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

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Abstract

Previous estimates of inequality of opportunity (IOp) are lower bounds because of the unobservability of the full set of endowed characteristics beyond the sphere of individual responsibility. Knowing the true size of unfair IOp, however, is important for the acceptance of (some) inequality and the design of redistributive policies as underestimating the true amount of IOp might lead to too little redistribution. This paper is the first to suggest an upper bound estimator. We illustrate our approach by comparing Germany and the US based on harmonized micro data. We find significant, sizeable and robust differences between lower and upper bound estimates - both for gross and net earnings based on either periodical or permanent income - for both countries. We discuss the cross-country differences and (surprising) similarities in IOp in the light of differences in social mobility and persistence.

JEL-Code: D630, H200, J620, J700.

Keywords: equality of opportunity, earnings inequality, mobility, circumstances, family background, redistribution.

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1 Introduction

Inequality is increasing in many countries resulting in recurring calls for policy interventions (see OECD (2011)). Preferences for redistribution, however, are systematically correlated with beliefs about the relative importance of effort and luck in the determination of outcomes (Alesina and Giuliano (2011)). Individuals are more willing to accept income differences which are due to effort (or laziness) rather than exogenous circumstances (Fong (2001)). Hence, theories of distributive justice distinguish ethically acceptable inequalities (e.g., due to differences in effort) from unfair inequalities (e.g., due to endowed characteristics). In empirical applications, the main problem is the identification of the latter, i.e., the amount of inequality which is due to circumstances beyond the sphere of individual responsibility (see, e.g., Almås et al. (2011)). It has been recognized that previous estimates of such inequality of opportunity (IOp henceforth) yield only lower bounds because of the unobservability of the full set of circumstances (e.g. Ferreira and Gignoux (2011)). Knowing the true size of unfair IOp, however, is important for the acceptance of (some) inequality and the design of redistributive policies (Piketty (1995)). In this paper, we suggest a new upper bound estimator of IOp and illustrate our approach by comparing Germany and the US.

The concept of equality of opportunity (EOp) has received considerable attention since the seminal contributions of Roemer (1993, 1998), Van de gaer (1993) and Fleurbaey (1995).[1] The traditional notion of equality of outcomes (EO) refers to an equal distribution of economic outcomes (e.g. well-being, consumption or income) across the population.[2] The EOp theory, in contrast, is interested in the sources of inequality and 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 or gender. Effort, on the other hand, comprises all choices within individual responsibility for which society holds the individual (partially) accountable, e.g. schooling or labor supply decisions. Income inequalities due to differences in effort are deemed acceptable, whereas inequalities due to endowed characteristics are not.

In empirical estimations of EOp it is impossible to observe all characteristics that constitute individual's circumstances (e.g. innate talent or ability). Hence, existing estimates of IOp are only lower bound estimates of the true share of unfair inequalities due to circumstances.[3] Estimating lower bounds of IOp has important implications

[1] See e.g. Roemer et al. (2003), Dardanoni et al. (2005), Betts and Roemer (2006), Lefranc et al. (2008, 2009), Devooght (2008), Checchi et al. (2010), Checchi and Peragine (2010), Dunnzlaff et al. (2011), Aaberge et al. (2011), Almås et al. (2011) as well as Björklund et al. (2011).

[2] See, e.g., Katz and Autor (1999) for an overview as well as Autor et al. (2008) and Dustmann et al. (2009) for recent applications to the US and Germany.

[3] An exception is Bourguignon et al. (2007) who simulate the magnitude of omitted variable bias

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 (2010)) – or to too much if the implicit assumption is that the upper bound is 100%. In addition, especially when comparing countries, the observed and unobserved circumstances might matter to different extents which can lead to different conclusions when looking only at an 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 (FE) model using panel data. We argue that the time-constant unobserved heterogeneity is the maximum amount of circumstances which an individual should not be held responsible for – as, by definition, it comprises all exogenous circumstances as well as some unchanging effort variables. Second, we use this estimated individual 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 lower bound estimator 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 our empirical application, we pay special attention to the treatment of luck (Lefranc et al. (2009)) as well as to different normative choices regarding the treatment of indirect effects of circumstances through effort on income (e.g., an effect of gender on years of schooling – see the discussion in Roemer (1998), Fleurbaey (2008) or Almås et al. (2011)). While previous empirical studies have mostly taken full compensation of (observed) indirect effects as granted, we define two different upper bound estimators for the two extremes of full and no compensation of indirect effects.

To empirically illustrate our new estimators, we rely on the Cross-National Equivalent Files (CNEF) for Germany and the US which contain harmonized micro data from comparable national surveys: the German Socio-Economic Panel (SOEP) and the Panel Study of Income Dynamics (PSID). Both panels cover long time periods and include a comprehensive set of income, circumstance and effort variables. The PSID has been used by Pistolesi (2009) to analyze IOp in the US, while Almås (2008) uses data from the Luxembourg Income Study (which are based on SOEP and PSID) to compare unfair inequalities for Germany and the US. She shows that the results depend on the fairness ideal and the measure used.[4] Comparing the US with a Continental European

to estimate bounds around the true effect of observed circumstances on income inequality.

[4]There are a number of studies investigating social and economic mobility (see, e.g., Corak and

country like Germany is interesting in itself (see, e.g., Piketty and Saez (2007)), as both countries have different welfare state regimes and people have different beliefs about redistribution (see Appendix Figure 5) and social mobility.[5]

Our analysis shows that upper bound IOp levels and shares are significantly (and about two times) larger than the lower bound estimates in both countries. This indicates that unobserved circumstances, such as ability and talent, are indeed important determinants of inequality (in line with findings when including IQ measures, see Björklund et al. (2011) for Sweden). While our estimates yield lower bound shares of 16% (28%) for the US (Germany), the upper bound shares are between 33–36% (47–62%) – depending on the treatment of indirect effects of circumstances through effort. The range for the upper bounds indicates that these effects are more important in Germany than in the US. When looking at permanent incomes, the level of outcome inequality as well as (lower and upper bound) IOp remains almost identical for Germany. In the US, outcome inequality is reduced whereas IOp levels increase. Now both countries have similar levels of EO but very different IOp levels. Therefore, the lower and upper bound shares increase to 30% and 70–75% respectively for the US, while for Germany we only find a large increase when accounting for indirect effects. We relate the country differences and similarities to different degrees of (intra- and intergenerational) mobility and persistence in different parts of the distribution (van Kerm (2004), Björklund and Jäntti (2009)). IOp shares are similar for gross and net earnings in both countries. This implies that there is no differential effect of redistribution on IOp, i.e. there is no implicit tagging on circumstances in both tax benefit systems. 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 switch from joint taxation to individual taxation significantly reduces IOp in Germany. Our results also indicate that unobserved effort (or luck) is more important in the US than in Germany.

The setup of the paper is as follows: In Section 2, we introduce the conceptual framework of EOp and the methodology 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 which are discussed in Section 5. Section 6 concludes.

Heisz (1999), Björklund and Jaentti (1997, 2009), or Björklund et al. (2010). While these studies only implicitly measure IOp, we can directly estimate it in our approach.

[5] According to Alesina and Glaeser (2004), Americans believe that social mobility is important and high in the US, whereas Europeans perceive lower chances to climb the social ladder. Hence, Germans are more in favor of redistribution than Americans (Alesina and Angeletos (2005)).

2 Conceptual Framework and Methodology

2.1 Measuring IOp: a simple model

In order to compare our new estimator to previous IOp estimates, we follow standard practice to define our theoretical and empirical approaches. In accordance with Roemer (1998), we distinguish between two generic determinants of individual outcome y_{is} of individual i at time point s. First, circumstances C_i are characteristics outside individual control (think of race, gender, family background) – and hence a source of inequitable inequalities in outcomes. Second, effort E_{is} is representing all factors affecting earnings that are assumed to be the result of personal responsibility.

Following Ferreira and Gignoux (2011), we assume that the outcome variable of interest depends both on exogenous, time-invariant circumstances C_i belonging to a finite set $\Gamma = \{C_1, C_2, ..., C_N\}$, as well as personal effort E_{is}, which can be shaped by C_i, belonging to a set $\Omega = \{E_1, E_2, ..., E_N\}$. In our analysis, we focus on (annual or permanent) labor earnings w_{is} of individual i at time point s which is generated by a function $f : \Gamma \times \Omega \to \mathbb{R}_+$:

$$w_{is} = f(C_i, E(C_i)_{is}). \tag{1}$$

As it is common in most parts of the EOp literature, we do not explicitly take into account the role of luck in our baseline estimations. Hence, we (implicitly) assume that luck belongs to the sphere of individual responsibility and in our deterministic model, the individual is held responsible for any random component that may affect the income and that cannot be attributed to the observed circumstances.[6] The same is true for potential measurement errors in the earnings data.

As Ferreira and Gignoux (2011), we employ the ex-ante approach of EOp and partition the population of agents $i \in \{1, ...N\}$ into a set of disjunct types $\Pi = \{T_1, T_2, ...T_k\}$, i.e., subgroups of the population that are homogeneous in terms of their circumstances. The income distribution within a type is a representation of the opportunity set which can be achieved for individuals with the same circumstances C_i by exerting different degrees of effort. Perfect EOp is achieved if the mean advantage levels μ are identical across types, i.e., $\mu^k(w) = \mu^l(w), \forall l, k | T_k, T_l \in \Pi$. Measuring IOp thus means capturing the extent to which $\mu^k(w) \neq \mu^l(w)$, for $k \neq l$. To compute a measure of IOp, a hypothetical smoothed distribution (Foster and Shneyerov (2000)) is constructed: $\mu^k(w) = f(C_i, \overline{E})$, which is obtained when each individual outcome w_i^k is replaced by the group-specific mean for each type $\mu^k(w)$ (for a given reference value of effort $\overline{E}$).

[6] We further discuss – and relax – this assumption in Section 5.3. See also Lefranc et al. (2009) for the extension of the EOp framework to explicitly take into account luck.

Based on this smoothed distribution, we compute for any (scale invariant) inequality index I the absolute inequality of opportunity level (IOL) $\theta_a = I(\{\mu_i^k\})$ and the inequality of opportunity ratio (IOR) $\theta_r = \frac{I(\{\mu_i^k\})}{I(w)}$ measuring the share of total inequality that can be attributed to circumstances. This approach allows decomposing the total income inequality into inequality within types (i.e. effort inequality) and inequality between types (i.e. opportunity inequality). 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 (Shorrocks (1980)) as inequality measure. By introducing the further requirement of *path-independent decomposability* (see Foster and Shneyerov (2000)), the set of eligible indices reduces to the *mean log deviation* (MLD) $I_0 = \frac{1}{N}\sum_i \ln \frac{\mu_w}{w_i}$.

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 (2011) 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 and cell sizes – which, unfortunately, is the case in the data that we use for our empirical illustration.[7] Log-linearization of equation (1) and adding an error term yields the following empirical specifications:

$$\ln w_{is} = \alpha C_i + \beta E_{is} + u_{is}, \tag{2}$$

$$E_{is} = HC_i + v_{is}. \tag{3}$$

Equation (2) represents the direct effect of circumstances on income while equation (3) models the indirect effect of circumstances on income through effort. Since it is unlikely that we will observe all relevant circumstance and effort variables that shape individuals' outcomes, estimating this model will likely yield biased estimates. However, in order to compute IOp shares, it is not necessary to estimate the structural model and to derive causal relationships. By substituting the effort equation (3) into

[7] In contrast, non-parametric methods avoid the arbitrary choice of a functional form on the relationship between outcome, circumstances and effort (e.g. Lefranc et al. (2009), Ferreira and Gignoux (2011) or Aaberge et al. (2011)). However, this approach has the drawback that considering more than one circumstance variable is difficult due to practical reasons in the presence of small cell sizes which is usually the case in survey data. Access to large-scale administrative panel data with information on circumstances (family background), which is not available in Germany and rather restrictive in the US, would allow to estimate lower and upper bounds of IOp also non-parametrically.

the earnings equation (2), we obtain the following reduced-form relationship:

$$\ln w_{is} = \underbrace{(\alpha + \beta H)}_{\psi} C_i + \underbrace{\beta v_{is} + u_{is}}_{\eta_{is}}. \tag{4}$$

This reduced-form equation can be estimated by OLS to derive the fraction of variance which is explained by circumstances. Including all observed circumstances C^K in equation (4), the estimates $\widehat{\psi}$ measure the overall effect of circumstances on labor earnings, combining both, the direct and indirect effects. Based on this, we can construct a parametric estimate of the smoothed distribution:

$$\widetilde{\mu}^{LB} = \exp[\widehat{\psi} C_i^K + \sigma^2/2]. \tag{5}$$

As we replace earnings outcomes by their predictions (with σ^2 being the estimated residual variance in the earnings equation, see Blackburn (2007)), all individuals with the same circumstances necessarily have the same advantage levels. Thus, in the case of absolute EOp, i.e. no income differences due to (observed) circumstances C_i^K, 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.

The approach has so far been in line with the existing literature such as Bourguignon et al. (2007), Checchi and Peragine (2010) and Ferreira and Gignoux (2011). It has been recognized that this procedure leads to lower bound estimates of the true share of unfair inequalities due to circumstances. The intuition to this is just like that of an R^2-measure which increases when adding another variable to the analysis (see Ferreira and Gignoux (2011) for an extensive discussion): Adding another circumstance variable to the analysis increases the explained variation (or at least does not decrease it in the case it is orthogonal), and hence the share of inequality due to circumstances cannot decrease (although coefficients might be upward or downward biased). However, usually not all (potential) circumstances are observable (in the data). Therefore, the extent of this underestimation bias is unclear (for instance, Bourguignon et al. (2007) show in their simulations that the omitted variable bias leads to a confidence band of 29-82% for their lower bound IOR). In the next step, we suggest a new estimator for IOp to tackle the lower-bound problem.

Upper bound of IOp In the previous EOp literature, the upper bound of IOp has implicitly been 100%. Our method to derive an actual estimate for it is based on a two-step procedure. First, we estimate a FE model using panel data to derive a measure of time-constant unobserved heterogeneity. Second, we use this estimated unit effect to estimate the maximum extent of inequality which can be attributed to inequality due to circumstances.[8] The intuition for the difference between lower and upper bounds of IOp is comparing the explained variance of an earnings equation with all observed circumstance variables (lower bound) to (one minus) the explained (within) variance of an FE regression (upper bound). However, instead of comparing the (explained) variances of the log earnings equations, we compute an inequality measure with well-defined properties based on the smoothed distributions.[9]

For the empirical implementation of the upper bound estimator, we have to explicitly deal with potential indirect effects of circumstances through effort on income (e.g., an effect of race or gender on hours worked or years of schooling). In the (theoretical and philosophical) literature on EOp, there is disagreement about the degree of compensation and where to draw the responsibility cut (see, e.g., the discussion in Roemer (1998) and Fleurbaey (2008)). So far, this discussion is only latent in empirical EOp studies which have mostly taken the full compensation of (observed) indirect effects as granted – as in equation (4) for the lower bound. For the upper bound, we make this choice explicit by looking at two extreme possibilities: (1) no compensation for the indirect effects (more in line with Fleurbaey (2008)), i.e. they are treated as effort, or (2) full compensation (following Roemer (1998)), i.e. the indirect effects are also treated as circumstances. Note that the first approach is in line with the literature on wage discrimination (see Altonji and Blank (1999) for an overview) where labor economists are usually interested in a 'clean' measure of the direct effect of circumstances. Suppose there is an unobservable aspect of effort which is correlated with an endowed characteristic. Then a regression of earnings on circumstances (e.g. a gender dummy) only overestimates the direct effect of gender on earnings because it confounds the effects of the endowed characteristic with a dimension of effort that it is correlated with. Hence, economists studying discrimination control for between-group differences in effort in order to arrive at a 'clean' measure of the direct effects of circumstances. In the second approach, in contrast, the confounding indirect effect (of circumstances on income via effort) is also seen as a source of unfair inequalities itself which should

[8] Following the standard approach, we (implicitly) assume that circumstances (and their effects on the outcome) do not change over time. This has two potential shortcomings. First, the effect of circumstance variables (e.g. race, gender) on the outcome (e.g. income) might change over time – for instance due to cultural or institutional changes. Second, one could make the case that also time-varying circumstances exist, like macro economic or weather shocks which are clearly beyond the control of the individual. We account for this by including time fixed-effects in the regressions and come back to these points when discussing the role of luck. However, note that while individual coefficients change, the explained variation in the regression of income on observed circumstances over time does not change (much). In addition, we can usually not reject the null that the respective coefficients are statistically equal at the 5%-level for any pair of years.

[9] We do this, because the variance of logarithms – in contrast to the MLD and other GE-measures – is not a good measure of inequality because it violates the Pigou-Dalton transfer principle as well as the Lorenz criterion (Foster and Ok (1999)).

be compensated and hence not be separated from the direct effect of circumstances on income. Therefore, the two approaches imply different normative choices about the compensation of indirect effects. In the following, we will describe and compare both approaches in more detail.

We start with approach (1). To estimate the FE model, we apply our setting to a longitudinal data structure. Individual earnings at time point t (with $t \neq s$) might be influenced by time-constant observable circumstances C_i (economically exogenous by definition), time-varying observable effort variables E_{it} as well as time-constant unobserved factors u_i. We employ the following log-linear empirical specification:

$$\ln w_{it} = \alpha C_i + \beta E_{it} + u_i + u_t + \varepsilon_{it}. \tag{6}$$

The time-specific effects u_t take up serial effects such as inflation and other time-specific earnings shocks which are common for all individuals while ε_{it} comprise unsystematic factors which influence wages. 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 is attributable to exogenous circumstances. Furthermore, assuming that no circumstance variables were observable, all circumstances were accounted for by the individual specific unit-effect $c_i^{(1)}$:

$$\ln w_{it} = \beta E_{it} + c_i^{(1)} + u_t + \varepsilon_{it}. \tag{7}$$

As data limitations do not allow us to look at the whole earnings history of individuals, we cannot be sure that there are no unobserved effects in $c_i^{(1)}$, which might rather be attributed to effort, such as long-term motivation and work effort. Therefore, we argue that the time-constant unobserved individual heterogeneity $\hat{c}_i^{(1)}$ is the maximum amount of circumstances which an individual should not be held responsible for.[10] In our final model of interest we use the estimated unit effect $\hat{c}_i^{(1)}$ as a circumstance variable which includes all unobservable and observable (which we treat as unobserved) time-constant circumstances of an individual – as by definition, it comprises all exogenous circumstances as well as some not changing effort variables. Note that in this

[10] Note that the estimation of the unit-effect relies on the consistent estimation of coefficients in the FE model. Omitting any effort variables that interact with circumstances biases our results upwards, emphasizing that we should interpret our results as upper bounds of IOp.

approach, as discussed above, the indirect effects of circumstances on (observed) effort variables are captured by the β-coefficients in equation (7) and hence treated as effort.

In approach (2), however, we want to compensate individuals also for the indirect effects which requires sterilizing the effort variables. In the first step, we estimate the (pure) FE model without including any effort variables:

$$\ln w_{it} = u_i + u_t + \varepsilon_{it}. \tag{8}$$

Then we use the estimate of the unit effect $\widehat{u}_i$ to sterilize all (observed) effort variables from the impact of all (observed and unobserved) circumstances:

$$E_{it} = \widehat{u}_i + u_t + e_{it}. \tag{9}$$

We then use the residuals from equation (9) in the FE model to get the estimates of the unit effect for the second-stage:

$$\ln w_{it} = \beta \widehat{e}_{it} + c_i^{(2)} + u_t + \eta_{it}. \tag{10}$$

Note that without using the sterilized effort variables in equation (10), the upper bound estimate would be 100%. The actual magnitude will depend on the availability of time-varying data on effort variables.

In the final stage, which is similar in both approaches ($k \in \{1, 2\}$), we estimate our model of interest by going back to a cross-sectional setting. Using the annual earnings $\ln(w_{is})$ of time point s (with $s \neq t$) as dependent variable (identical with the lower bound estimation), we estimate the following reduced-form model:

$$\ln w_{is} = \psi \hat{c}_i^{(k)} + \upsilon_{is}. \tag{11}$$

where we use the estimated unit effect $\hat{c}_i^{(k)}$ as the maximum extent of inequality which can be attributed to circumstances. As in the lower bound case, we construct a parametric estimate of the smoothed distribution by replacing individual earnings by their predictions $\widetilde{\mu}^{UB} = \exp[\widehat{\psi} \hat{c}_i^{(k)} + \sigma^2/2]$. Based on these predicted counterfactual levels, we derive upper bound measures of the IOL and IOR. Again, as the unit effect includes all observed and unobserved time-constant characteristics of an individual which might have an influence on earnings, these measures can be interpreted as upper bound estimates of IOp. Thus, by accounting for observed and unobserved circumstances, we are able to estimate lower and upper bounds of IOL and can identify a reasonable range for the true values of IOp. Note that the second upper bound will generally be higher than the first because of the inclusion of indirect effects and the difference between the two estimators indicates the importance of those effects.

3 Data

We use the CNEF version of the SOEP for Germany and the PSID for the US for our estimations. The CNEF contains harmonized data from the respective national panel surveys. The SOEP is a representative panel study of households and individuals in Germany that has been conducted annually since 1984.[11] 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 (since 1997 only biennially) and the most current wave is from 2007. In our analysis we use information from 1981 onwards, since specific information on the occupation and industry of the individual is not available in previous PSID waves.[12]

In line with the previous literature, the units of our analysis are individuals aged 25-55 who are in (part- or full-time) employment at each point in time included in the analysis. The dependent variables are log real (annual or permanent) labor earnings, adjusted by consumer prices indices. Inequality measures are based on the corresponding absolute levels of earnings. To derive satisfying estimates of the unit-effect in the FE estimations, 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.[13] We further restrict our sample to individuals with data on parental background. Thus, in our baseline FE estimations the panel is unbalanced in the sense that the consecutive time points of different individuals do not necessarily overlap. Within our robustness checks, we also restrict our analysis to a balanced panel.

In the second-stage OLS estimations, we first estimate lower bounds of IOp by using log annual earnings of the most current wave (2009 for Germany, 2007 for the US). In a second set of estimations, we rely on permanent log earnings which are computed as the individual's average real earnings over her available observation period.[14] When using permanent incomes, the number of observations is higher since individuals do not necessarily need valid information on all variables in the most current wave - as it is the case in the estimations relying on annual incomes.

[11] A detailed overview of the SOEP is provided by Haisken-DeNew and Frick (2003) and 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 SOEP Service Group.

[12] 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.

[13] This is a rather arbitrary restriction. However, as our robustness checks show the number of time points does not qualitatively change the results.

[14] In principle, it would be possible to compute more sophisticated measures of permanent income as, e.g., recently proposed by Aaberge et al. (2011).

As *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. Additionally, we include a variable for the US which indicates the race of the individual. Summary statistics on the mean annual earnings and all employed circumstance variables are illustrated in Table 2 in the Appendix.

In our longitudinal FE earnings regressions, we include as *effort variables* weekly working hours, age-standardized experience, individual's education in years, as well as industry dummies. We term these variables effort variables since they can be (partly) affected by responsible individual choices. In the case that these variables do not vary over time, they are included in the FE and hence counted as a circumstances. This is why the FE model gives an upper bound for IOp. Summary statistics of these variables are illustrated in Table 3 in the Appendix.

4 Empirical results

4.1 Estimation of earnings equations

Derivation of lower bound of IOp The first step of our analysis is the estimation of the log earnings equation (4) for the most current survey wave on all observable circumstances which are expected to have an impact on labor earnings. The results of these reduced-form OLS regressions are illustrated in Appendix Table 5. The specifications in the first columns are based on the whole sample, in the second and third columns the sample is restricted to male and female individuals, respectively. The first (second) set of regressions for each country is based on periodical (permanent) incomes.

The first column for each set reveals the well-known gender wage gap, i.e. women have significantly lower earnings than men in all specifications. 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 (result not shown), implying that there are further negative opportunities for women.

The effect of being born in a foreign country is negative and significant in Germany. In the US, being 'non-white' reveals an earnings decreasing effect for permanent incomes but not for annual incomes.[15] Being born in a disadvantaged region is re-

[15] The 'non-effect' of race for periodical incomes might be explained with the fact that blacks are

lated to significantly lower earnings in both countries. In Germany, the effect is more pronounced in the male subsample, whereas in the US, this is the case in the female subsample. Individuals who were born in a larger city have on average larger earnings than individuals who grew up in the countryside.

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 seems to be particularly favorable for the earnings acquisition of their children.

As expected, younger individuals have lower earnings and this effect is more pronounced 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 26.3% of the overall variation in log earnings in Germany, and up to 29.5% in the US. In a world of equal opportunities, these exogenous circumstances should actually have no effect on earnings – suggesting that some degree of IOp exists in both countries.

Derivation of upper bound of IOp To derive upper bounds of IOp according to approach (1), the first step is the FE estimation of the earnings equation (7) on the observable time-varying effort variables. Table 6 in the Appendix presents the results.[16] Again, we run separate regressions for periodical and permanent income as well as men and women. Overall, the models explain up to 42% of the within-variation of real earnings in Germany and up to 36% in the US. The unexplained part is a first hint for the existence (and size) of the upper bound IOp.

We find a clear non-linear relationship between age-standardized experience and earnings in almost all specifications – with the exception of the male subsample in the US. Not surprisingly, working hours have a significant positive impact on earnings in both countries. The same is true for education. In both countries, most industries in the private sector (except sales and services) are associated with higher earnings than the public sector (reference).

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more likely to be out of the labor force or even in prison, which leads to underestimated racial wage gaps in cross-sectional data (Chandra (2000)).

[16] For brevity, we do not report 'first-stage' results for approach (2), i.e. equations (8)–(10), which are qualitatively similar to approach (1) and available upon request.

4.2 Lower and upper bounds of IOp

In order to derive lower bound IOL, the coefficients of the reduced-form OLS regression (4) are used to predict counterfactual advantage levels $\widetilde{\mu}^{LB}$ in annual earnings which are only due to differences in circumstances. Thus, if there were an absolute EOp, all predicted advantage levels $\widetilde{\mu}^{LB}$ would be exactly the same. This smoothed distribution $\widetilde{\mu}^{LB}$ is then used to compute the lower bound IOp measures.

The upper bound measures are based on the predicted unit-effects (equations (7) or (10)). We use these indicators of the maximum amount of circumstances $\hat{c}_i^{(k)}$ as independent variables to estimate equation (11). Now, the dependent variable is the individual's log labor earnings in the last year available in the data – just as for the lower bound log earnings equation. The coefficients of this OLS regression are then used to predict counterfactual advantage levels $\widetilde{\mu}^{UB}$ in annual earnings which are only due to differences in the unobserved heterogeneity.

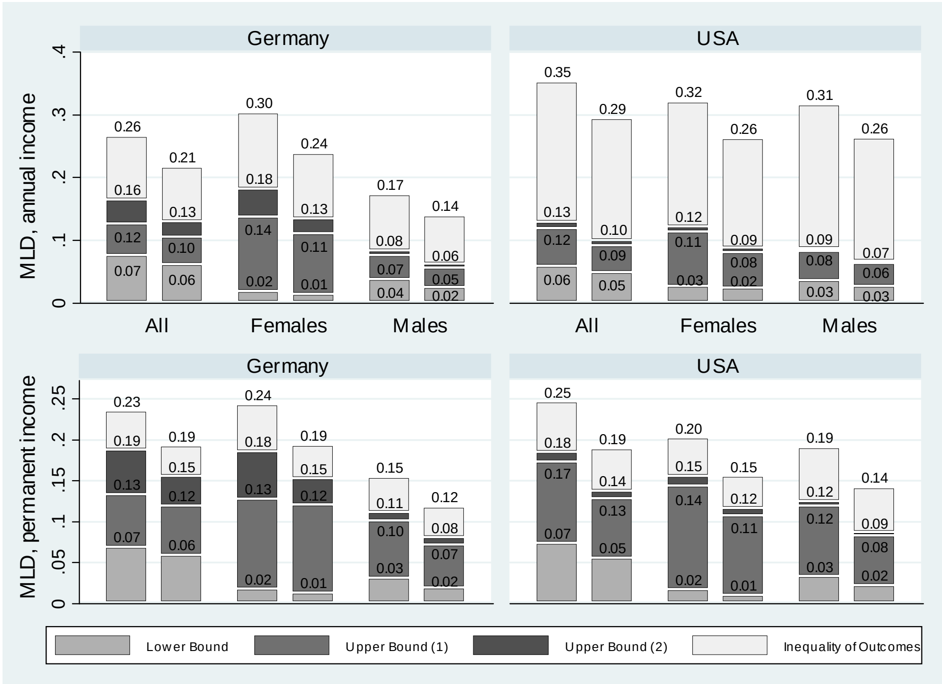
Inequality levels The MLD for inequality in outcomes (total bar) as well as the counterfactual smoothed distributions for the lower (light grey) and the two upper (darker greys) bounds are presented in Figure 1. Inequality in periodical (permanent) incomes is reported in the upper (lower) panel for the full sample as well as separated by gender. For each subgroup, the left bar is based on gross earnings whereas the right bar is based on net earnings.

We start by examining annual earnings (upper panel). Our results reveal a MLD of 0.26 (0.21) in Germany and 0.35 (0.29) in the US for gross (net) earnings. Not surprisingly, redistribution reduces outcome inequality in all samples. The level of redistribution is rather similar in both countries. Inequality of outcomes is substantially larger in the US than in Germany in all samples, which is in line with previous findings. In Germany, earnings inequality is substantially smaller (higher) if we look at the male (female) sample separately. This indicates that men are more likely employed in full-time jobs and thus earnings are distributed more homogenously than among women – which have a much higher variation in hours worked. In the US, the outcome inequality levels are similar in the male and female subsamples.

Inequality in permanent incomes is substantially lower in the US than inequality in annual incomes. In Germany, this is only the case for the female subsample whereas the decrease is rather small for the full sample which could hint at lower intra-generational income mobility (volatility) in Germany (van Kerm (2004)). As a consequence, inequality in permanent incomes is surprisingly similar between Germany and the US.

The lower bound IOp estimations control for a full range of observed circumstance variables (e.g. gender, country of origin, as well as father's education and occupa-

Figure 1: Upper and lower bound levels of IOp (IOL)



Source: Own calculations based on SOEP and PSID. The top (bottom) graphs illustrate IOL in annual (permanent) incomes. The left (right) bar is based on gross (net) incomes.

tion). Based on annual incomes, the MLD levels are rather similar between Germany (0.07) and the US (0.06) for the full samples. However, the difference is statistically significant as suggested by the bootstrapped confidence intervals in Appendix Table 4. Redistribution has only a small effect on the lower bounds in both countries. When looking at the male and female subsamples separately, the IOp levels decrease. This is a first indication that gender is an important (observed) circumstance and in line with the large male-female wage gap found in Table 5. The results for permanent incomes are almost identical suggesting no great difference between the two income concepts in terms of (lower bound) IOp levels.

The upper bound IOp levels according to approach (1) are also rather similar for annual income in all samples in both countries. With MLD values of 0.12 for both countries in the full sample, the IOp levels are significantly (and about two times) larger than the lower bound estimates that control for a comprehensive set of observed circumstances. Again, 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.[17] The significant differences between lower and upper bounds suggest

[17]It should be noted that the upper bounds of IOp decrease if we, e.g., add marital status or number of children, which can be expected to have an indirect impact on annual earnings, in the FE

that previous (lower bound) estimates of IOp might indeed demand for too little redistribution in order to equalize unfair inequalities. When looking at permanent incomes, the pictures changes. The IOp level is similar to annual incomes only for Germany in the full sample and the male subsample. When looking at the female subsample separately as well as in all US samples, the IOp levels increase significantly.

For the second upper bound approach, the IOp levels increase as expected due to the inclusion of the indirect effects of circumstances on the observed effort variables. While these indirect effects seem to play a negligible role in the US (both for annual and permanent earnings), they are very important in Germany for all samples. It is especially high when using permanent incomes and - again - in the male subsample. Hence, when referring to the second upper bound estimator, the IOp levels in Germany are higher than in the US for annual incomes (except for the female subsample) and rather similar for permanent incomes.

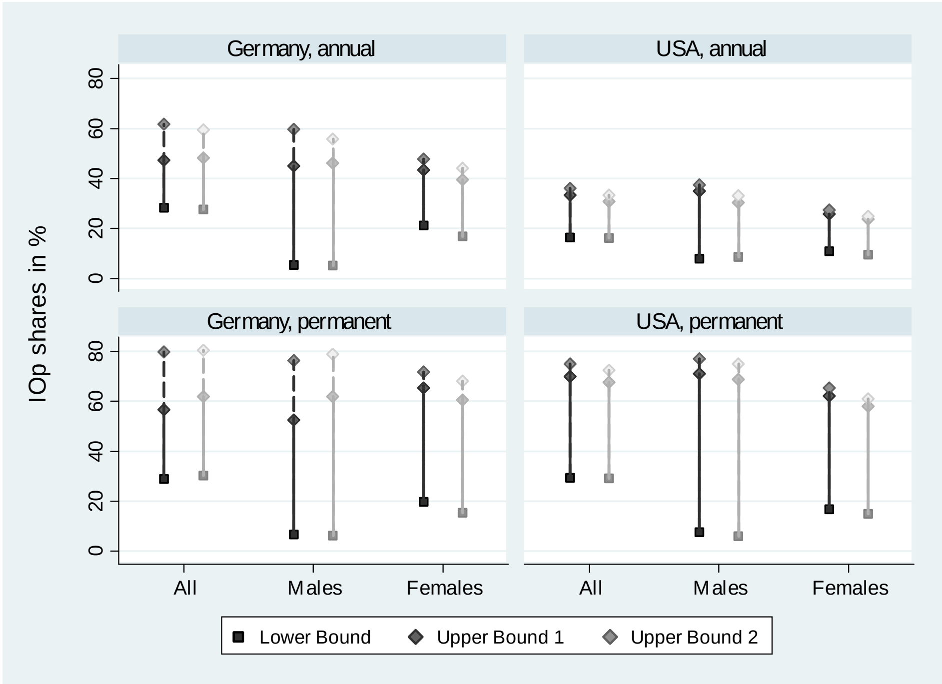
IOp shares In order to assess the relative importance of IOp, Figure 2 presents the IOR, i.e. the IOL divided by the outcome inequality (between group inequality as fraction of total inequality). The square corresponds to the lower bound while the two diamonds represent the two upper bounds. Again, results are presented for periodical (permanent) incomes in the upper (lower) panel for the full sample as well as separated by gender for gross (left, darker bar) and net (right, lighter bar) earnings.

The IOp shares are significantly higher for Germany than for the US for annual incomes, which is due to lower absolute levels of outcome inequality while having similar values of IOp – which is in line with the findings of Almås (2008). The lower bound shares equal 30% in Germany and 16% in the US – the latter is comparable to the results of Pistolesi (2009). Based on these results, it would be possible to deduce 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 significantly higher upper bounds of around 47% (33%) in Germany (the US) for approach (1). Again, indirect effects of circumstances are more important in Germany than in the US as the second upper bound reveals values of 62% (36%).

Thus, it seems that there is substantially less IOp in the US compared to Germany. However, using permanent instead of annual incomes matters for inequality levels, especially in the US, where IOp levels are much higher for permanent incomes (comparable to the findings of Pistolesi (2009)). In Germany, the difference between inequality levels for the two income concepts is much smaller. Therefore, IOL (and hence IOR) are similar for both income concepts. Hence, the IOp shares for permanent incomes

regressions. This provides additional evidence that our results can be interpreted as upper bounds.

Figure 2: IOp shares (IOR) in outcome inequality



Source: Own calculations based on SOEP and PSID. The top (bottom) graphs illustrate IOR in annual (permanent) incomes. The left (right) line is based on gross (net) incomes.

are rather similar in Germany and the US.

The lower bound IOR are substantially smaller when looking at the female and male samples separately which again hints at gender as an important source of IOp. However, the effect is weaker for the upper bounds indicating that a large part of the outcome inequality can be explained by unobserved heterogeneity of individuals.

5 Discussion of Results

5.1 Explaining the results

Annual vs. permanent incomes IOp levels are lower for current incomes than for permanent incomes in the US (in line with findings for Norway by Aaberge et al. (2011)) but less so in Germany. This interesting cross-country difference could result from lower inter-generational mobility or greater (intra-generational) volatility in US income processes. Indeed, intra-generational mobility is higher in the US (van Kerm (2004)). Yet, in the US much higher persistence and hence lower inter-generational mobility – compared to European countries – is observed at the tails of the distribution (Björklund and Jäntti (2009)). Whereas in countries like Germany mobility is on average lower, it is more equally spread across the distribution. In the US, in contrast, there is much higher mobility in the middle, but, compared to other countries, the probability for the poor (rich) to make it to the top (bottom) is much lower. This persistence of inequality at the tails of the distribution might help to explain why US IOp levels in permanent incomes are much higher than those for annual incomes, i.e., the rags-to-riches story is less common than usually thought. This in line with findings for Norway that IOp is generally higher at the tails (Aaberge et al. (2011)).

Indirect effects of circumstances The indirect effects of circumstances on effort are more important (i.e., the difference between the two upper bounds is larger) in Germany than in the US. Several explanations are possible. Firstly, this finding might indicate that the US is more meriocratic (with higher incentives for effort) while effort choices depend more on circumstances (and less on incentives) in Germany. For instance, Schnabel et al. (2002) show that the effect of parental background on educational outcomes is larger in Germany than in the US. Alternatively, the importance of indirect effects in Germany might be explained with higher discrimination in the labor market entry or wage setting. Additionally, traditional gender-roles seem to be more pronounced in Germany (for instance, women in Germany tend to work more part-time and less hours than women in the US).

Policy simulation As we have seen, gender differences play an important role for the EOp gap. Most of it was due to the indirect effect that women tend to work fewer hours. Part of this is due to the tax benefit rules – especially the system of joint taxation which yields high marginal tax rates for the second earner – usually the wife. Based on IZA's behavioral microsimulation model for the German tax and transfer system (IZAΨMOD, see Peichl et al. (2010) for an overview), we simulate the abolishment of the joint taxation system in Germany by introducing pure individual taxation to illustrate the importance of policy for the extent of EOp. The abolishment of joint taxation increases (decreases) married women's (men's) labor supply. When looking at the resulting IOp levels, we find that this policy change indeed leads to lower IOp (the upper and lower bound indices decrease by more than 10% each). Given the fact that this policy affects only married couples and that we focus on the intensive margin, this reduction is quite substantial.[18] Furthermore, this policy is also associated with higher tax revenue which could be used to promote child care policies to further increase female labor force participation and reduce IOp in this dimension.

[18] The largest effect of the policy change can be observed at the extensive margin, which is not relevant in our case since we only look at individuals who are already working.

Gross vs. net incomes The differences between gross and net income inequality, i.e., the redistributive effects of the tax benefit systems, are rather similar in both countries. This might be surprising at a first glance, since European welfare states are usually said to be more redistributive. However, the main difference in redistribution between Germany and the US is due to benefits and not due to the progressivity of the income tax which is rather similar in both countries (Dolls et al. (2012)). In addition, we have seen that there is basically no difference between the IOp *shares* for gross and net earnings in both countries. However, this does not imply that policy does not matter – in contrast, the IOp *levels* for net earnings are indeed considerably lower than those for gross earnings in both countries. Yet, the results indicate that there is no differential effect of the tax benefit system. This is not surprising for two reasons. First, tagging, i.e. the use of exogenous circumstances to determine tax liabilities and benefit eligibility, is usually not explicitly used in existing tax benefit systems due to anti-discrimination laws. Second, we focus on the working individuals between 25-55 which usually pay taxes but receive little benefits in both countries. Implicit tagging, i.e. designing rules and conditions such that individuals with certain circumstances are more likely to be eligible for it, is much less common in the tax system than for benefits. Hence, one would expect that existing tax benefit systems do not account for the source of inequalities – whether equitable (due to effort) or not (due to circumstances) – when redistributing income. Therefore, in order to improve the fairness (and efficiency) of the redistributive system, explicit tagging on (IOp relevant) exogenous circumstances would have to be increased (Ooghe and Peichl (2011)).

5.2 Robustness checks

Different samples In order to check the sensitivity of our results, we examine different samples. The results are illustrated in Table 1. First, we restrict our sample to individuals who work at least 25 hours per week. We choose this definition of full-time employment to ensure a satisfactory sample size in the case of annual incomes. For Germany, this restriction leads to a substantial decrease of the lower bound share, especially for annual incomes. This decrease may be explained by the less explanatory power of the gender dummy when only looking at full-time employed individuals. The upper bounds increase and the indirect effects of effort become substantially less important. This is not surprising because the selection into part-time employment, which is one of the main explanation for the indirect effects, is not relevant anymore. For the US, the results remain fairly similar to those in the baseline sample. Here the impact of the indirect effects on IOp almost diminishes. Though, the qualitative differences between Germany and the US remain. Second, when we restrict our sample to individuals aged 30-45, the results are very similar to the baseline, except for the US where we find a substantial increase in the upper bound shares.

Table 1: Sensivity analysis for different samples

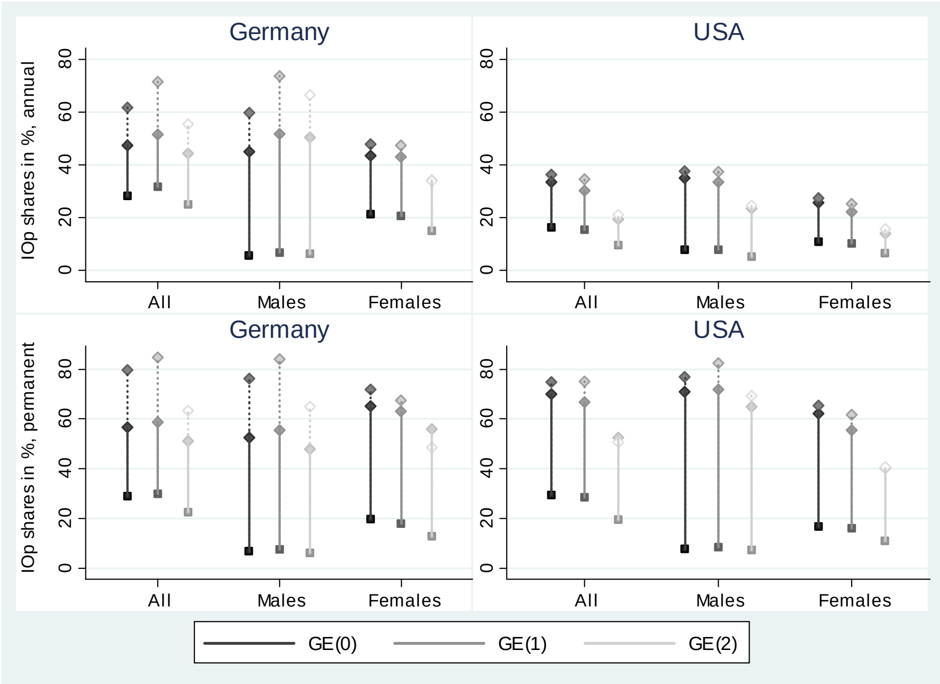
Germany	Annual				Permanent			
	N	LB	UB_1	UB_2	N	LB	UB_1	UB_2
Baseline	3,410	28.2	47.3	61.8	7,632	29.0	56.6	79.6
Full-time employed	2,558	21.9	64.8	67.1	6,146	25.0	71.1	74.1
Age range 30-45	1,364	29.5	56.7	63.9	4,767	35.0	71.5	84.4
Balanced-panel								
2008-1999	1,327	27.3	63.6	72.0	1,503	31.1	78.6	90.7
1998-1989	841	33.1	43.8	63.9	889	38.9	60.0	82.6
Missing values circumstance variables								
Without father's occ.	3,856	26.0	48.5	63.2	9,296	28.9	55.1	78.4
Without father's occ., region, ethnicity, urbanity	4,091	23.9	45.8	61.6	9,801	26.0	52.3	77.2
Only gender, birth, height	4,633	20.6	45.2	60.5	11,273	22.8	52.1	77.1
US	Annual				Permanent			
	N	LB	UB_1	UB_2	N	LB	UB_1	Ub_2
Baseline	1,293	16.3	33.5	36.2	7,081	30.2	70.0	74.9
Full-time employed	989	15.7	36.6	36.8	6,112	26.7	65.9	66.0
Age range 30-45	375	22.3	46.3	52.9	5,199	30.1	79.7	82.4
Balanced-panel								
2005-1992	859	19.1	44.6	46.1	1,498	40.2	76.0	78.5
1991-1982	1,704	20.1	52.9	55.0	2,427	33.5	86.7	89.7
Missing values circumstance variables								
Without father's occ.	1,475	14.8	31.3	34.1	8,026	28.1	69.2	74.1
Without father's occ., region, ethnicity, urbanity	1,634	14.2	32.1	35.0	8,938	24.8	68.4	73.6
Only gender, birth, height	1,741	9.7	32.2	35.2	9,850	18.4	67.1	72.5

Source: Own calculations based on SOEP and PSID. N denotes the number of observations, LB (UB) the lower (upper) bound IOp share. All robustness checks rely on log gross earnings as dependent variables.

In our baseline estimations we derive the unit-effect based on observations from unbalanced panels. Thus, we also run estimations based on balanced panels over a time period of ten years. In general, the upper bounds increase in this setting. Finally, we also test the responsiveness of our results with respect to sample selection due to missing values in circumstances variables. As expected, the lower bound decreases when reducing the circumstance set. In line with our model the results for the upper bound IOp shares remain very stable and are therefore independent of the circumstances set.

Different inequality measures Although other measures from the GE family violate the path-independent decomposability axiom, it is still insightful to see that our main results are not driven by the choice of MLD – as seen in Figure 3.

Figure 3: IOp shares in outcome inequality for different inequality measures



Source: Own calculations based on SOEP and PSID. The two graphs on the top illustrate IOp shares in annual incomes; the graphs at the bottom IOp shares in permanent incomes. The left (right) line is based on gross (net) incomes.

To sum up, while the point estimates depend on some of the choices made, the significant difference between lower and upper bounds of IOp does not. In addition, the (qualitative) differences between Germany and the US are also very robust.

5.3 The role of luck

So far, we have assumed that luck belongs to the sphere of individual responsibility. In the (philosophical) debate about whether luck should be compensated or not, a distinction is made between 'brute luck' on the one hand and 'option luck' on the other. The former is a random shock not associated with any (effort-related) choices (e.g., being struck by a lightning), whereas the latter is a consequence of a choice (e.g., winning or losing money while gambling) and should not be compensated. Hence, by neglecting (brute) luck, we (implicitly) assumed that all individual shocks are option luck, which was reasonable since our empirical analysis was mainly meant to illustrate the difference between lower and upper bound estimates.

Additionally accounting for brute luck gives the 'true' upper bound. However, the empirical identification of the two forms of luck is not straightforward. Nonetheless, the upper bound estimation can be extended following Lefranc et al. (2009). In order to illustrate this, and as a further robustness check, we now assume that all unobserved factors are non-responsibility characteristics, i.e. brute luck. Note that, by construction, the upper bound for the second approach is 100% when making this assumption. Therefore, we focus only on the first approach in this subsection. Hence, we modify equation (11) in the following way in order to separate the effect of observed effort variables and unobserved factors:

$$\ln(w_{is}) = \psi \hat{c}_i^{(1)} + \beta E_{is} + \upsilon_{is} \tag{12}$$

We then construct a parametric estimate of the smoothed distribution explicitly taking into account the error term υ_{is} :

$$\widetilde{\mu}^{UB,L} = \exp[\widehat{\psi}\hat{c}_i^{(1)} + \widehat{\upsilon}_{is} + \sigma^2/2] \tag{13}$$

Based on these predicted counterfactual levels, we then derive new upper bound measures of IOp taking into account luck. This gives an *upper* upper bound estimate of IOp as we do not only capture time-constant effort (in the unit effect) but also unobserved effort as well as option luck in the error term. The results are illustrated in Figure 4. The darker grey line shows the range between the lower and upper bounds (approach 1) as previously defined, whereas the upper, lighter grey line shows the difference to the new upper bound when additionally accounting for luck.

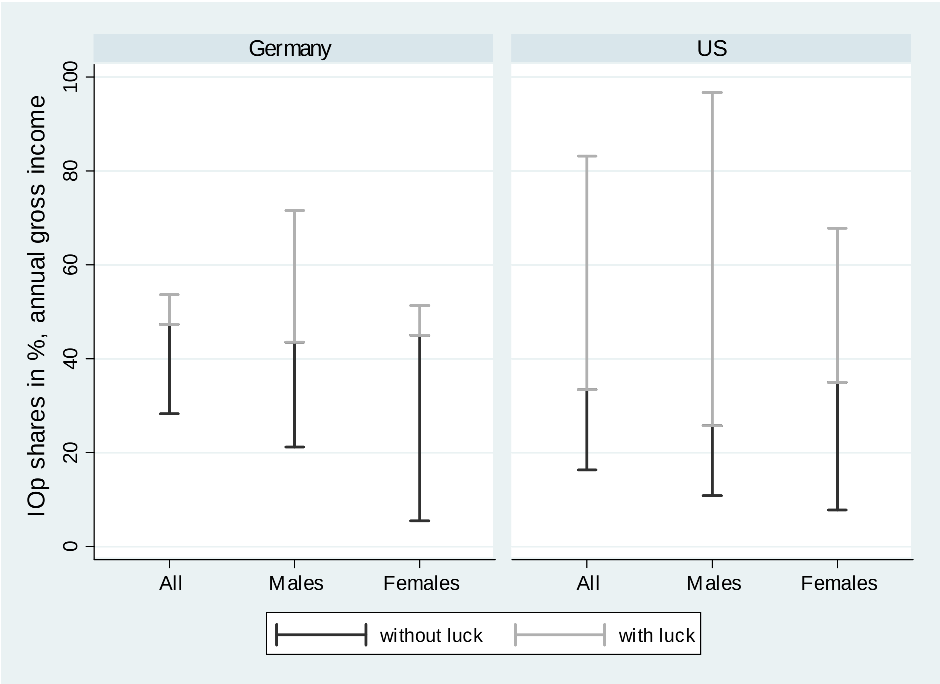
When taking into account luck, the upper bound does not change much in the German data for the full sample and the female subsample. The change is larger for the male subsample as well as in the US data for all samples. These results point towards a greater importance of unobserved effort or indeed luck in the cases where the luck-adjusted upper bound is much higher. The results for the US are also much more in line with the findings for permanent incomes, where we found higher upper bound IOR for the US than for Germany.

To sum up, our approach of estimating an upper bound does not depend on the assumption about the responsibility cut for luck. With the appropriate data and identification strategy that would allow for separating brute luck from option luck, it would be possible to estimate the 'true' upper bound for both approaches.

5.4 Ex-ante vs. ex-post – bounds for effort inequality

In the (empirical) EOp literature, two different approaches have been used to estimate IOp (see, e.g., Fleurbaey and Peragine (2009)): ex-ante vs. ex-post. The former partitions the population into types, i.e. groups of individuals endowed with the same set of circumstances, and IOp is measured as inequality between types. In the latter

Figure 4: Upper and lower bounds (UB1) IOp shares when accounting for luck



Source: Own calculations based on SOEP and PSID.

case, individuals are classified into responsibility groups (tranches) of individuals at the same effort level and inequality within tranches is investigated.

The ex-ante (lower-bound) IOR are smaller than the ex-post IOR (Checchi et al. (2010)). The difference between the two approaches can be explained with the treatment of unobserved factors. The ex-ante (lower bound) approach differentiates between inequality due to observed circumstances vs. residual inequality which is assigned to effort. This gives a lower bound for IOp – as described above – and hence an upper bound for effort inequality. Our (ex-ante) upper bound for circumstance inequality is also a lower bound for effort inequality, as the unobserved (not changing) residual effort is picked up by the circumstance IOp in this case.

While the ex-ante approach focuses on measuring inequality between types (individuals with the same circumstances), the ex-post approach looks at inequality within tranches of individuals, i.e. people at the same quantile of the effort/outcome distribution with different circumstances. Due to practical reasons, however, the number of circumstances which are incorporated in the analysis is limited to a small number of types (e.g. 3 types according to father's education). By doing this, the residual is implicitly assigned to IOp. This is, however, not an upper bound as adding another circumstances variable in this setting can still increase the contribution of explained variance due to circumstances.[19] In principle, it is possible to apply our method for an upper bound to the ex-post setting as well by defining types based on the unit effect. In the extreme case that everybody is his/her own type, the upper bound of IOp equals outcome inequality, i.e. the share is 100%. In our empirical application, we had to focus on the ex-ante approach due to practical reasons and data limitations.[20]

6 Conclusion

The existing literature provides only lower bound estimates of IOp. In contrast, we suggest an upper bound estimator based on a FE model to tackle this issue. The maximum amount of circumstances which an individual should not be held responsible for is the person's FE, as, by definition, it comprises all exogenous circumstances as well as some time-constant effort variables. Using this unit effect as a circumstance measure enables us to quantify the maximum amount of inequality which can be attributed to IOp. We apply the method to a rich set of harmonized panel data for Germany and the US in order to empirically illustrate our new estimator. In the empirical application, we pay special attention to indirect effects of circumstances on effort which leads to the definition of two different upper bound estimators.

The upper bound IOp levels and shares are always significantly higher than the lower bounds. For annual incomes, the IOp levels are rather similar between Germany and the US. For permanent incomes, only the lower bound levels are similar while the upper bound levels are higher in the US. While having similar IOp levels, the IOp shares are higher in Germany (28-47/62%) than in the US (16-33/36%) for annual incomes. This is due to lower absolute levels of outcome inequality. This result might help to explain why attitudes towards inequality and redistribution differ substantially between both countries (Figure 5 in the Appendix).[21] However, when moving to permanent

[19] Almås (2008) argues that the ex-post approach treats the unexplained variation as a circumstance which would result in an upper bound. This, however, is only true for a given set of (observed) circumstances. The fact that the ex-post approach gives lower bounds only is also discussed by Aaberge and Colombino (2011). They recognize that for the (ex-post) EOp approach "*[...] there might be other exogenous factors that affect individuals' achievements*" which are not captured by the observed circumstances. Hence, the within-type distribution of income might still depend on unobserved circumstances. Their solution (partially) accounts for the within-type inequality and yields an intermediate case with an IOp measure between the lower and the upper bound. Defining the upper bound as in our case (observed vs. unobserved circumstances), gives lower and upper bounds both for the ex-ante and ex-post approaches.

[20] In our application, we have more than 500 types for the lower bound approach. In order to apply the ex-post approach based on percentiles of the earnings distribution, we would need at least 100 observations per cell, i.e. in total more than 50,000 observations per year. Unfortunately, we do not have access to such a large panel data set.

[21] 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.

incomes, we find larger (lower and upper bound) IOp shares for the US, which increase to 30% and 70/75%, respectively. However, we do not find a substantial increase for Germany. We explain this difference with different degrees of mobility and persistence in different parts of the distribution (van Kerm (2004), Björklund and Jäntti (2009)). The persistence of inequality at the tails of the distribution suggests that the rags-to-riches (or vice versa) story is less common than usually thought. This might help to explain why perceptions of social mobility seem to change in the US – at least since the Great Recession. In addition, our results indicate that unobserved effort (or luck) is more important in the US than in Germany while indirect effects of circumstances are more important in Germany than in the US.

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 increases female labor supply – such as the move from joint to individual taxation – indeed reduces IOp bounds. This suggests that policies can be a useful tool to change IOp – and also that existing policies might actually increase IOp. Analyzing the IOp reducing potential of tax benefit systems based on exogenous characteristics (Ooghe and Peichl (2011)) is an interesting path for future research.

To sum up, we find significant and robust differences between lower and upper bound estimates for both countries in all specifications. At a first sight, the high IOp shares for the upper bounds might seem surprising. However, it should be noted that our estimate of unobserved heterogeneity also includes all unobserved abilities and innate talent. This is in line with Björklund et al. (2011), who indicate that IQ is the most important circumstance among the variables that they consider to explain differences in earnings. In addition, results from the literature on sibling correlations also emphasize the importance of family background and genetic material (Solon (1999), Björklund et al. (2009)). Furthermore, recent results from the literature on the effect of human capital on wage dispersion show that individual characteristics (e.g. Bagger et al. (2010)) as well as initial conditions (e.g. Hugget et al. (2011)) account for most of the variation in annual as well as lifetime earnings. Although we do not claim that our upper bound estimates represent the true amount of IOp – which will be between the bounds, they provide evidence that the existing lower bound estimates substantially underestimate IOp and thus might demand too little redistribution to equalize inequalities due to circumstances. In addition, the sizable share of total inequality that can be attributed to endowed characteristics calls for other policies to 'level the playing field' – e.g., institutional reforms to provide better access to education and the labor market for individuals with disadvantageous circumstances.

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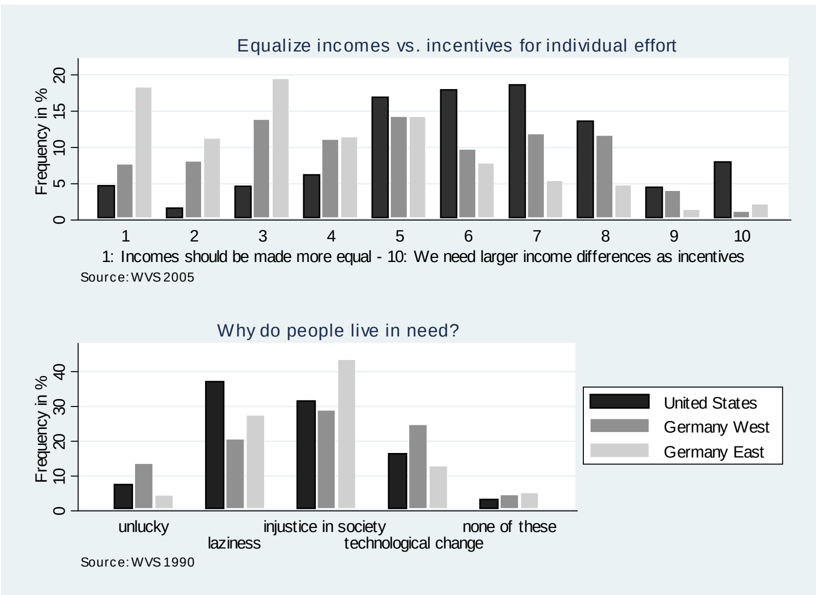
Appendix

Figure 5: Attitudes towards inequality and redistribution



Source: Own calculations based on WVS.

Table 2: Descriptive statistics – circumstance variables (cross-sectional data)

	Germany						USA					
	Annual Incomes			Permanent Incomes			Annual Incomes			Permanent Incomes		
	All	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female
Mean gross earnings in $	52042.93	65433.91	37162.22	35792.16	44976.36	25629.46	61070.60	75872.79	40181.17	40381.58	51668.01	27009.21
Mean net earnings in $	37488.91	46986.76	26934.43	26274.02	33028.10	18800.35	46919.01	57203.8	32404.71	30904.41	38767.91	21587.59
Female (%)	47.37	0.00	100.00	47.47	0.00	100.00	41.47	0.00	100.00	45.77	0.00	100.00
Ethnicity (foreigner / non-white, %)	4.95	5.56	4.26	5.63	5.99	5.24	28.39	22.26	37.04	30.69	27.14	34.90
Region (East/ South, %)	28.78	26.81	30.96	27.65	26.89	28.48	35.01	31.67	39.72	40.62	38.85	42.70
Education of father (%)												
Lower-secondary (reference)	2.37	2.61	2.10	2.44	2.79	2.04	2.75	2.17	3.58	6.48	5.42	7.74
Secondary	66.74	66.30	67.24	69.77	69.62	69.94	67.00	64.71	70.24	71.01	70.83	71.21
Intermediate	17.45	17.74	17.12	15.87	15.76	15.98	12.13	12.22	12.01	9.74	10.23	9.16
Upper-secondary	13.44	13.35	13.54	11.92	11.82	12.03	18.11	20.90	14.18	12.77	13.52	11.88
Occupation of father (%)												
Worker (reference)	51.52	49.17	54.14	52.35	51.36	53.44	49.15	42.44	58.62	54.33	49.92	59.55
Farmer	2.99	3.62	2.29	3.49	3.99	2.93	7.20	7.51	6.77	12.15	12.79	11.39
White-collar	16.01	15.91	16.13	15.47	15.37	15.59	8.00	7.33	8.94	7.54	7.11	8.05
Professional	14.14	14.52	13.72	12.60	12.47	12.75	24.58	33.21	12.39	16.23	20.91	10.68
Self employed	6.67	7.23	6.06	7.40	7.58	7.20	11.07	9.50	13.28	9.76	9.27	10.34
Civil servant	8.67	9.57	7.66	8.69	9.23	8.09						
Place of birth (%)												
Countryside (reference)	38.26	38.32	38.20	38.05	38.21	37.87	13.67	14.57	12.39	19.64	20.39	18.76
Small city	40.49	40.93	39.99	40.38	40.21	40.57	51.54	54.03	48.02	44.30	44.90	43.60
Large city	21.25	20.75	21.82	21.57	21.58	21.56	34.80	31.40	39.59	36.05	34.71	37.64
Birth	1964.05	1964.11	1963.99	1959.96	1959.74	1960.20	1960.84	1961.44	1960.00	1953.29	1953.80	1952.70
Height (in meter)	174.35	180.59	167.41	173.55	179.64	166.80	174.71	180.72	166.24	173.20	179.78	165.40
N	3410	1795	1615	7632	4009	3623	1293	712	581	7081	3840	3241

Source: Own calculations based on SOEP and PSID.

Table 3: Descriptive statistics – effort variables (longitudinal data)

	Germany						USA					
	Annual incomes			Permanent incomes			Annual incomes			Permanent incomes		
	All	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female
Mean gross earnings in $	36387.13	44783.87	26019.72	36325.09	44717.64	26017.85	42946.78	54501.67	28782.89	42927.45	54426.67	28778.46
Mean net earnings in $	26733.54	32978.3	19023.17	26694.91	32943.8	19020.38	32585.49	40659.38	22688.59	32591.35	40623.01	22708.94
Weekly work hours	34.49	39.25	28.62	34.45	39.21	28.60	38.58	42.65	33.59	38.60	42.65	33.62
Education in years	12.69	12.72	12.66	12.69	12.72	12.67	13.45	13.50	13.40	13.45	13.49	13.40
Age	40.95	40.71	41.24	40.85	40.64	41.12	38.73	38.50	39.02	38.67	38.41	38.98
Experience in years	16.52	18.07	14.61	16.42	17.99	14.50	10.61	10.22	11.08	10.69	10.32	11.15
Industry (%)												
Public (reference)	9.78	9.44	10.20	9.76	9.45	10.14	5.58	5.85	5.26	5.61	5.87	5.28
Energy Mining	14.19	19.65	7.45	14.15	19.61	7.44	9.32	14.04	3.53	9.27	13.96	3.51
Engineering	7.16	9.93	3.74	7.15	9.91	3.76	7.95	10.27	5.12	7.92	10.22	5.08
Manufacturing	5.64	5.63	5.67	5.62	5.59	5.65	8.37	9.45	7.04	8.32	9.37	7.03
Construction	8.06	12.79	2.22	8.02	12.75	2.20	6.32	10.58	1.11	6.34	10.59	1.10
Sales	13.09	10.07	16.81	13.09	10.09	16.77	14.95	15.08	14.78	14.94	15.05	14.82
Transport	5.55	7.01	3.74	5.55	7.02	3.75	7.24	9.35	4.65	7.26	9.38	4.65
Financial	3.60	3.42	3.83	3.59	3.41	3.80	4.74	3.08	6.78	4.75	3.10	6.77
Service	13.63	12.43	15.10	13.66	12.47	15.13	15.12	13.52	17.08	15.23	13.65	17.18
Education	8.57	5.42	12.47	8.64	5.49	12.50	10.53	5.32	16.91	10.48	5.31	16.83
Health	10.73	4.22	18.77	10.79	4.20	18.87	9.87	3.47	17.72	9.89	3.51	17.75
N	78137	43261	34876	82673	45569	37104	82859	45567	37292	85827	47347	38480

Source: Own calculations based on SOEP and PSID.

Table 4: Bootstrapped confidence intervals

	Germany						USA					
	All		Male		Female		All		Male		Female	
	P	CI	P	CI	P	CI	P	CI	P	CI	P	CI
Annual incomes												
Lower bound gross	0.075	(0.071 0.079)	0.036	(0.032 0.040)	0.017	(0.015 0.020)	0.057	(0.054 0.061)	0.034	(0.031 0.037)	0.025	(0.022 0.029)
Lower bound net	0.059	(0.057 0.062)	0.023	(0.021 0.026)	0.012	(0.011 0.014)	0.047	(0.044 0.050)	0.025	(0.023 0.027)	0.023	(0.019 0.026)
Upper bound gross$_1$	0.125	(0.116 0.135)	0.074	(0.066 0.085)	0.136	(0.121 0.152)	0.117	(0.106 0.129)	0.081	(0.070 0.091)	0.111	(0.096 0.129)
Upper bound gross$_2$	0.163	(0.141 0.185)	0.082	(0.066 0.097)	0.180	(0.150 0.207)	0.127	(0.105 0.152)	0.086	(0.062 0.114)	0.120	(0.090 0.159)
Upper bound net$_1$	0.104	(0.096 0.112)	0.054	(0.047 0.061)	0.109	(0.097 0.122)	0.090	(0.081 0.099)	0.062	(0.053 0.070)	0.079	(0.067 0.093)
Upper bound net$_2$	0.128	(0.109 0.148	0.061	(0.048 0.074)	0.132	(0.109 0.158)	0.098	(0.080 0.119)	0.065	(0.046 0.089)	0.086	(0.063 0.117)
LB share gross	28.2	(25.5 31.5))	21.2	(18.3 24.8)	5.5	(4.7 6.7)	16.3	(14.3 18.5)	10.9	(9.2 13.2)	7.9	(6.3 10.0)
LB share net	27.7	(25.0 31.1)	17.0	(14.5 20.0)	5.1	(4.3 6.2)	16.1	(14.0 18.3)	9.6	(8.1 11.7)	8.7	(7.1 11.0)
UB share gross$_1$	47.3	(42.9 52.3)	43.6	(36.7 52.3)	45.0	(39.8 51.8)	33.5	(29.6 38.5)	25.7	(21.5 30.9)	35.0	(29.6 41.6)
UB share gross$_2$	61.8	(55.5 68.4)	47.8	(38.0 57.6)	59.7	(52.5 66.5)	36.2	(31.7 41.0)	27.3	(21.5 33.5)	37.6	(31.2 45.8)
UB share net$_1$	48.2	(43.4 53.6)	39.5	(32.7 48.0)	46.1	(40.3 53.6)	30.8	(27.0 35.6)	23.7	(19.7 28.9)	30.4	(25.4 36.9)
UB share net$_2$	59.6	(53.3 65.9)	44.1	(35.3 54.0)	55.9	(48.6 62.8)	33.4	(28.8 38.1)	25.0	(19.0 31.5)	33.1	(26.3 41.2)
Permanent incomes												
Lower bound gross	0.068	(0.066 0.069)	0.030	(0.029 0.031)	0.016	(0.016 0.017)	0.074	(0.072 0.076)	0.037	(0.035 0.038)	0.016	(0.015 0.017)
Lower bound net	0.058	(0.057 0.059)	0.018	(0.017 0.019)	0.012	(0.011 0.013)	0.055	(0.054 0.056)	0.024	(0.023 0.025)	0.010	(0.009 0.010)
Upper bound gross$_1$	0.132	(0.127 0.138)	0.100	(0.093 0.107)	0.127	(0.120 0.134)	0.172	(0.166 0.178)	0.118	(0.112 0.125)	0.142	(0.137 0.149)
Upper bound gross$_2$	0.186	(0.179 0.194)	0.110	(0.103 0.117)	0.184	(0.174 0.195)	0.183	(0.177 0.191)	0.124	(0.117 0.131)	0.154	(0.148 0.161)
Upper bound net$_1$	0.118	(0.113 0.123)	0.071	(0.066 0.076)	0.119	(0.113 0.126)	0.127	(0.123 0.132)	0.081	(0.077 0.086)	0.106	(0.101 0.111)
Upper bound net$_2$	0.154	(0.148 0.160)	0.079	(0.074 0.084)	0.151	(0.143 0.160)	0.136	(0.132 0.142)	0.086	(0.081 0.091)	0.115	(0.110 0.121)
LB share gross	29.0	(27.7 30.4)	19.7	(18.3 21.2)	6.8	(6.3 7.3)	30.2	(28.9 31.6)	19.3	(17.8 21.0)	7.9	(7.4 8.5)
LB share net	30.4	(29.1 31.8)	15.4	(14.3 16.6)	6.3	(5.8 6.7)	29.3	(28.0 30.6)	17.2	(15.8 18.7)	6.2	(5.7 6.6)
UB share gross$_1$	56.6	(54.4 59.2)	65.2	(61.6 69.8)	52.4	(49.6 55.2)	70.0	(68.0 72.4)	62.2	(59.3 66.2)	71.0	(67.9 74.3)
UB share gross$_2$	79.6	(77.5 82.1)	71.8	(68.5 75.9)	76.3	(73.4 79.2)	74.9	(72.8 77.2)	65.3	(62.4 69.4)	76.9	(73.9 80.2)
UB share net$_1$	61.8	(59.6 64.2)	60.6	(57.0 65.1)	62.0	(58.9 65.0)	67.6	(65.3 70.0)	57.9	(54.9 61.8)	68.8	(65.5 72.3)
UB share net$_2$	80.5	(78.4 82.7)	68.0	(64.9 72.1)	78.7	(75.9 81.8)	72.5	(70.4 74.9)	61.0	(57.9 64.9)	75.0	(71.7 78.4)

Source: Own calculations based on SOEP and PSID. P indicates point estimates, CI the boostrapped confidence intervals (500 replications).

Table 5: OLS reduced-form regressions – lower bound of IOp

Dependent variable: Log gross real earnings

VARIABLES		Germany						USA					
		Annual incomes			Permanent incomes			Annual incomes			Permanent incomes		
		All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Female		-0.483***			-0.542***			-0.546***			-0.561***		
		(0.034)			(0.021)			(0.065)			(0.020)		
Ethnicity (foreigner/ non-white)		-0.208***	-0.159***	-0.253***	-0.131***	-0.144***	-0.117**	-0.023	-0.152	0.125	-0.171***	-0.285***	-0.061**
		(0.051)	(0.052)	(0.094)	(0.033)	(0.036)	(0.056)	(0.070)	(0.096)	(0.102)	(0.018)	(0.023)	(0.028)
Region (East/ South)		-0.242***	-0.448***	-0.032	-0.198***	-0.447***	0.064**	-0.148***	-0.129*	-0.171**	-0.055***	-0.092***	-0.017
		(0.031)	(0.034)	(0.054)	(0.017)	(0.019)	(0.028)	(0.053)	(0.070)	(0.081)	(0.017)	(0.021)	(0.026)
Education of father	Secondary	0.143**	0.496***	-0.180	-0.039	-0.038	-0.024	0.190	0.372	0.071	0.188***	0.182***	0.192***
(Reference:		(0.072)	(0.080)	(0.120)	(0.050)	(0.052)	(0.088)	(0.196)	(0.292)	(0.259)	(0.030)	(0.041)	(0.044)
Lower-secondary)	Intermediate	0.263***	0.663***	-0.087	0.064	0.077	0.063	0.170	0.547*	-0.165	0.277***	0.304***	0.242***
		(0.078)	(0.086)	(0.131)	(0.053)	(0.056)	(0.094)	(0.206)	(0.304)	(0.275)	(0.039)	(0.051)	(0.059)
	College	0.318***	0.799***	-0.143	0.128**	0.181***	0.075	0.494**	0.875***	0.098	0.424***	0.434***	0.385***
		(0.083)	(0.091)	(0.141)	(0.056)	(0.059)	(0.098)	(0.206)	(0.303)	(0.280)	(0.040)	(0.051)	(0.062)
Occupation of father	Farmer	0.034	-0.144*	0.284**	0.073*	0.012	0.097	0.059	0.235	-0.191	0.080***	0.087***	0.077*
(Reference:		(0.074)	(0.075)	(0.138)	(0.040)	(0.041)	(0.073)	(0.113)	(0.146)	(0.180)	(0.027)	(0.033)	(0.043)
Worker)	White-collar	0.122***	0.084**	0.145**	0.140***	0.112***	0.173***	0.107	0.081	0.156	0.159***	0.154***	0.168***
		(0.035)	(0.037)	(0.062)	(0.021)	(0.023)	(0.036)	(0.079)	(0.110)	(0.113)	(0.029)	(0.037)	(0.044)
	Professional	0.268***	0.230***	0.272***	0.204***	0.152***	0.280***	0.144**	-0.003	0.394***	0.125***	0.164***	0.155***
		(0.045)	(0.047)	(0.082)	(0.026)	(0.029)	(0.044)	(0.068)	(0.086)	(0.116)	(0.025)	(0.028)	(0.047)
	Self-employed	-0.020	-0.011	-0.022	0.085***	0.033	0.143***	0.111	-0.038	0.269***	0.215***	0.253***	0.181***
		(0.052)	(0.056)	(0.090)	(0.029)	(0.031)	(0.049)	(0.072)	(0.102)	(0.099)	(0.026)	(0.033)	(0.040)
	Civil servant	0.062	0.024	0.112	0.148***	0.057*	0.266***						
		(0.051)	(0.054)	(0.091)	(0.029)	(0.031)	(0.051)						
Place of birth	City	0.029	-0.018	0.059	0.077***	0.054***	0.090***	0.134*	0.130	0.072	0.099***	0.096***	0.106***
(Reference:		(0.028)	(0.030)	(0.049)	(0.017)	(0.018)	(0.028)	(0.081)	(0.098)	(0.142)	(0.023)	(0.028)	(0.037)
Countryside)	Large city	0.044	-0.028	0.100	0.114***	0.050**	0.159***	0.143	0.208*	-0.033	0.150***	0.120***	0.168***
		(0.034)	(0.036)	(0.061)	(0.020)	(0.022)	(0.034)	(0.087)	(0.108)	(0.150)	(0.024)	(0.030)	(0.039)
Year of birth		-0.009***	-0.009***	-0.008**	-0.003***	-0.007***	0.002	-0.003	-0.005	0.003	-0.005***	-0.012***	0.003**
		(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
Height		1.282***	1.026***	1.490***	0.811***	0.994***	0.586***	-0.130	0.577	-1.036**	0.504***	0.638***	0.316**
		(0.190)	(0.193)	(0.348)	(0.114)	(0.120)	(0.198)	(0.321)	(0.421)	(0.487)	(0.099)	(0.123)	(0.155)
Constant		25.687***	25.790***	22.873***	14.750***	22.419***	5.238**	16.215**	18.718*	5.244	19.258***	32.556***	3.097
		(3.603)	(3.954)	(6.162)	(1.463)	(1.573)	(2.489)	(7.290)	(9.534)	(11.546)	(1.470)	(1.824)	(2.358)
N		3410	1795	1615	7632	4009	3623	1293	712	581	7081	3840	3241
R^2		0.234	0.204	0.044	0.263	0.207	0.058	0.162	0.107	0.075	0.295	0.195	0.071

Standard errors in parentheses; annual income estimations for Germany rely on SOEP wave 2009; estimations for the USA on PSID wave 2007;
*** p<0.01, ** p<0.05, * p<0.1

Table 6: FE earnings regressions – deriving the unit-effect

Dependent variable: Log gross real earnings

VARIABLES		Germany						USA					
		Annual incomes			Permanent incomes			Annual incomes			Permanent incomes		
		All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Experience		0.257***	0.360***	0.207***	0.256***	0.358***	0.207***	0.174***	0.202***	0.108***	0.180***	0.209***	0.117***
		(0.008)	(0.011)	(0.014)	(0.008)	(0.010)	(0.013)	(0.011)	(0.016)	(0.015)	(0.010)	(0.016)	(0.015)
Experience squared		-0.063***	-0.087***	-0.029***	-0.063***	-0.087***	-0.032***	-0.010**	0.000	-0.014**	-0.010**	0.001	-0.015**
		(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)
Working hours		0.024***	0.016***	0.032***	0.024***	0.016***	0.032***	0.026***	0.020***	0.034***	0.026***	0.020***	0.033***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education		0.058***	0.082***	0.028***	0.063***	0.088***	0.032***	0.040***	0.044***	0.035***	0.039***	0.043***	0.034***
		(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)
Industry	Energy and Mining	0.041***	0.046***	0.041*	0.044***	0.048***	0.040*	0.049***	0.085***	0.002	0.043**	0.078***	0.003
(Reference:		(0.014)	(0.016)	(0.025)	(0.014)	(0.016)	(0.024)	(0.017)	(0.021)	(0.031)	(0.017)	(0.021)	(0.031)
Public)	Engineering	0.046***	0.046***	0.065**	0.049***	0.046***	0.076***	0.044**	0.068***	0.016	0.041**	0.067***	0.013
		(0.015)	(0.017)	(0.029)	(0.015)	(0.017)	(0.028)	(0.018)	(0.022)	(0.030)	(0.017)	(0.021)	(0.029)
	Manufacturing	-0.013	0.050**	-0.063**	-0.008	0.050***	-0.053**	0.005	0.019	-0.002	0.006	0.021	-0.002
		(0.016)	(0.020)	(0.026)	(0.016)	(0.019)	(0.025)	(0.018)	(0.022)	(0.029)	(0.017)	(0.022)	(0.028)
	Construction	0.036**	0.064***	-0.067**	0.036**	0.058***	-0.053*	-0.014	0.011	-0.033	-0.021	0.006	-0.042
		(0.015)	(0.017)	(0.033)	(0.015)	(0.016)	(0.032)	(0.019)	(0.022)	(0.042)	(0.018)	(0.021)	(0.041)
	Sales	-0.074***	-0.051***	-0.089***	-0.067***	-0.049***	-0.077***	-0.091***	-0.043**	-0.140***	-0.093***	-0.047**	-0.139***
		(0.014)	(0.017)	(0.022)	(0.014)	(0.017)	(0.022)	(0.016)	(0.020)	(0.025)	(0.016)	(0.020)	(0.024)
	Transport	-0.025	-0.036*	0.040	-0.023	-0.031*	0.033	0.022	0.045**	0.056*	0.021	0.043*	0.056*
		(0.017)	(0.019)	(0.032)	(0.017)	(0.018)	(0.031)	(0.019)	(0.023)	(0.033)	(0.018)	(0.022)	(0.032)
	Financial	0.069***	0.137***	0.011	0.050*	0.094***	0.027	0.034*	-0.007	0.042	0.038*	-0.003	0.046*
		(0.026)	(0.031)	(0.044)	(0.026)	(0.030)	(0.043)	(0.020)	(0.030)	(0.029)	(0.020)	(0.029)	(0.028)
	Service	-0.056***	-0.004	-0.101***	-0.056***	-0.004	-0.102***	-0.103***	-0.025	-0.182***	-0.106***	-0.028	-0.184***
		(0.013)	(0.016)	(0.020)	(0.013)	(0.015)	(0.020)	(0.015)	(0.020)	(0.024)	(0.015)	(0.019)	(0.023)
	Education	-0.023	-0.079***	-0.010	-0.022	-0.087***	-0.005	-0.074***	-0.092***	-0.079***	-0.077***	-0.096***	-0.082***
		(0.015)	(0.020)	(0.022)	(0.014)	(0.020)	(0.021)	(0.018)	(0.027)	(0.026)	(0.018)	(0.027)	(0.026)
	Health	-0.006	-0.013	-0.020	-0.012	-0.022	-0.024	0.025	-0.013	-0.003	0.021	-0.008	-0.009
		(0.015)	(0.024)	(0.022)	(0.015)	(0.023)	(0.021)	(0.018)	(0.030)	(0.026)	(0.018)	(0.029)	(0.025)
Constant		8.050***	8.194***	7.936***	7.971***	8.117***	7.875***	8.626***	9.036***	8.195***	8.633***	9.032***	8.211***
		(0.050)	(0.055)	(0.090)	(0.049)	(0.054)	(0.088)	(0.071)	(0.100)	(0.100)	(0.068)	(0.096)	(0.096)
N		78137	43261	34876	82673	45569	37104	82859	45567	37292	85827	47347	38480
R^2		0.390	0.421	0.403	0.399	0.428	0.413	0.262	0.186	0.358	0.264	0.190	0.360
No of individuals		7408	3907	3501	7632	4009	3623	6865	3705	3160	7081	3840	3241

Standard errors in parentheses; all estimations include period effects; annual (permanent) income estimations for Germany rely on SOEP waves 1984 - 2008 (2009), estimations for the USA on PSID waves 1981 - 2006 (2007); *** p<0.01, ** p<0.05, * p<0.1