the next step, we use these indicators of the maximum amount of circumstances $\hat{c}_i$ as independent variables to estimate equation (17). Now, the dependent variable are the individual's logarithmic labor earnings in 2009 for Germany (2007 for the US). The coefficients of this simple OLS regression are then used to predict counterfactual advantage levels $\widetilde{\mu}$ in annual earnings which are only due to differences in the unobserved heterogeneity. The results are also illustrated in table 3.

Based on the unit-effect as circumstance variable, we reveal an IOL of 0.171 for the whole sample in Germany, which corresponds to an IOp share of 68.7 percent. Therefore, according to our estimates, around two third of the inequality of outcomes can be explained by the unobserved heterogeneity of individuals. On the contrary, for the US we find an IOL of 0.134 (IOR of 37.5 percent). Thus, the upper bound in the US only accounts for slightly more than one third of the inequality of outcomes and is substantially smaller than in Germany. We interpret these numbers as upper bounds of IOp since they represent all constant characteristics of an individual which may have an impact on labor earnings.[13] In the German (US) male and female sample this IOR decreases to 63.66 (33.3) and 66.0 (36.8) percent, respectively. In Germany, the estimates for the upper bound of IOp remain very similar if we restrict our sample to full-time employed individuals. In the US the upper slightly increases in the sample of the full-time employed (more sharply in the female subsample, which is obviously due to the lower outcome inequality and the small sample size). Figures 1 and 2 summarize our results. First, the graphs nicely illustrate that our upper bound IOp shares are indeed substantially higher than the lower bound estimates in all cases. Also, we see the tremendous drop in the lower bound IOp share when we look at the male and female subsample on the left-hand side graph (in particular in Germany), which is not observable in the full-time employed sample. Therefore we can identify a substantial gender opportunity gap which is due to the selection of women in part-time jobs. Finally, we also see that outcome inequality is much more similar across different samples in the US as compared to Germany.

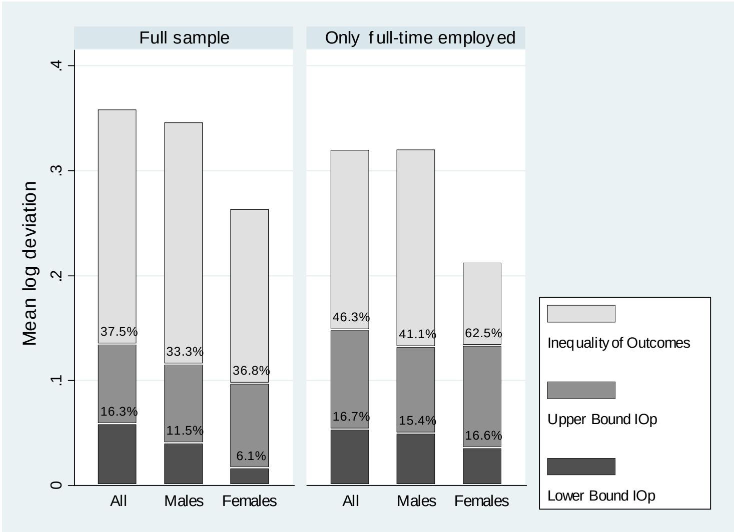
Figure 1: Germany: Upper and Lower Bound Indices of IOp



Source: Own calculations based on SOEP. The graph on the left-hand side includes individuals in part-time and full-time employment, the graph on the right-hand side only includes full-time employed individuals.

[13]It should be noted that the upper bounds of IOp decrease if we for example add the marital status or the number of children in the FE wage regressions, which can be expected to have an indirect impact on annual earnings. This provides additional evidence that our results can indeed be interpreted as upper bounds of IOp.

Figure 2: US: Upper and Lower Bound Indices of IOp



Source: Own calculations based on PSID. The graph on the left-hand side includes individuals in part-time and full-time employment, the graph on the right-hand side only includes full-time employed individuals.

5 Policy Simulation

5.1 Data and Methods

Our analysis is based on IZA's behavioral microsimulation model for the German tax and transfer system (IZAΨMOD) using GSOEP data (see Peichl, Schneider and Siegloch (2010) for an overview). IZAΨMOD comprises all relevant features of the German tax and benefit system, such as income taxation and social insurance contribution rules, as well as unemployment, housing and child benefits.[14] Our calculations are representative for Germany by using the GSOEP population weights. For the labor supply estimation, we assume that certain individuals do not supply labor or have an inelastic labor supply (such as pensioners, people in education, civil-servants or the self-employed). By assumption, those groups do not adjust their labor market behavior due to a policy reform; they are nonetheless part of the sample (for the analysis of fiscal or distributional effects).

The basic steps for the calculation of the personal income tax under German tax law are as follows. The income of a taxpayer from different sources is allocated

[14] We apply the rules as of January 2009.

to seven forms of income defined in the German income tax law (e.g. earnings, business income, capital and property income). For each type of income, the tax law allows for certain specific income related expenses. Then, general deductions like contributions to pension plans or charitable donations are taken into account and subtracted from the sum of incomes, which gives taxable income as a result. Finally, the income tax is calculated by applying the tax rate schedule to taxable income. After simulating the tax payments and the received benefits, we can compute the disposable income for each household. Based on these household net incomes we estimate the distributional and the labor supply effects of the analyzed tax reform.

For the econometric estimation of labor supply behavior, we construct a discrete choice, random utility model to estimate the labor supply behavior of individuals, based on a structural specification of preferences. The main advantage of this model over continuous ones is the possibility to account for non-linearities and non-convexities in the budget set. Those kinds of models have become quite standard in the last 15 years (see Aaberge et al. (1995), Van Soest (1995) and Blundell et al. (2000)), and so we focus here on the fundamental, underlying assumptions for the estimation. Following Van Soest (1995), we rely on a translog specification of utility. The (deterministic) utility of a couple household i for each discrete choice $j = 1, ..., J$ can be written as:

$$\begin{aligned} U_{ij} \quad = \quad & \alpha_{ci} \ln c_{ij} + \alpha_{h_f i} \ln h^f_{ij} + \alpha_{h_m i} \ln h^m_{ij} + \alpha_{h_{ff}} \left(\ln h^f_{ij}\right)^2 + \\ & \alpha_{h_{mm}} \left(\ln h^m_{ij}\right)^2 + \alpha_{cc} \left(\ln c_{ij}\right)^2 + \alpha_{ch_f} \ln c_{ij} \ln h^f_{ij} + \\ & \alpha_{ch_m} \ln c_{ij} \ln h^m_{ij} + \alpha_{h_m h_f} \ln h^f_{ij} \ln h^m_{ij} + \beta_f D^f_{ij} + \beta_m D^m_{ij} \end{aligned} \tag{21}$$

with household consumption c_{ij} and spouses' worked hours h^f_{ij} (female) and h^m_{ij} (male) and $D^{m/f}_{ij}$ being part-time dummies representing fixed costs of work. We assume seven discrete hours categories: $0, 10, 20, 30, 40, 50$ and 60 hours for each individual.[15] Hence, the $J = 49$ choices in a couple correspond to all combinations of the spouses' working-time categories. Coefficients on consumption and worked hours vary linearly with several taste-shifters (for instance age, age squared, presence of children, region).

The direct utility function is estimated using McFadden's conditional logit model (McFadden (1973)), maximizing the probability that the household chooses the ob-

[15] Our results are robust with respect to different discretizations and specifications of the utility function.

served working-hour category, given its characteristics and its calculated consumption. In addition to this deterministic part, the household's random utility level depends on a stochastic error term. We calibrate the random part of the utility function by drawing error terms from the Extreme Value Type-I distribution in order to guarantee that the observed choices yield the maximum random utility (see Duncan and Weeks (1998) and Creedy and Kalb (2005)).

5.2 Results

In a first step, our policy simulation involves the simulation of an abolishment of the joint taxation in Germany using IZAΨMOD. We base this policy simulation on data from the SOEP wave 2009. For the estimation of the upper bounds we again rely on the estimated unit effects from the previous FE regressions. The abolishment of joint taxation induces an increase in the labor supply for married females, a decrease for married males, respectively. Generally, the largest effect of such a policy change can be observed at the extensive margin, which is not relevant in our case since we only look at the working population. However, we can also observe labor supply effects at the intensive margin which then lead to different individual earning outcomes for married couples. When looking at the resulting IOp levels, we find that this policy change indeed leads to lower IOp (the upper bound decreases by more than two percentage points and the lower bound by approximately one percentage point, from 68.7 percent to 66.1 and 28.7 to 27.8 respectively). Given the fact that this policy effect only affects married couples and that we can only observe reactions at the intensive margin, this reduction is quite substantial. Furthermore, this policy is also associate with higher tax revenue which could be used to foster child care policies to further increase female labor force participation and reduce IOp.

6 Conclusion

The existing literature on EOp only provides lower bound estimates of IOp. We suggest a two-stage estimator to tackle this issue. First, we apply a fixed effects model to derive estimates of constant unobserved heterogeneity. We argue that this is the maximum amount of circumstances which an individual should not be held responsible for – as, by definition the unit effect comprises all exogenous circumstances as well as some not changing effort variables. Second, we use this circumstance measure to quantify the maximum amount of inequality which can be attributed to IOp. We apply the method to a rich set of harmonized micro level panel data for Germany and the US in order to empirically illustrate our new estimator. Together with the well-known lower bound we thus provide a range for the extent of IOp which allows to better compare income distributions and to give guidelines for the design of public policies in order to reach the optimal level of redistribution.

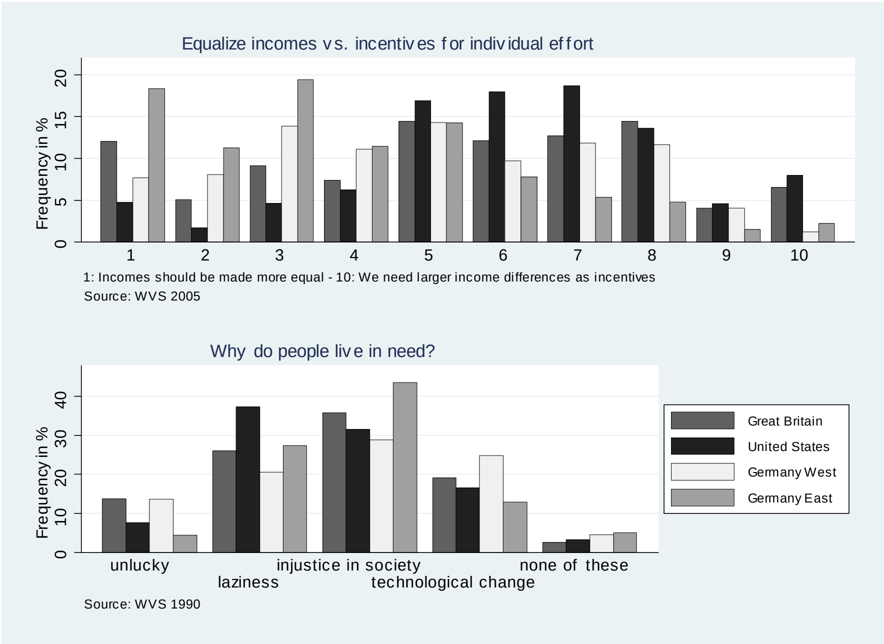
The lower bound estimations control for a full range of observed circumstance variables such as gender, country and region of origin, height as well as father's education and occupation. For this specification, we find IOp shares of the observed inequality in individual labor earnings of around 30% for Germany and 16% for the US, which are comparable to previous findings. Based on these results, one could conclude that individual earnings are mainly driven by individual's effort choices and only to a lesser extent by circumstances. Our upper bound estimates, however, suggest that earnings are to a larger extent pre-determined by exogenous circumstances. We find upper bounds of IOp of around 70% in Germany and 40% in the US. At a first sight, the high IOp share in Germany might seem surprising. However, it should be noted that our estimate of unobserved heterogeneity also includes all unobserved abilities and innate talent. This would be in line with Björklund et al. (2010) who indicate that IQ is the most important circumstance which explains differences in earnings. Although we do not claim that our upper bound estimates present the true amount of IOp, they provide evidence that the existing lower bound estimates substantially underestimate IOp and thus might demand for too little redistribution to equalize inequalities due to circumstances. The results are robust across different specifications.

From our analysis, one can conclude that equality of opportunity is higher in the "land of opportunities". This result is in line with recent findings on income mobility in both countries (Van Kerm (2004)) and might help to explain why attitudes towards inequality and redistribution differ substantially between both countries (Figure 3 in the appendix). Contrary to Germany, the majority of respondents in the US thinks that larger income differences are necessary as incentives while 40% of the respondents think that the most important reason why people live in need is laziness – the numbers are only half as high in Germany.

Our results also reveal the importance of gender as one driving force of IOp. The effect of gender is considerably smaller when only looking at full-time employed individuals. Thus, the *gender opportunity gap* is mainly due to the indirect effect of gender on earnings: Women are more likely employed in part-time jobs. Introducing a policy change which is likely to increase female labor supply - such as the move from joint to individual taxation - indeed reduces the IOp bounds by about two percentage points. This suggests that policies can be a useful tool to change IOp - and also that existing policies might actually boost IOp.

Appendix

Figure 3: Attitudes towards inequality and redistribution



Source: Own calculations based on WVS.

Table 4: Germany: Cross-sectional data - Circumstance variables

	Full sample			Only full-time employed		
	All	Male	Female	All full	Male full	Female full
Economic Advantage						
Mean real earnings in Euro	37969.33	47903.36	27106.50	46348.50	49830.74	37703.99
Circumstances						
Female	47.77	0.00	100.00	28.72	0.00	100.00
Born in foreign country	4.54	5.20	3.82	4.35	4.42	4.17
Born in East Germany	27.22	25.20	29.43	29.09	24.73	39.91
Lower Secondary	2.25	2.38	2.11	1.89	2.12	1.32
Secondary	67.11	65.72	68.62	65.74	65.90	65.35
Intermediate	16.97	17.70	16.18	17.76	17.31	18.86
Upper Secondary	13.67	14.20	13.09	14.61	14.66	14.47
Worker	50.76	47.29	54.55	47.48	46.82	49.12
Farmer	2.76	3.49	1.95	2.96	3.36	1.97
White-collar	15.96	16.06	15.85	16.44	16.08	17.32
Professional	14.52	15.61	13.33	16.44	16.17	17.11
Self employed	6.56	7.21	5.85	6.68	7.42	4.82
Civil servant	9.44	10.33	8.46	10.01	10.16	9.65
Countryside	37.28	36.58	38.05	35.96	36.84	33.77
Small city	41.36	42.53	40.08	41.44	41.70	40.79
Large city	21.36	20.89	21.87	22.61	21.47	25.44
Year of birth	1963.49	1963.72	1963.23	1963.67	1963.58	1963.87
Height	174.17	180.50	167.24	176.85	180.60	167.54
Number of observations	2575	1345	1230	1588	1132	456

Source: Own calculations based on wave 2009 of SOEP.

Table 5: US: Cross-sectional data - Circumstance variables

	Full sample			Only full-time employed		
	All	Male	Female	All full	Male full	Female full
Economic Advantage						
Mean real earnings in $	61467.95	76538.24	40473.61	80631.12	89325.40	51433.92
Circumstances						
Female	41.79	0.00	100.00	22.95	0.00	100.00
Born in foreign country	0.33	0.38	0.27	0.57	0.59	0.50
Born in the South	35.02	31.74	39.58	35.39	31.85	47.26
Non-white	28.25	22.40	36.39	25.68	20.74	42.29
Lower Secondary	2.55	2.00	3.32	2.05	1.33	4.48
Secondary	66.87	64.92	69.59	66.67	64.30	74.63
Intermediate	12.38	12.11	12.75	12.56	13.19	10.45
Upper Secondary	18.20	20.97	14.34	18.72	21.19	10.45
Worker	49.06	42.80	57.77	44.29	39.11	61.69
Farmer	7.10	7.44	6.64	7.99	8.15	7.46
White-collar	7.88	7.05	9.03	7.53	7.56	7.46
Professional	24.53	33.17	12.48	29.57	35.26	10.45
Self employed	11.43	9.53	14.08	10.62	9.93	12.94
Countryside	13.60	14.30	12.62	14.50	14.22	15.42
Small city	51.83	54.34	48.34	53.65	55.11	48.76
Large city	34.57	31.36	39.04	31.85	30.67	35.82
Year of birth	1960.83	1961.44	1959.98	1961.32	1961.72	1959.97
Height	174.68	180.69	166.31	177.36	180.75	165.98
Number of observations	1802	1049	753	876	675	201

Source: Own calculations based on wave 2007 of PSID.

Table 6: Germany: Longitudinal Data - Effort variables

	Full sample			Only full-time employed		
	All	Male	Female	All	Male	Female
Economic advantage						
Mean real earnings in Euro	34040.70	41686.44	24432.25	40282.69	43246.58	32728.20
Effort variables						
Weekly work hours	35.52	40.06	29.80	40.57	41.24	38.86
Education in years	12.73	12.79	12.66	12.83	12.78	12.98
Age	41.42	41.12	41.81	41.18	41.31	40.86
Experience	17.00	18.46	15.17	18.38	18.80	17.33
Agriculture	1.77	2.41	0.97	2.13	2.47	1.25
Energy Mining	11.81	16.62	5.76	14.19	16.56	8.15
Engineering	6.98	9.91	3.29	8.23	9.96	3.83
Manufacturing	5.25	5.56	4.87	5.27	5.44	4.85
Construction	6.88	10.82	1.92	8.04	10.38	2.08
Sales	12.54	9.44	16.45	10.06	9.51	11.46
Transport	5.90	7.39	4.02	6.91	7.63	5.09
Financial	3.94	3.77	4.14	4.64	4.13	5.95
Service	13.15	12.35	14.16	12.86	12.46	13.89
Education	9.36	6.09	13.46	6.80	5.27	10.67
Health	11.41	4.81	19.71	8.26	4.56	17.69
Public	11.02	10.84	11.23	12.61	11.64	15.08
Number of observations	63928	35600	28328	43090	30948	12142

Source: Own calculations based on waves 1984 - 2008 of SOEP.

Table 7: US: Longitudinal Data - Effort variables

	Full sample			Only full-time employed		
	All	Male	Female	All	Male	Female
Economic advantage						
Mean real earnings in $	43429.66	55098.26	29103.59	54784.08	61627.54	37109.43
Effort variables						
Weekly work hours	38.82	42.88	33.84	45.42	46.69	42.16
Education in years	13.28	13.33	13.22	13.30	13.39	13.08
Age	38.78	38.53	39.10	38.76	38.50	39.44
Experience	9.30	9.38	9.20	9.58	9.97	8.58
Agriculture	2.02	3.31	0.43	2.60	3.52	0.24
Energy Mining	7.28	10.83	2.93	9.33	11.31	4.22
Engineering	7.90	10.27	4.98	10.05	10.97	7.65
Manufacturing	8.28	9.41	6.89	9.18	9.42	8.55
Construction	6.28	10.47	1.13	6.44	8.53	1.06
Sales	14.66	14.86	14.41	15.33	15.75	14.25
Transport	7.31	9.49	4.64	8.33	9.65	4.94
Financial	4.78	3.11	6.83	4.76	3.49	8.03
Service	15.19	13.62	17.11	13.84	13.42	14.90
Education	10.70	5.36	17.24	5.71	4.50	8.82
Health	9.93	3.42	17.92	7.81	3.12	19.92
Public	5.68	5.85	5.48	6.62	6.32	7.41
Number	81531	44933	36598	50552	36442	14110

Source: Own calculations based on waves 1981 - 2005 of PSID.

Table 8: Germany: FE real log earnings regressions on observed effort variables

Dependent variable: Log annual earnings

VARIABLES	(1) All	(2) Males	(3) Females	(4) All	(5) Males	(6) Females
Experience	0.172***	0.271***	0.144***	0.241***	0.249***	0.224***
	(0.009)	(0.011)	(0.015)	(0.011)	(0.013)	(0.022)
Experience squared	-0.080***	-0.093***	-0.042***	-0.032***	-0.039***	-0.011
	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.008)
Working hours	0.015***	0.009***	0.021***	0.002***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.025***	0.039***	0.004	0.007**	0.013***	-0.010*
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)
Energy and Mining	0.097***	0.071***	0.115**	-0.001	0.033	-0.146***
	(0.025)	(0.026)	(0.049)	(0.021)	(0.023)	(0.050)
Engineering	0.101***	0.075***	0.120**	0.012	0.041*	-0.110**
	(0.025)	(0.026)	(0.050)	(0.021)	(0.024)	(0.051)
Manufacturing	0.040	0.060**	-0.006	0.006	0.041	-0.140***
	(0.025)	(0.028)	(0.048)	(0.022)	(0.025)	(0.051)
Construction	0.090***	0.077***	0.085	0.017	0.049**	-0.125**
	(0.025)	(0.026)	(0.053)	(0.021)	(0.023)	(0.054)
Sales	-0.001	0.008	-0.026	-0.041*	-0.003	-0.195***
	(0.024)	(0.026)	(0.046)	(0.021)	(0.024)	(0.048)
Transport	0.057**	0.057**	0.034	0.014	0.055**	-0.167***
	(0.026)	(0.028)	(0.052)	(0.023)	(0.025)	(0.056)
Financial	0.037	0.081**	-0.032	-0.028	0.001	-0.170***
	(0.033)	(0.037)	(0.059)	(0.029)	(0.034)	(0.060)
Service	0.012	0.028	-0.028	-0.027	0.012	-0.190***
	(0.024)	(0.025)	(0.046)	(0.021)	(0.023)	(0.048)
Education	0.054**	-0.000	0.050	-0.017	0.019	-0.174***
	(0.025)	(0.029)	(0.048)	(0.022)	(0.026)	(0.049)
Health	0.059**	0.012	0.047	-0.013	0.049*	-0.193***
	(0.026)	(0.032)	(0.048)	(0.023)	(0.029)	(0.049)
Public	0.046*	0.034	0.030	-0.027	0.014	-0.193***
	(0.024)	(0.026)	(0.048)	(0.021)	(0.023)	(0.049)
Constant	9.040***	9.304***	8.777***	10.051***	10.004***	10.264***
	(0.047)	(0.051)	(0.087)	(0.045)	(0.050)	(0.097)
Observations	61353	34255	27098	41502	29816	11686
R^2	0.225	0.229	0.258	0.146	0.158	0.123
Number of persnr	6224	3341	2883	4398	3049	1349

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on SOEP. All estimations include period effects; specifications (1)-(3) include individuals in part-time and full-time employment, specifications (4)-(6) only full-time employed individuals

Table 9: US: FE real log earnings regressions on observed effort variables

Dependent variable: Log annual earnings

VARIABLES	(1) All	(2) Males	(3) Females	(4) All	(5) Males	(6) Females
Experience	0.014***	0.031***	0.012**	0.036***	0.044***	0.023***
	(0.004)	(0.007)	(0.005)	(0.005)	(0.008)	(0.007)
Experience squared	-0.004*	0.004	-0.012***	-0.003	-0.000	-0.011***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Working hours	0.025***	0.019***	0.033***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Education	0.030***	0.024***	0.035***	0.013***	0.013**	0.011
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)
Energy and Mining	0.141***	0.173***	0.000	0.090***	0.110***	-0.141
	(0.026)	(0.028)	(0.059)	(0.026)	(0.028)	(0.087)
Engineering	0.111***	0.130***	0.004	0.043	0.058**	-0.155*
	(0.026)	(0.029)	(0.058)	(0.026)	(0.028)	(0.085)
Manufacturing	0.072***	0.089***	-0.028	0.025	0.045	-0.193**
	(0.026)	(0.029)	(0.057)	(0.026)	(0.028)	(0.085)
Construction	0.065**	0.083***	-0.017	0.044*	0.057**	-0.082
	(0.027)	(0.028)	(0.065)	(0.027)	(0.028)	(0.096)
Sales	0.010	0.047*	-0.114**	0.032	0.056**	-0.202**
	(0.025)	(0.027)	(0.055)	(0.025)	(0.027)	(0.084)
Transport	0.104***	0.129***	0.027	0.077***	0.099***	-0.172*
	(0.027)	(0.029)	(0.059)	(0.027)	(0.029)	(0.088)
Financial	0.097***	0.052	0.026	0.010	-0.015	-0.116
	(0.029)	(0.036)	(0.058)	(0.030)	(0.035)	(0.087)
Service	-0.024	0.039	-0.175***	0.024	0.039	-0.175**
	(0.025)	(0.027)	(0.055)	(0.025)	(0.027)	(0.083)
Education	0.014	-0.040	-0.066	-0.026	-0.038	-0.182**
	(0.027)	(0.034)	(0.056)	(0.029)	(0.034)	(0.085)
Health	0.095***	0.078**	-0.015	0.006	-0.004	-0.168**
	(0.027)	(0.036)	(0.056)	(0.029)	(0.037)	(0.084)
Public	0.066**	0.066**	-0.025	0.015	0.032	-0.174**
	(0.028)	(0.031)	(0.059)	(0.028)	(0.031)	(0.086)
Constant	8.736***	9.293***	8.245***	9.929***	10.042***	9.740***
	(0.059)	(0.076)	(0.096)	(0.065)	(0.078)	(0.132)
Observations	79729	43884	35845	49676	35767	13909
R^2	0.249	0.173	0.345	0.090	0.089	0.105
Number of persnr	6676	3619	3057	4703	3149	1554

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on PSID. All estimations include period effects; specifications (1)-(3) include individuals in part-time and full-time employment, specifications (4)-(6) only full-time employed individuals

References

Aaberge, R., Dagsvik, J. and Strøm, S. (1995). Labor Supply Responses and Welfare Effects of Tax Reforms, *Scandinavian Journal of Economics* **97**: 635–659.

Aaberge, R., Mogstad, M. and Peragine, V. (2011). Measuring Long-Term Inequality of Opportunity, *Journal of Public Economics* **95**((3-4)): 193–204.

Alesina, A. and Giuliano, P. (2010). Preferences for redistribution, *in* J. M. Benhabib, J. and A. Bisin (eds), *Handbook of Social Economics*, North-Holland: Elsevier.

Alesina, A. and Glaeser, E. (2004). *Fighting Poverty in the U.S. and Europe: A World of Difference*, Oxford University Press.

Arneson, R. (1989). Equality and Equality of Opportunity for Welfare, *Philosophical Studies* **56**: 77Ű93.

Betts, J. and Roemer, J. (2006). Equalizing opportunity for racial and socioeconomic groups in the united states through educational finance reform, *in* L. Woessmann and P. Peterson (eds), *Schools and the Equal Opportunity Problem*, MIT Press, Cambridge.

Björklund, A. and Jäntti, M. (1997). Intergenerational income mobility in sweden compared to the united states, *American Economic Review* **87**(5): 1009–1018.

Björklund, A. and Jäntti, M. (2009). Intergenerational income mobility and the role of family background, *Handbook of Economic Inequality*.

Björklund, A., Jäntti, M. and Roemer, J. (2010). Equality of Opportunity and the Distribution of Long-run Income in Sweden, Mimeo.

Björklund, A., Jäntti, M. and Roemer, J. (2011). Equality of Opportunity and the Distribution of Long-Run Income in Sweden, *Social Choice and Welfare* p. forthcoming.

Blundell, R., Duncan, A., McCrae, J. and Meghir, C. (2000). The Labour Market Impact of the Working Families' Tax Credit, *Fiscal Studies* **21**(1): 75–104.

Bourguignon, F., Ferreira, F. H. G. and Menendez, M. (2007). Inequality of Opportunity in Brazil, *Review of Income and Wealth* **53**(4): 585–618.

Checchi, D. and Peragine, V. (forthcoming). Regional Disparities and Inequality of Opportunity: The Case of Italy, *Journal of Economic Inequality* .

Checchi, D., Peragine, V. and Serlenga, L. (2010). Fair and Unfair Income Inequalities in Europe, IZA Disccusion Paper No. 5025.

Cohen, G. (1989). On the Currency of Egalitarian Justice, *Ethics* **99**: 906Ű944.

Corak, M. and Heisz, A. (1999). The Intergenerational Earnings and Income Mobility of Canadian Men: Evidence from Longitudinal Income Tax Data, *Journal of Human Resources* **34**(3): 504Ű533.

Creedy, J. and Kalb, G. (2005). Discrete Hours Labour Supply Modelling: Specification, Estimation and Simulation, *Journal of Economic Surveys* **19**(5): 697–734.

Dardanoni, V., Fields, G. S., Roemer, J. and Sanchez-Puerta, M. L. (2005). How demanding should equality of opportunity be, and how much have we achieved?, *in* D. G. S. Morgan and G. Fields (eds), *Mobility and Inequality: Frontiers of Research in Sociology and Economics*, Stanford University Press, Stanford.

Duncan, A. and Weeks, M. (1998). Simulating Transitions Using Discrete Choice Models, *Proceedings of the American Statistical Association* **106**: 151–156.

Dunnzlaff, L., Neumann, D., Niehues, J. and Peichl, A. (2010). Equality of Opportunity and Redistribution in Europe, *IZA Discussion Paper* **No. 5375**.

Dworkin, R. (1981a). What is equality? part 1: equality of welfare, *Philosophy & Public Affairs* **10**: 185Ű246.

Dworkin, R. (1981b). What is equality? part 2: equality of resources, *Philosophy & Public Affairs* **10**: 283Ű345.

Ferreira, F. H. G. and Gignoux, J. (2010). The Measurement of Inequality of Opportunity: Theory and an Application to Latin America, The World Bank Policy Research Working Papers, 4659.

Fleurbaey, M. (1995). Three Solutions for the Compensation Problem, *Journal of Economic Theory* **65**: 505Ű521.

Fong, C. (2001). Social Preferences, Self-Interest, and the Demand for Redistribution, *Journal of Public Economics* **82**(2): 225Ű46.

Foster, J. and Shneyerov, A. (2000). Path independent inequality measures, *Journal of Economic Theory* **91**: 199–222.

Fuchs-Schuendeln, N., Krueger, D. and Sommer, M. (2010). Inequality Trends for Germany in the Last Two Decades: A Tale of Two Countries, *Review of Economic Dynamics* **13**(1): 103–132.

Gaertner, W. and Schokkaert, E. (2011). *Empirical Social Choice*, Cambridge: Cambridge University Press, forthcoming.

Haisken De-New, J. and Frick, J. (2003). DTC - Desktop Compendium to The German Socio- Economic Panel Study (GSOEP).

Konow, J. (2003). Which is the Fairest One of All? A Positive Analysis of Justice Theories, *Journal of Economic Literature* **41**(4): 1188–1239.

Lefranc, A., Pistolesi, N. and Trannoy, A. (2008). Inequality of Opportunities vs. Inequality of Outcomes: Are Western Societies All Alike?, *Review of Income and Wealth* **54**(4): 513–543.

Lefranc, A., Pistolesi, N. and Trannoy, A. (2009). Equality of Opportunity and Luck: Definitions and Testable Conditions, with an Application to Income in France, *Journal of Public Economics* **93**: 1189–1207.

Luongo, P. and Peragine, V. (2010). The Implication of Partial Observability of Circumstances on the Measurement of EOp, Mimeo.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behaviour, *in* P. Zarembka (ed.), *Frontiers in Econometrics*, Academic Press, New York, pp. 105–142.

Peichl, A., Pestel, N. and Schneider, H. (2010). Does Size Matter? The Impact of Changes in Household Structure on Income Distribution in Germany, IZA Discussion Paper No. 4770.

Peichl, A., Schneider, H. and Siegloch, S. (2010). Documentation IZAΨMOD: The IZA Policy SImulation MODel, IZA Discussion Paper No. 4865.

Pistolesi, N. (2009). Inequality of Opportunity in the Land of Opportunities, 1968Ű2001, *Journal of Economic Inequality* **7**(4): 411–433.

Roemer, J. E. (1993). A Pragmatic Theory of Responsibility for the Egalitarian Planer, *Philosophy and Public Affairs* **22**: 146–166.

Roemer, J. E. (1998). *Equality of Opportunity*, Harvard University Press. Cambridge, Massachusetts.

Roemer, J. E., Aaberge, R., Colombino, U., Fritzell, J., Jenkins, S. P., Marx, I., Page, M., Pommer, E., Ruiz-Castillo, J., Segundo, M. J. S., Tranæs, T., Wagner, G. G. and Zubiri, I. (2003). To What Extent Do Fiscal Regimes Equalize Opportunities for Income Acquisition Among Citizens?, *Journal of Public Economics* **87**((3-4)): 539–565.

Sen, A. (1980). Equality of what?, *in* S. McMurrin (ed.), *Tanner Lectures on Human Values*, Cambridge University Press, Cambridge.

Sen, A. (1985). *Commodities and Capabilities*, North-Holland, Amsterdam.

Sen, A. (1992). *Inequality Reexamined*, Clarendon Press, Oxford.

Shorrocks, A. (1980). The Class of Additively Decomposable Inequality Measures, *Econometrica* **48**: 613–625.

Van der gaer, D. (1993). *Equality of Opportunity and Investment in Human Capital*, KU Leuven, Faculteit Economische.

Van Kerm, P. (2004). What Lies Behind Income Mobility? Reranking and Distributional Change in Belgium, Western Germany and the USA, *Economica* **71**(281): 223–239.

Van Soest, A. (1995). Structural Models of Family Labor Supply: A Discrete Choice Approach, *Journal of Human Resources* **30**: 63–88.

Wagner, G. G., Frick, J. R. and Schupp, J. (2007). The German Socio-Economic Panel (SOEP) - Scope, Evolution and Enhancements, *Schmoller's Jahrbuch - Journal of Applied Social Science Studies* **127**(1): 139–169.