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Judith Niehues and Andreas Peichl
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Abstract

Previous estimates of unfair inequality of opportunity (IOp) are only lower bounds because of the unobservability of the full set of endowed circumstances beyond the sphere of individual responsibility. In this paper, we suggest a new estimator based on a fixed effects panel model which additionally allows identifying an upper bound. We illustrate our approach by comparing Germany and the US based on harmonized micro data. We find significant and robust differences between lower and upper bound estimates – both for gross and net earnings based either on periodical or permanent income – for both countries. We discuss the cross-country differences and similarities in IOp in the light of differences in social mobility and persistence.

JEL Codes: D31, D63, H24, J62

Keywords: Equality of Opportunity, Fairness, Redistribution, Wage Inequality

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1 Introduction

Preferences for redistribution are systematically correlated with beliefs about the relative importance of effort and luck in the determination of outcomes (see Konow (2003), Alesina and Giuliano (2011) 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 (e.g. due to differences in effort) from unfair inequalities (e.g. due to endowed characteristics).[1] 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. 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. Bourguignon et al. (2007) and Ferreira and Gignoux (2011)). In this paper, we suggest a new estimator of IOp based on a fixed effects model which additionally allows identifying an upper bound for unfair inequalities in order to provide the full range of IOp estimates. We illustrate our approach by comparing estimates for Germany and the US – two countries with different welfare state regimes, attitudes towards inequality and redistribution (see Figure 5 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 Roemer (1993, 1998), Van de 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.[4] 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

[1] See Sen (1980, 1985, 1992), Dworkin (1981a,b), Arneson (1989), Cohen (1989), Roemer (1993, 1998, 2002) and Fleurbaey (2008).

[2] 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)).

[3] 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 (2011), Dunnzlaff et al. (2011), Aaberge et al. (2011), Almås et al. (2011) as well as Björklund et al. (2011).

[4] 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.

not be held responsible, such as parental education, gender or ethnic origin. Effort, on the other hand, comprises all actions and choices within individual responsibility for which society holds the individual (partially) accountable, e.g. schooling or labor supply decisions. Inequalities (in income) due to differences in effort are deemed equitable, whereas inequalities due to endowed circumstances are not.[5]

In empirical estimations of EOp it is impossible to observe all characteristics that constitute individual's circumstances (e.g. 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.[6] Estimating lower bounds of IOp 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 (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 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 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

[5] This is related to the literature on wage discrimination (see, e.g., Altonji and Blank (1999) for an overview). However, a fundamental differences exists between the two fields. Labor economists studying discrimination are usually interested in estimating the direct effect of endowed characteristics (e.g. race, gender) on income and try to separate it from confounding effects due to between-group differences in effort. In contrast, the EOp literature believes that the confounding indirect effect is also a source of unfair inequalities, i.e. a circumstance, itself that should not be separated from the direct effect of circumstances on income (see, e.g., the discussion in Roemer (1998)). We discuss this issue in more detail in Section 2.

[6] This is due to the fact that adding another circumstance variable to the analysis increases the explained variation and hence the share of inequality due to circumstances – just like an R^2-measure increases when adding another variable to the analysis. See Ferreira and Gignoux (2011) for an extensive discussion.

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.

To empirically illustrate our new estimator, we rely on the Cross-National Equivalent Files (CNEF) for Germany and the US which contain harmonized micro-level panel data from national surveys which cover long time periods and include a comprehensive set of income, circumstance and effort variables. The German Socio-Economic Panel (SOEP) data has been widely used for income inequality analyses (see, e.g. Fuchs-Schuendeln et al. (2010), Peichl et al. (2011)). However, it has not yet been used to analyze IOp. We compare our estimates to US data taken from the Panel Study of Income Dynamics (PSID) which has been used by Pistolesi (2009) to analyze 'IOp in the land of opportunities'. Comparing the US with a Continental European 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 and social mobility.[7] Almås (2008) uses data from the Luxembourg Income Study to compare estimates of unfair inequalities for Germany and the US and shows that the results depend on the fairness ideal and the measure used.[8]

Our lower bound estimates yield IOp shares of up about 16% for annual earnings in the US, which is comparable to previous findings. The upper bound of IOp, in contrast, accounts for around 35% of the observed inequality. Results for Germany are significantly higher with shares of 30% and 50% respectively – which is in line with the findings of Almås (2008). The significant differences between lower and upper bounds suggest that previous (lower bound) estimates of IOp might demand

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

[8] Two different approaches have been used in literature 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 case, individuals are classified into responsibility groups (tranches) of individuals at the same effort level and inequality within tranches is investigated. Note that Almås (2008) argues that the ex-ante approach gives a lower bound because it treats the unexplained variation as an responsibility variable (see also the discussion in Ferreira and Gignoux (2011)), whereas the ex-post approach would give an upper bound because it treats the residual as a circumstance. This, however, is only true for a given set of (observed) circumstances. Defining the upper bound as in our case, gives lower and upper bounds both for the ex-ante and ex-post approaches. In our empirical application, we focus on the ex-ante approach due to practical reasons and data limitations. We discuss the two approaches in more detail in Section 2.

for too little redistribution in order to equalize unfair inequalities. Furthermore, our results based on annual incomes seem to indicate that EOp is higher in the "land of opportunities". However, as it has been shown in the literature, IOp is usually higher in permanent than in annual incomes (Aaberge et al. (2011)). We are able to confirm this result for the lower and upper bound shares for the US, which increase to 30% and 70% respectively. However we do not find a large increase for Germany. Hence, when looking at permanent income, IOp is even slightly higher in the US. We relate this interesting country difference to different degrees of mobility and persistence in different parts of the distribution (Björklund and Jäntti (2009)).

Results are similar for gross and net earnings. This implies that there is no differential effect of redistribution on IOp, i.e. there is no implicit tagging on circumstances in the tax systems of Germany and the US. Our results further indicate that unobserved circumstances, such as ability and talent, are important determinants of inequality (in line with findings for Sweden, see Björklund et al. (2011)). 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.

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.

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 in the literature 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 Roemer (1998), we explicitly recognize the fact that effort is shaped by circumstances, i.e. that the distribution of effort within each type is itself a characteristic of the type. This approach, which is common in the literature on EOp, differs from the literature on wage discrimination (see Altonji and Blank (1999) for an overview) where economists are usually interested in a 'clean' measure of the direct effect of circumstances. Suppose there in an unobservable aspect of effort that is correlated with an endowed characteristic. Then a regression of earnings on circumstances only (e.g. a gender dummy) 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 literature on EOp, in contrast, the confounding indirect effect (of circumstances on income via effort) is also seen as a source of unfair inequalities itself which should be compensated and hence not be separated from the direct effect of circumstances on income[9]. Therefore, IOp is related to wage discrimination, but it is not the same. Unfair income differences in the IOp framework can be indeed caused by discrimination, but they could also be due to between-group differences in productivity or preferences. Therefore, the two approaches imply different normative choices about the compensation of the indirect (confounding) effect. While we focus on the traditional notion of EOp in this paper, the different normative choices of the underlying fairness principles can be made explicit (see Fleurbaey (2008) or Almås et al. (2011)) and, in principle, it is possible to extend our approach of estimating an upper bound to other normative frameworks as well.

We assume that the outcome variable of interest depends both on exogenous, i.e. 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 $f : \Gamma \times \Omega \rightarrow \mathbb{R}_+$:

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

As it is common in most parts of the literature, we do not explicitly take into

[9]Note, however, that there is disagreement about the degree of compensation (see, e.g., the discussion in Roemer (1998) and Fleurbaey (2008))

account the role of luck. 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.[10] The same is true for potential measurement errors in the earnings data.

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.[11] 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. EOp is achieved if the mean advantage levels μ are identical across types:

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

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 $\overline{E}$).

Based on this smoothed distribution, we compute two scalar measures of IOp for any (scale invariant) inequality index I:

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

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

where θ_a is a measure of the absolute inequality of opportunity level (IOL), and θ_r is the inequality of opportunity ratio (IOR) measuring the share of total inequality that can be attributed to circumstances. This allows to decompose the total income inequality into inequality within types (i.e. effort inequality) and inequality between

[10] 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.

[11] See Fleurbaey and Peragine (2009) or Checchi et al. (2010) for a extensive discussion of ex-ante vs. ex-post approaches. We choose the ex-ante approach in our context because it is easier to estimate it empirically when accounting for numerous circumstance variables and a large number of types in the presence of small samples or cell sizes. Our method is, in general, also applicable to the ex-post approach which will be discussed in more detail later on.

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 logarithmic deviation* (MLD) $I_0 = \frac{1}{N} \sum \ln \frac{\mu_w}{w_i}$.

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.[12] Log-linearization of equation (1) and adding an error term yields the following empirical specifications

$$\ln(w_{is}) = \alpha C_i + \beta E_{is} + u_{is} \tag{5}$$

$$E_{is} = HC_i + v_{is} \tag{6}$$

Equation (5) represents the direct effect of circumstances, equation (6) 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 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 (6) into the earnings equation (5), we obtain the following reduced-form relationship:

[12] 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)). The drawback of the non-parametric approach, however, is that a consideration of 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.

$$\ln(w_{is}) = \underbrace{(\alpha + \beta H)}_{\psi} C_i + \underbrace{\beta v_{is} + u_{is}}_{\eta_{is}} \tag{7}$$

This reduced-form equation can then be simply estimated by OLS to derive the fraction of variance which is explained by circumstances. Including all available k observed circumstances C^K in equation (7), 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:

$$\widetilde{\mu}^{LB} = \exp[\widehat{\psi} C_i^K + \sigma^2/2] \tag{8}$$

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. By inserting (8) into (3), we derive a measure of the absolute IOp level (IOL), whereas inserting (8) into (4) gives a measure of the relative IOp share (IOR).

The approach has so far been in line with the existing literature such as Bourguignon et al. (2007), Checchi et al. (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: 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. In the next step, we suggest a new estimator for IOp to tackle the lower-bound problem.

Upper bound of IOp Our method to derive an upper bound of IOp is based on a two-step approach. First, we estimate a fixed effects 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. 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 fixed effects 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.[13]

To estimate the fixed-effects model, 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}:

$$w_{it} = f(C_{i,} E_{it}, u_{i,} u_t, \varepsilon_{it}) \tag{9}$$

Log-linearization yields the empirical specification

$$\ln(w_{it}) = \alpha C_i + \beta E_{it} + u_i + u_t + \varepsilon_{it} \tag{10}$$

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 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 $c_{i.}$:

[13] 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)).

$$\ln(w_{it}) = \beta E_{it} + c_i + u_t + \varepsilon_{it} \tag{11}$$

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 rather be attributed to effort, such as long-term motivation and work effort. As 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.[14] Estimating equation (11) by a simple FE model with period dummies then yields estimates for $\hat{c}_i$:

$$\hat{c}_i = \bar{w}_i - \sum \hat{\beta}_k^{FE} \bar{x}_{ik} - \bar{\varepsilon}_i \tag{12}$$

We use this estimate of the person effect as an indicator for the maximum value of time-constant circumstances which an individual should not be held responsible – as by definition, it comprises all exogenous circumstances as well as some not changing effort variables. 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 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:

$$\ln(w_{is}) = \psi \hat{c}_i + \upsilon_{is} \tag{13}$$

Again, as in the lower bound case, we construct a parametric estimate of the smoothed distribution by replacing individual earnings by their predictions:

$$\widetilde{\mu}^{UB} = \exp[\widehat{\psi} \hat{c}_i + \sigma^2/2] \tag{14}$$

Based on these predicted counterfactual levels, we derive upper bound measures of IOp, by inserting (14) into (3) for the upper bound IOp level and into (4) for the upper bound IOp share in total inequality. Again, as our estimated circum-

[14] 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.

stance variable 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 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.

Ex-ante vs. ex-post – upper and lower 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 (lower-bound) IOp shares from the ex-ante approach are smaller than the IOp shares from the ex-post approach (Checchi et al. (2010)). The difference between the two approaches can be explained with how unobserved factors are treated. Almås (2008) argues that the ex-ante approach treats the unexplained variation as an responsibility variable and hence gives a lower bound, whereas the ex-post approach, in contrast, treats it as a circumstance which would give an upper bound. This, however, is only true for a given set of (observed) circumstances. 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.[15]

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

[15] The fact that the ex-post approach gives lower bounds only is also discussed by Aaberge and Colombino (2011) who estimate optimal income tax rules using different social welfare functions (SWF). 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 is using an inequality measure based on an 'extended EOp-SWF' which (partially) accounts for the within-type inequality. Applying this approach in our setting yields an intermediate case with an IOp measure between the lower and the upper bound.

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. It is straightforward to apply our method for an upper bound of IOp 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 focus on the ex-ante approach due to practical reasons and data limitations.[16]

3 Data

We use the Cross-National Equivalent Files (CNEF) 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.[17] 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.[18]

In line with the previous literature, the units of our analysis are individuals aged 25-55 who are in (part- or full-time) employment. The dependent variables are logarithmic 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, a long time period is needed. Consequently, we base our analysis only on those individuals who report

[16] 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.

[17] 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.

[18] 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.

positive earnings for at least five subsequent points in time.[19] We further restrict our sample to individuals with data on parental background.

We first estimate lower bounds of IOp by using either log annual earnings of the most current wave (2009 for Germany, 2007 for the US) or log permanent incomes – proxied by average real earnings over the whole period[20]. In a second set of estimations, we rely on permanent log earnings which are computed as the individual's mean income over the observation period.

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 fixed effects 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 affected by responsible individual choices. In the case that these variables do not vary over time, they are included in the fixed effect 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 (7) for the most current survey wave (Germany: SOEP 2009; US: PSID 2007) on all observable circumstances which are expected to have an impact on individual labor earnings. The results of these reduced-form

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

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

OLS regressions are illustrated in Table 5 in the Appendix. The specifications in the first column are based on the whole sample, in the second and third columns the sample is restricted to male and female individuals, respectively. The first set of regressions for each country is based on periodical incomes, the second set on permanent incomes.

The first column for each set shows that women have significantly lower labor earnings than men in all specifications – the well-known gender wage gap, with values around 50%. 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 available upon request), 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.[21] 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, 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, later born (i.e. younger) individuals have 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 26.3% of the overall variation in log earnings in Germany, and up

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

to 29.5% in the US. In a world of equal opportunities, these exogenous circumstances should actually have no effect on earnings – hinting that at least some degree of IOp exists in both countries.

Derivation of upper bound of IOp To derive upper bounds of IOp, the first step is the FE estimation of the earnings equation (11) on the observable time-varying effort variables. Table 6 in the Appendix presents the results. 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.

In Germany, 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 and the effect is robust across all specifications. The same is true for education. With regard to the industry dummies, in both countries, an occupation in the energy and mining, manufacturing, construction, transportation, financial (only in the US) and health sector is associated with higher earnings than if you are employed in the public sector (reference).

4.2 Lower and upper bounds of IOp

In the next step, the coefficients of the reduced-form OLS regression (7) 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 derived from the FE model. Based on the first-stage FE wage regressions, we predict the unit-effects for all individuals, as suggested by equation (12). In the next step, we use these indicators of the maximum amount of circumstances $\hat{c}_i$ as independent variables to estimate equation (13). Now, the dependent variable are the individual's logarithmic labor earnings in 2009 (2007) for Germany (the US). 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.

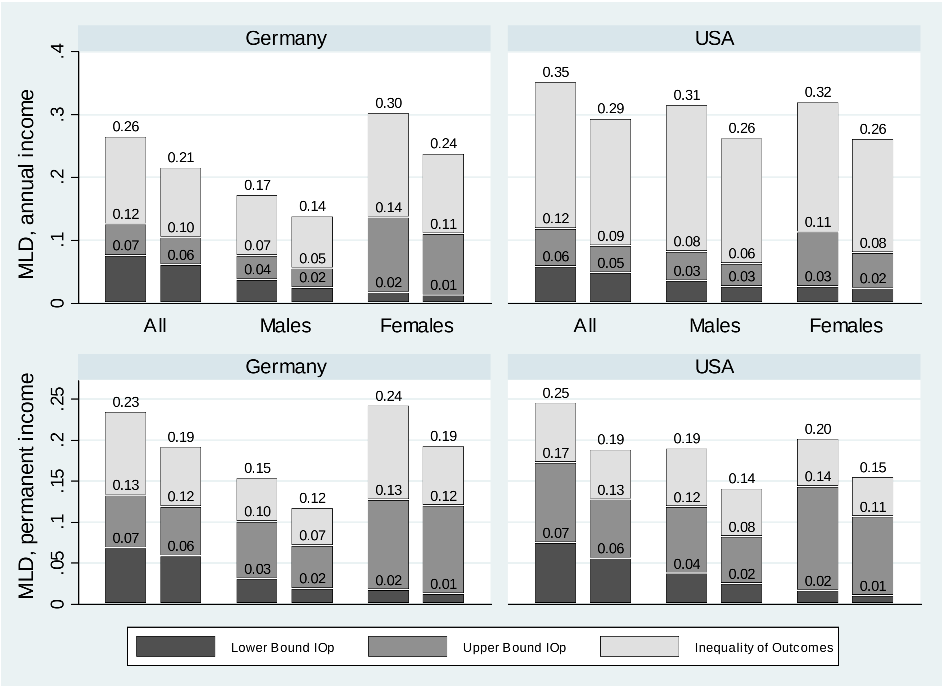
The MLD for inequality in outcomes (total bar) as well as the counterfactual smoothed distributions for the lower (dark grey) and upper (medium grey) bounds are presented in Figure 1. Inequality in periodical (permanent) incomes is reported in the upper (lower) panel both for the US and Germany for the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

Inequality levels We start by examining annual labor earnings (upper panel). Our results reveal a MLD of 0.26 (0.21) for Germany and 0.35 (0.29) in the US for gross (net) earnings. Not surprisingly, redistribution reduces outcome inequality in both countries and in all samples. Inequality of outcomes is substantially 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 (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 across 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 income mobility in Germany (van Kerm (2004)). Therefore, 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 such as gender, country and region of origin, height as well as father's education and occupation. 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 Table 4 in the Appendix. 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 are also rather similar for annual income in all

Figure 1: Upper and lower bound indices of IOp



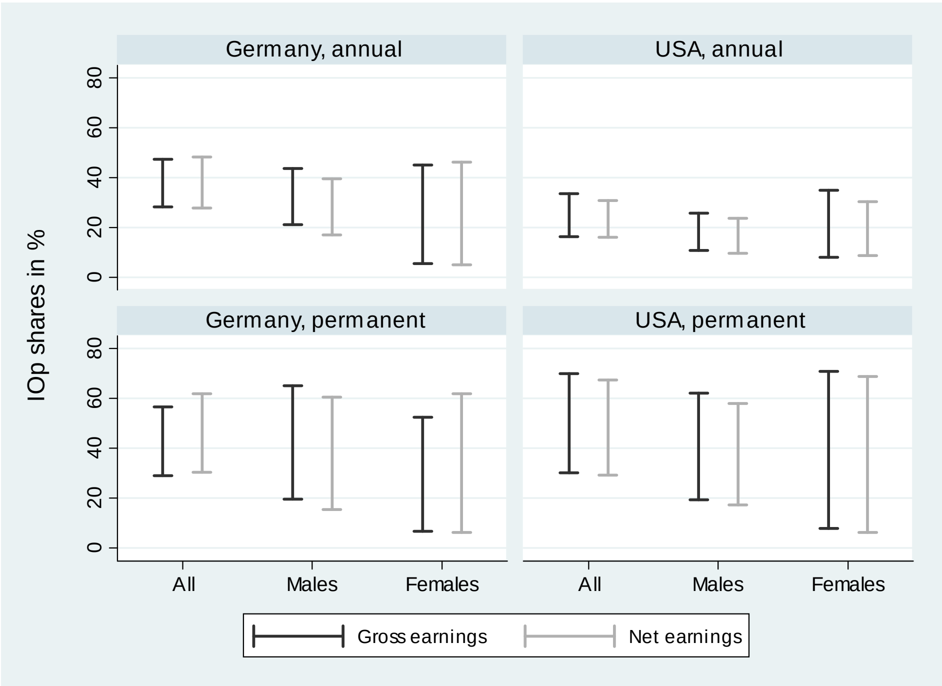
Source: Own calculations based on SOEP and PSID. The two graphs on the top illustrate IOp levels in annual incomes (2009 for Germany, 2007 for the US); the graphs at the bottom IOp levels in permanent incomes.

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.[22] 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.

[22]It should be noted that the upper bounds of IOp decrease if we, e.g., 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.

IOp shares In order to get a feeling for the relative importance of IOp, Figure 2 presents the range for IOp shares, i.e. the IOp levels divided by the MLD for outcome inequality (between group inequality as fraction of total inequality). The upper (lower) line corresponds to the upper (lower) bound share. Again, results are presented for periodical (permanent) incomes in the upper (lower) panel both for the US and Germany for the full sample as well as separated by gender for gross (left, darker bar) and net (right, lighter bar) earnings.

Figure 2: IOp shares in outcome inequality



Source: Own calculations based on SOEP and PSID. The two graphs on the top illustrate IOp shares in annual incomes (2009 for Germany, 2007 for the US); the graphs at the bottom IOp shares in permanent incomes.

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 previous findings (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 upper bounds of IOp of around 50% in Germany and 35% in the US. The differences are statistically significant.

Thus, it seems that there is substantially less IOp in the US compared to Germany, i.e. one could conclude that equality of opportunity is higher in the "land of opportunities". 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, inequality levels (and hence the IOp shares) are similar for both income concepts. Hence, the IOp shares for permanent incomes are higher in the US than in Germany.

Again, the lower bound IOp shares are substantially smaller when we look at the female and male sample separately. This again hints at gender as an important source of IOp. However, the effect is not as strong for the upper bounds based on the unit-effect as circumstance variable. This indicates that a large share of the inequality in outcomes can be explained by unobserved heterogeneity of individuals.

Gross vs. net incomes We find that the differences between gross and net income inequality, i.e. the redistributive effects of the tax benefit systems, are rather similar between Germany and the US. This might be surprising at a first glance, since European welfare states are usually said to be more redistributive. But in our exercise, as we focus on the working age population, this is not the case. The main difference in redistribution between Germany and the US is due to benefits (especially for the unemployed) and not due to the progressivity of the income tax which is rather similar in both countries. In our sample, we focus on individuals who are working. They pay taxes and receive almost no benefits – except for child credits which are comparable between both countries. Hence, the redistributive effects for this subgroup of the population is rather similar between Germany and the US.

5 Discussion of Results

5.1 'Explaining' the results

Annual vs. permanent incomes The result that IOp in permanent incomes in the US is much higher than for annual incomes – which is not the case for Germany, might be explained by different mobility patterns between both countries. In general, mobility is higher in the US (van Kerm (2004)). However, in the US much higher persistence and hence lower 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 IOp levels in permanent incomes are much higher in the US, i.e. the rags-to-riches story is less common than usually thought, as it has been shown that IOp is generally higher at the tails (Aaberge et al. (2011)).

Gross vs. net incomes We have seen that there is basically no difference between the IOp shares between gross and net earnings in both countries. This does not imply that policy does not matter – in contrast, the IOp levels are considerably lower in both countries. However, the results indicate that there is no differential effect of the tax benefit system in our sample. This is not surprising for two reasons. First, tagging, i.e. the use of exogenous circumstance information 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 population between 25-55. These individually usually pay taxes but receive little benefits in both countries. Implicit tagging, i.e. designing rules and conditions such that individual 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, tagging on circumstances has to be increased (Ooghe and Peichl (2010)).

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.[23] 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. 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.

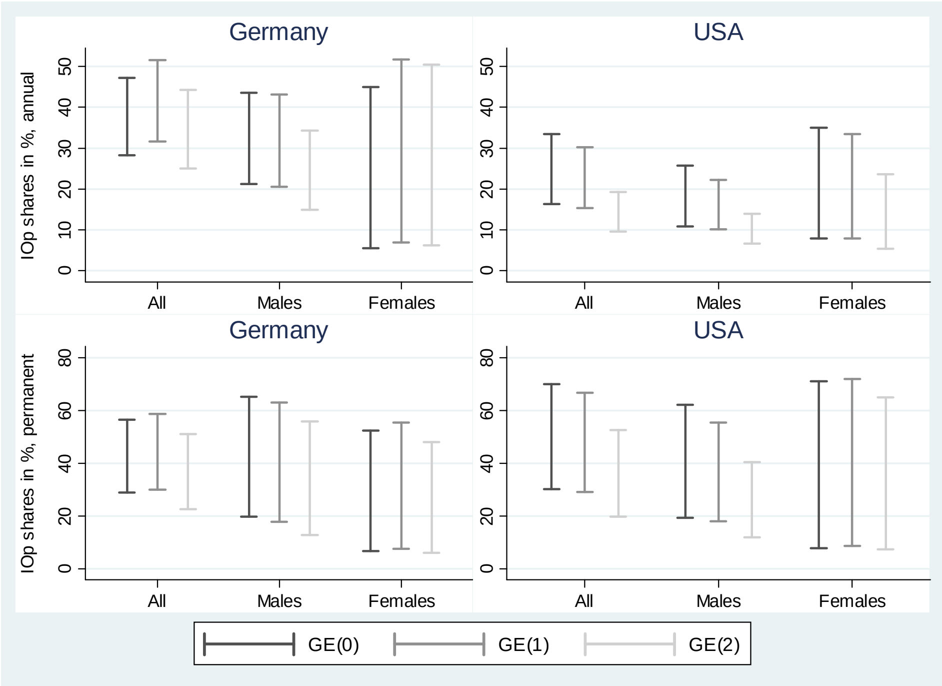
5.2 Robustness checks

Different inequality measures Although the other measures from the GE family violate the path-independent decomposability axiom, it is still insightful to see that the results are not driven by the choice of MLD which can be seen in Figure 3. For both, Germany and the US, the resulting lower and upper bound IOp shares of the MLD compared to the Theil (1) index (GE(1)) are very similar. With respect to the half squared coefficient of variation (GE(2)), which is particularly sensitive to changes at the top of the income distribution, we do observe some differences. Using this inequality measure generally leads to lower IOp shares in all samples. The differences are more pronounced in the US than in Germany, and the range of IOp shares particularly decreases in the case of annual incomes.

Different samples In order to further check the sensitivity of our results, we examine different samples. The results are illustrated in Table 1. First, we restrict

[23] 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. However, we can also observe labor supply effects at the intensive margin which then lead to different individual earning outcomes for married couples.

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 (2009 for Germany, 2007 for the US); the graphs at the bottom IOp shares in permanent incomes.

our sample to full-time employed individuals. For Germany, this leads to a decrease of the lower bound share of IOp of almost ten percentage points. This substantial decrease may be explained by the less explanatory power of the gender dummy when only looking at full-time employed individuals. The upper bound increases, on the other hand. For the US, the results remain fairly similar to those in the baseline sample. Thus, the qualitative differences between Germany and the US remain. Note, however, that the sample size are substantially smaller than in the baseline estimations. When we restrict our sample to prime-aged 30-45 aged individuals, the results are very similar as those in the baseline estimations, except for the US where we find a substantial increase in the upper bound IOp share.

In our baseline estimations we derive the unit-effect based on observations from unbalanced panels. Thus, we also run estimations which we base on balanced panels over a time period of ten years. The results for the most current balanced panel are very similar as our baseline results. For Germany, however, we find a considerable

Table 1: Sensitivity analysis

	Germany						US					
	Annual			Permanent			Annual			Permanent		
	N	LB	UB	N	LB	UB	N	LB	UB	N	LB	UB
Baseline	3,410	28.2	47.3	7,632	29.0	56.6	1,293	16.3	33.5	7,081	30.2	70.0
Full-time employed only	1,894	19.1	67.9	5034	21.8	72.7	590	15.4	32.9	4,539	26.7	55.5
Age range 30-45 only	1,364	29.5	56.7	4,767	35.0	71.5	375	22.3	46.3	5,199	30.1	79.7
Balanced-panel 10 years												
2008-1999 (2005-1992)	1,327	27.3	63.6	1,503	31.1	78.6	859	19.1	44.6	1,498	40.2	76.0
1998-1989 (1991-1982)	841	33.1	43.8	889	38.9	60.0	1,704	20.1	52.9	2,427	33.5	86.7
Missing values circumstance variables												
Without father's occ.	3,856	26.0	48.5	9,296	28.9	55.1	1,475	14.8	31.3	8,026	28.1	69.2
Without father's occ., region, ethnicity, urbanity	4,091	23.9	45.8	9,801	26.0	52.3	1,634	14.2	32.1	8,938	24.8	68.4
Only gender, birth, height	4,633	20.6	45.2	11,273	22.8	52.1	1,741	9.7	32.2	9,850	18.4	67.1

Source: Own calculations based on SOEP and PSID. N illustrates the underlying number of observations, LB (UB) the lower (upper) bound IOp share. Year intervals without (with) brackets indicate time periods for Germany (the US). All robustness checks rely on log gross earnings as dependent variables.

decrease of the upper bound for the previous time period, whereas in the US the upper bound share is larger when looking at the earlier time period.

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.

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, our approach of estimating an upper bound 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. Hence, we modify equation (13) in the following way in order to separate the effect of observed effort variables and unobserved factors:

$$\ln(w_{is}) = \psi \hat{c}_i + \beta E_{is} + \upsilon_{is} \tag{15}$$

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

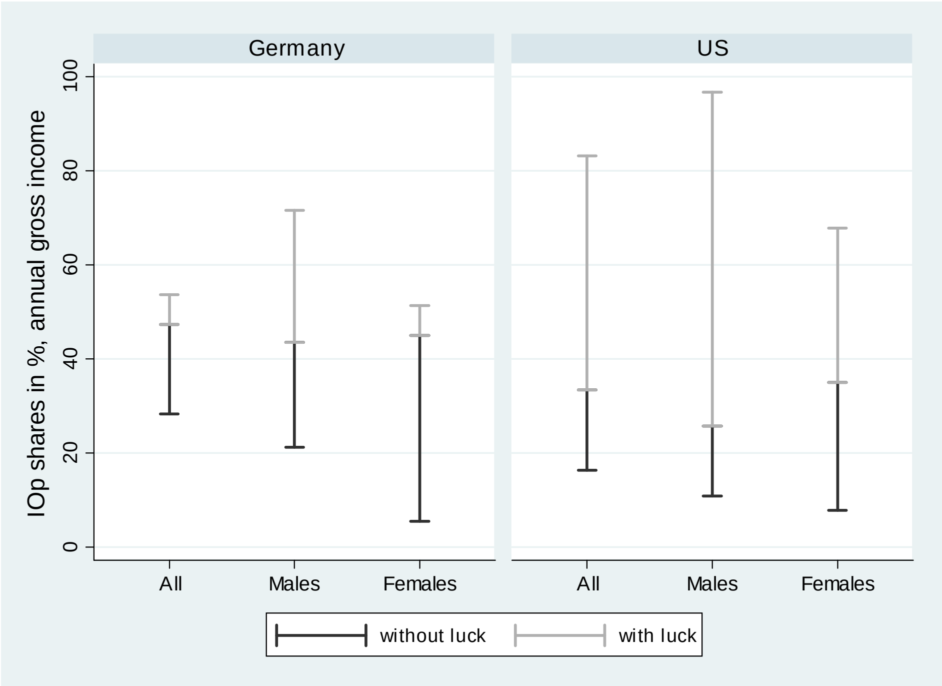
$$\widetilde{\mu}^{UB,L} = \exp[\widehat{\psi} \hat{c}_i + \widehat{\upsilon}_{is} + \sigma^2/2] \tag{16}$$

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 bar line shows the range between the lower and upper bound as previously defined, whereas the upper, lighter grey line shows the difference to the upper bound when additionally accounting for luck.

When accounting for luck, the upper bound does not change much in the German data for the full sample and the female subsample. The change is higher for the male subsample as well as in the US data for all samples. These results point towards a higher 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 IOp shares 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.

Figure 4: Upper and lower bounds of IOp when accounting for luck



Source: Own calculations based on SOEP and PSID.

6 Conclusion

The existing literature on EOp provides only lower bound estimates of IOp. We suggest a two-stage estimator based on a fixed effects model to tackle this issue. The maximum amount of circumstances which an individual should not be held responsible is the person's fixed effect, as by definition, it comprises all exogenous circumstances as well as some not changing 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 micro-level panel data for Germany and the US in order to empirically illustrate our new estimator and to compare it to the well-known lower bound.

The IOp levels are rather similar between Germany and the US in terms of the lower and upper bounds for annual incomes and the lower bound for permanent incomes. For the latter, the upper bound levels are higher in the US than in Germany. The IOp shares are higher for Germany (30-50%) than for the US (16-35%) for annual incomes which is due to lower absolute levels of outcome inequality while having similar values of IOp. This result might help to explain why attitudes towards inequality and redistribution differ substantially between both countries (Figure 5 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. However, when moving to a measure of permanent income, we find larger (lower and upper bound) IOp shares for the US, which increase to 30% and 70% 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 (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.

To sum up, we find significant and robust differences between lower and upper bound estimates for both countries for all specifications. At a first sight, the high IOp shares for the upper bound 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 the intelligence quotient (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 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.

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 increase IOp. It would be interesting to analyze the effect of tax systems that are based on exogenous characteristics (Ooghe and Peichl (2010)) on IOp in future research.

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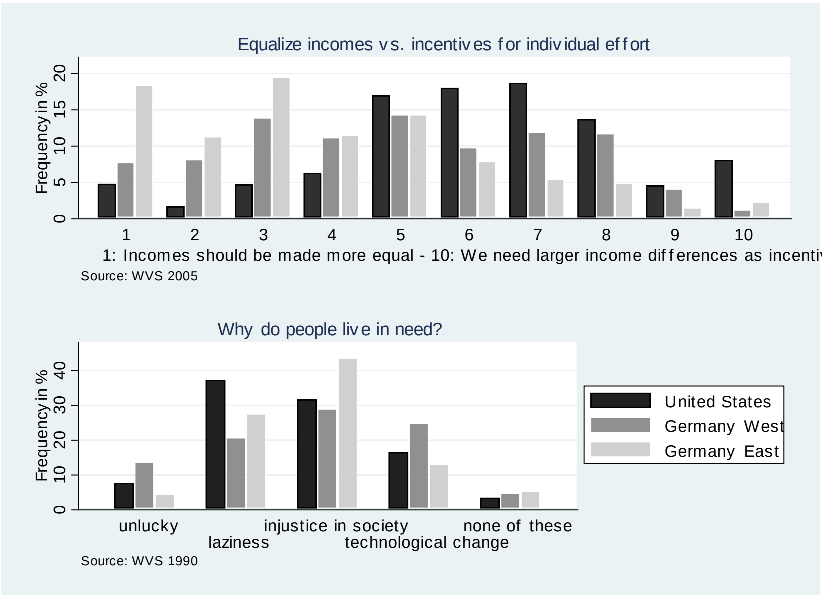
Appendix

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 $												
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
Lower-secondary	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
Worker	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						
Countryside	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	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	3410.00	1795.00	1615.00	7632.00	4009.00	3623.00	1293.00	712.00	581.00	7081.00	3840.00	3241.00

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 $												
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	16.52	18.07	14.61	16.42	17.99	14.50	10.61	10.22	11.08	10.69	10.32	11.15
Public	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	78137.00	43261.00	34876.00	82673.00	45569.00	37104.00	82859.00	45567.00	37292.00	85827.00	47347.00	38480.00

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	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 net	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)
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	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 net	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)
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	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 net	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)
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	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 net	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)

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

	Germany						USA					
VARIABLES	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)		
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)
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***
	(0.072)	(0.080)	(0.120)	(0.050)	(0.052)	(0.088)	(0.196)	(0.292)	(0.259)	(0.030)	(0.041)	(0.044)
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)
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*
	(0.074)	(0.075)	(0.138)	(0.040)	(0.041)	(0.073)	(0.113)	(0.146)	(0.180)	(0.027)	(0.033)	(0.043)
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)						
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***
	(0.028)	(0.030)	(0.049)	(0.017)	(0.018)	(0.028)	(0.081)	(0.098)	(0.142)	(0.023)	(0.028)	(0.037)
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)
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)
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
	(0.014)	(0.016)	(0.025)	(0.014)	(0.016)	(0.024)	(0.017)	(0.021)	(0.031)	(0.017)	(0.021)	(0.031)
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