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ORIGINAL PAPER

Gender and inequality of opportunity in Sweden

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Abstract This paper considers the role of gender in generating inequality of opportunity. Using data on long-run income for Swedish men and women, we explore to what extent income inequality is due to circumstances beyond individuals' control, such as gender and parental income, rather than to differences in individuals' choices. The key idea is that a society has achieved equality of opportunity if there is no income inequality that is due to circumstances. Analyzing men and women separately, we find that circumstances account for up to 31% of income inequality among men and up to 25% among women. We conclude that there is greater equality of opportunity among women than among men. When we analyze men and women together, treating gender as a circumstance, at most 38% of income inequality can be attributed to circumstances. Gender accounts for up to 13% of income inequality, making gender the single most important circumstance in accounting for inequality in long-run income in Sweden.

1 Introduction

Economic inequality is of substantial academic and public-policy interest. There are many conceptual approaches to its empirical measurement. Although the economics

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literature has traditionally focused on inequality of *outcomes*, in recent years there has been an upsurge of interest in inequality of *opportunity* (see, for example, Almås et al. 2011; Björklund et al. 2012; Checchi and Peragine 2010; Ferreira and Gignoux 2011). The equality of opportunity literature leans on the idea that individual outcomes depend in part on individual effort and in part on circumstances that are beyond an individual's control, such as parental income and childhood standard of living. The core argument is that inequalities due to effort differences are ethically defensible, while those due to differences in circumstances are not. Thus, a society is said to have achieved equality of opportunity if circumstances have no influence on outcomes.

A fast-growing empirical literature measures inequality of opportunity by estimating the share of outcome inequality that can be attributed to circumstances.[1] One circumstance that could be seen as a natural starting point – gender – has largely been ignored, although admittedly there is some debate in the conceptual literature as to whether it should be viewed as such (see Roemer and Trannoy 2015). The purpose of this paper is to address this gap in the empirical research by analyzing equality of opportunity in long-run income for Swedish men and women. Analyzing men and women separately, we examine if there are gender differences in inequality of opportunity and in the role of particular circumstances. Next we pool men and women and treat gender as a circumstance, allowing us both to assess inequality of opportunity in the overall population and to compare the importance of gender to that of other circumstances, such as parental income and parental education.

More insight into the extent to which income inequality can be attributed to unequal opportunities, and identifying the relative contribution of different circumstances, is informative for policymakers concerned with equality of opportunity. Sweden provides an interesting case for the analysis of equality of opportunity and gender, as the Swedish labour market is characterized by low levels of income inequality (Gottschalk and Smeeding 1997; Björklund and Freeman 1997) as well as by a low gender pay gap relative to other countries (Blau and Kahn 2003).[2]

Our paper extends the work of Björklund et al. (2012), who estimate inequality of opportunity in long-run income for Swedish men using the most comprehensive set of circumstances so far in the literature. As circumstances, they include parental long-run income, parental education, family structure, IQ and body mass index. They find that about one third of the inequality in long-run income among Swedish men can be attributed to these circumstances, and that the most important circumstances are parental income and own IQ. While using the same empirical approach and to some extent the same data, our paper differs from theirs primarily in that we study both men and women, allowing us to analyze gender differences in inequality of opportunity and to include gender among the circumstances. In addition, we include non-cognitive ability in the vector of circumstances (but exclude body mass index from our analysis as it turned out to be of minor importance among men).

[1] A wide variety of approaches have been proposed to measure inequality of opportunity. See Ramos and Van de gaer (2016), Ferreira and Peragine (2016), Roemer and Trannoy (2015) and Roemer and Trannoy (2016) for excellent reviews.

[2] Although the average gender pay gap is relatively low in Sweden, the gender gap increases at the top of the income distribution indicating the existence of a glass ceiling for women (Albrecht et al. 2003).

Our data on IQ and non-cognitive ability stem from the military enlistment tests. Because these tests were mandatory and therefore widely available only for men, we approximate women's IQ and non-cognitive ability by those of their brothers. Our dataset contains about 370,000 Swedish men and women born between 1952 and 1964. We examine the inequality of total market pretax income averaged over seven years (ages 37–43 in the main analysis).

Like Björklund et al. (2012), we measure inequality using four inequality indices (the Gini and the GE family using parameter values 0, 1, and 2), measure the contribution of each circumstance using a Shapley-value decomposition, and allow for circumstances to contribute to inequality both directly (by shifting expected income) and indirectly (by shifting income dispersion), as the distribution of income for given circumstances may vary.

We find that opportunities are slightly more equal among women than among men, as circumstances account for up to 25% of income inequality among women and up to 31% of income inequality among men, but that the same circumstances—parental income, IQ, non-cognitive ability and differences in the distribution of effort—are roughly equally important determinants of inequality. Pooling men and women and treating gender as a circumstance, circumstances account for at most 38% of income inequality, so roughly two fifths of inequality in long-run income in Sweden can be attributed to inequality of opportunity. Gender accounts for the largest share, up to 13% of overall inequality, or almost a third of overall inequality of opportunity.

The rest of the paper is structured as follows. In Sect. 2, we provide a literature review. In Sect. 3 we present the method and in Sect. 4 we describe the data. Section 5 reports the results. Finally, in Sect. 6, we summarize our findings and provide a concluding discussion.

2 Literature review

In this section, we selectively review equality of opportunity research with a focus on gender. We then turn to discussing how our approach differs from that typically taken in studies of gender differences in labour market outcomes.

Equality of opportunity literature

Research on empirical equality of opportunity is rapidly expanding and also varies along several dimensions, including the definition of equality of opportunity, the set of circumstances examined and the estimation method employed.[3] One feature that many of the papers share, however, is that they rarely consider gender. The importance of gender in comparison to other circumstances, such as parental income and education, is largely unknown. There is also limited evidence on gender differences in inequality of opportunity as well as on the relative importance of different circumstances.

Most papers only study men, but we provide here an overview of empirical research on equality of opportunity that includes both men and women. We limit the review to

[3] See Ramos and Van de gaer (2016) for a comprehensive review of the literature and Fleurbaey and Peragine (2013) for a discussion of the distinction between *ex ante* and *ex post* equality of opportunity.

papers that study inequality of opportunity in income. We start by summarizing four studies that include gender as a circumstance.[4]

Niehues and Peichl (2014) examine inequality of opportunity in Germany and the US, using as outcomes gross as well as net earnings, measured both annually and in the long-run. Measuring inequality using the mean log deviation, they estimate lower bounds on inequality of opportunity including as circumstances gender, height at birth, year of birth, indicators for whether the individual was born in a foreign country, born in East Germany (Germany), or born in the South (US), race (US), degree of urbanization of the place where the individual was born, father's occupation and father's education. They rely on kinship information to estimate upper bounds which obviates the need to specify the circumstances. However, they do not report the importance of gender in comparison to the other circumstances included in the analysis.

In addition to including gender as a circumstance, Niehues and Peichl (2014) also conduct separate analyses for men and women and, while they do not comment on gender differences, their results (in Table 4) allow us to assess this. For both countries, most lower bound estimates of inequality of opportunity are higher for men than for women, while there seems to be a gender difference in the opposite direction for the upper bound estimates. They do point out that when men and women are analyzed separately, inequality of opportunity is lower than when the samples are pooled and gender is treated as a circumstance. They argue that gender is an important driving force of inequality of opportunity and that the main reason for this is that women work fewer hours than men.

Peichl and Ungerer (2016) explore how inequality of opportunity varies when circumstances are expanded to include characteristics of their partners. The standard in the literature is that partners' characteristics are not regarded as circumstances, but, examining the same inequality measure, outcomes, and individual circumstances as Niehues and Peichl (2014), they also include some of the individuals' spouse's characteristics to again explore lower bounds of inequality of opprtunity. They do not report how important gender is relative to the other circumstances but they do provide separate analyses of inequality of opportunity by gender. In line with the results in Niehues and Peichl (2014), they find that inequality of opportunity is generally higher for men than for women. When a partner's characteristics are treated as circumstances, inequality of opportunity increases more for women than for men, decreasing the gender difference in inequality of opportunity.

Ferreira and Gignoux (2011), in turn, examine inequality of opportunity in Brazil, Colombia, Ecuador, Guatemala, Panama and Peru. Using household income and consumption expenditures per capita as well as individual labour earnings, they develop a scalar measure based on the mean log deviation. Their circumstance vector includes ethnicity, father's occupation, father's education, mother's education and birth region. When examining individual labour earnings, gender is also included in the set of circumstances. They then find that gender accounts for between 0.2% (Colombia) and 5.8% (Guatemala) of inequality, suggesting that gender is much less important than

[4] Almås et al. (2011), Devooght (2008), Almås (2008) and Checchi et al. (2010) also include gender as a circumstance, but they do not report to what extent gender accounts for inequality of opportunity. Therefore, we do not include these papers in this review.

other circumstances, such as parental education and father's occupation. To put the importance of gender into perspective, it can be compared to that of mother's education, which accounts for between 9.4 (Panama) and 11.9% (Brazil) of total inequality in individual labour earnings. It is not possible to draw any conclusions about whether there are any gender differences in the relative importance of circumstances from the results they present. A related study, de Barros et al. (2009) also includes Mexican data and find that gender accounts for 3–4% of inequality in individual labour earnings. In comparison to the importance of the other circumstances, gender plays a small role. The Mexican results on gender are thus in line with the results from the other Latin American countries.[5]

Having summarized the papers that include gender among the circumstances, we now proceed to the papers that investigate equality of opportunity separately for men and women. Studying Italy using the mean log deviation of gross earnings and parental education as the sole circumstance, Checchi and Peragine (2010) find that between 15 and 20% of income inequality in the overall population can be attributed to inequality of opportunity, depending on its definition.[6] They do not comment on gender differences in inequality of opportunity but results reported in their Tables 4 and 5 suggest that parental education accounts for a larger share of income inequality for men than for women although it is unclear whether this gender difference is statistically significant (standard errors are not provided).

Bourguignon et al. (2003) analyze inequality of opportunity in Brazil in both individual earnings and household per capita income. Measuring circumstances by parental education, father's occupation, race and region of origin, they find inequality of opportunity to be high in Brazil (compared to other countries), measured by both the Gini coefficient and the Theil index, and that parental education is the most important circumstance. They also find that, when circumstances are equalized, the Gini coefficient for individual earnings decreases by 8–10% points for both men and women. They do not comment on whether there is a gender difference in the shares of total earnings inequality that can be attributed to inequality of opportunity (and it is difficult to draw any conclusions about this from the graphs presenting the results).

Finally, Nilsson (2005) analyzes inequality of opportunity in Sweden. Unlike the above papers, Nilsson (2005) does not explicitly examine the share of inequality of opportunity in conventional income inequality measures. Instead, he regresses labour income and disposable income on circumstances, which include a wide range of parental, family and parish characteristics. Since the circumstances are associated with income, he concludes that Sweden has not achieved equality of opportunity. He also estimates conditional indirect opportunity sets showing that men whose parents belong to the 25th percentile in the income distribution must exert more effort to reach the average income than men whose parents belong to the 75th percentile. For women,

[5] This is a book chapter that is based on Ferreira and Gignoux (2008), which in turn is the working paper version of Ferreira and Gignoux (2011). In contrast to Ferreira and Gignoux (2008), Ferreira and Gignoux (2011) and de Barros et al. (2009) include Mexico in the analysis. Since the results for the other countries have been summarized above, we now only focus on Mexico.

[6] When they pool the male and female samples they still measure circumstances only by parental education. Thus, no conclusion regarding the role of gender as a circumstance can be drawn from this analysis.

the difference depending on parents' income percentile is not statistically significant. These findings may thus suggest that women have more equal opportunities than men.

To summarize, we contribute to the existing literature on equality of opportunity in income by (1) including both men and women, (2) analyzing men and women separately, and (3) exploring the importance of gender, relative to other circumstances, in generating income inequality.

Gender differences in labour market outcomes

Above, we discuss papers on (in)equality of opportunity that address gender, either including it as a circumstance or by analyses separately for men and women. Here, we discuss how our paper relates to research on gender differences in labour market outcomes (see e.g. Altonji and Blank 1999). Our approach to measuring the importance of gender in the labour market differs from the approaches typically taken in this literature in two main ways.

First, an individual's counterfactual income is defined differently. In typical studies of gender income gaps, female mean income is compared to that of men, so the female counterfactual mean is the male mean ("income" can mean hourly or annual wages or earnings as well as other concepts). In research that explores the extent to which gender income gaps can be attributed to discrimination, the female counterfactual income is typically taken to be that of a man with the same income-generating characteristics. By contrast, we define the counterfactual income of a woman as the income she would have, conditional on her other circumstances, if the gender difference in income was zero.

Second, our approach to aggregating individual incomes is different. Most papers on gender differences focus on the average difference between an counterfactual and actual incomes. Jenkins (1994) points out that one drawback of this is that it is consistent with very different income distributions. Differences across the male and female distributions can and have been studied e.g. using conditional quantile regressions. This has for instance been done to examine if there is a "glass ceiling" in the labour market (e.g. Albrecht et al. 2003; Arulampalam et al. 2007). We go one step further and investigate to what extent inequality can be attributed to inequality of opportunity and thus account for differences across the whole distribution.[7]

3 Methods

We now turn to our methods. We start by describing the conceptual framework, including the regression-based approach we take, followed by a description of our decomposition method. Finally, we outline the consequences of using proxy measures for IQ and non-cognitive ability.

[7] Although we aggregate distributions using scalar indices, our approach could be expanded to examine, say, quantile group shares.

Conceptual framework and regression specifications

Our approach is based on Keane and Roemer (2009), Betts and Roemer (2007), Lee (2008) and Björklund et al. (2012). We are interested in what fraction of inequality of long-run income, Y with distribution F_Y, can be attributable to *circumstances* and *effort*, respectively. Inequality of long-run income is measured using four relative inequality indices namely the Gini coefficient (Gini), the mean log deviation (GE[0]), the Theil index (GE[1]), and one half of the squared coefficient of variation (2× GE[2], CV^2). As is well known, the indices vary by their sensivity to income differences in the middle (Gini), lower tail (GE[0] and GE[1]), and upper tail (CV^2) (Jenkins and Van Kerm 2009).

Circumstances are captured by partitioning the population (and sample) into discrete *types*, indexed by t, one for each unique set of circumstances. The key idea is that an individual should not be held accountable for income differences due to type.

Denote each of the J circumstances by X_j, which can take K_j specific values. The types t are elements of the set $\mathcal{T}$, each element of which consists of a particular combination of circumstances $\mathbf{X}^t = (X_1 = x_1^t, X_2 = x_2^t, X_3 = x_3^t, \ldots, X_J = x_J^t)$, so a sample individual i of type t has $\mathbf{X}_i^t$. The effort of an individual of a certain type is defined here as the deviation of the individual's actual income Y_i^t from her expected income, given type, $\mathrm{E}[Y|\mathbf{X}^t]$, defined through the regression

$$\ln Y_i^t = \mu + \sum_{j=1}^{J} \mathbf{X}'_{ji}\boldsymbol{\beta}_j + \varepsilon_i^t. \tag{1}$$

Circumstances are included in the regression as a set of indicators, so with J circumstances, each with K_j categories, $\sum_j K_j - J$ is the total number of indicators in the regression equation. We measure an individual's effort by the residual from estimating this regression.[8]

One issue with this approach is that the distribution of the regression error may vary across types, i.e., the distribution of effort may be heterogeneous across types. Each type is characterized by an expected income $\mathrm{E}[\ln Y|\mathbf{X}^t]$, but may in addition be characterized by a distribution of effort ε^t, F_ε^t. Recall that the key idea is that an individual should not be held responsible for income differences attributable to type. As the type-specific *distribution* of effort is a consequence of circumstances, individuals should not be held accountable for differences due to circumstance-related differences in the *distribution* of effort. Thus, we need to adjust also for differences in type-specific heteogeneity.

We follow Björklund et al. (2012) and treat the error in Eq. 1 as being heteroscedastic, so each type t has its own variance $\sigma_t^2 = \mathrm{Var}[\varepsilon^t|\mathbf{X}^t]$. In order to capture the importance of that heterogeneity, we add and subtract a term that has a homogeneous variance. The most natural candidate for standardizing the distribution of effort across types is to choose the overall variance, which, since the expectation of the error is

[8] We regress the natural logarithm of long-run income rather than its level on $\mathbf{X}$ as this is conventional in earnings regressions. Results using the level rather than the natural logarithm are similar to those we report here.

zero in all groups, is given by the weighted average of the variance within types as $\sigma^2 = \sum_t f_t \sigma_t^2$, where f_t is the population share of type t. This allows us to distinguish between one error term, $\widetilde{\varepsilon}_i^t = \varepsilon_i^t - u_i$, whose variance $\widetilde{\sigma}_t^2$ varies across types and is treated as a circumstance, and one, u_i, whose variance σ^2 is constant and is treated as effort, leading to the regression equation

$$\begin{aligned}\ln Y_i^t &= \mu + \sum_{j=1}^{J} \mathbf{X}'_{ji}\boldsymbol{\beta}_j + \varepsilon_i^t \\ &= \mu + \sum_{j=1}^{J} \mathbf{X}'_{ji}\boldsymbol{\beta}_j + \varepsilon_i^t - \underbrace{\varepsilon_i^t \sigma/\sigma_t}_{u_i} + \underbrace{\varepsilon_i^t \sigma/\sigma_t}_{u_i} \\ &= \mu + \sum_{j=1}^{J} \mathbf{X}'_{ji}\boldsymbol{\beta}_j + \widetilde{\varepsilon}_i^t + u_i.\end{aligned} \tag{2}$$

To implement this, we first estimate all β coefficients and then, based on the OLS residuals, the type-specific variances σ_t^2. In practice, however, some types have very few observations or very small estimated variances, leading to very large standardized residuals $\hat{u}_i$. For this reason, we regress the estimated variances on the background characteristics, and use the fitted values from that regression as the basis for $\varepsilon_i^t \sigma/\sigma_t$. This procedure smooths out the more extreme values.

Empirical decomposition of inequality

We now turn to the decomposition of income inequality. With J circumstances, type-specific effort and individual effort, we have $J + 2$ factors whose impact on inequality we want to measure. The importance of a factor is measured by comparing the inequality of long-run income when the factor is "on"—i.e., the factor is allowed to vary as it does in the population—to when it is "off"—i.e., variation due to the factor is eliminated by replacing for every observation its actual value with its mean value. For the circumstances, the mean value equals the average proportion in each category of the circumstance weighted by the corresponding coefficients.

Formally, from Eq. 1, a circumstance j contributes $\mathbf{X}'_{ji}\boldsymbol{\beta}_j$ to income. We compare inequality when we allow the circumstance to contribute $\mathbf{X}'_{ji}\widehat{\boldsymbol{\beta}}_j$ to the income of individual i (providing the actual variation in the circumstance j to income) with one in which we have replaced that by $\overline{\mathbf{X}}'_j\widehat{\boldsymbol{\beta}}_j$, thus eliminating variation across individuals from that circumstance.

The contribution of a factor to inequality may depend on what other factors vary (are "on"). That is, the contribution depends on the order in which we eliminate factors. We take this into account by estimating the contribution of a factor by its average contribution across all possible elimination sequences, a procedure that is called Shapley-value decomposition (Shorrocks 2013; Chantreuil and Trannoy 2013).

To do this, we first generate the powerset of the $J + 2$ factors. For each element in the powerset, we construct the income for each observation counterfactually by allowing the factors included in the element to vary and eliminating the rest. That is, for each element in the powerset, we have a set of factors that we turn “on”, while we let the rest of the factors be “off”. For instance, the element {parental income, gender} dictates that we should let parental income and gender be “on”, and the rest of the factors be “off”. We then take the antilog of the counterfactual incomes calculated in this way and compute the inequality indices.

Then, for each of the factors, we take every element of the powerset that *does not* include it, and compare inequality in that set with the set that is otherwise identical but *does* include the factor. The importance of a factor is measured as the average of all such comparisons.[9] The Shapley-value decomposition approach has several benefits (see Shorrocks 2013; Chantreuil and Trannoy 2013). Among others, it results in an additive decomposition of inequality, that is, the sum of all contributions is the value of overall inequality.[10]

Our method is based on discrete types. In order to fit continuous circumstances into this framework, we divide them into groups. This approach ignores some within-type variation in circumstances and thus underestimates the importance of circumstances and overestimates the role of effort. However, one advantage of using types is that our underlying regression model has a quite flexible functional form. It is a challenging task for future research to develop the analysis of equality of opportunity to the case of continuous circumstances.[11]

Consequences of using brothers’ characteristics as proxies

The inclusion of women and treatment of gender as a cirumstance is a key difference between this paper and Björklund et al. (2012). As enlistment data is unavailable for women, we use their brothers’ IQ and non-cognitive ability as proxies for own IQ and non-cognitive ability. For symmetry, in our main specification, we measure IQ and non-cognitive ability of men also using the information of their brothers. The use of proxy measures has several consequences for our analysis.

First, we need to restrict our main analysis to only those individuals who have a brother who has taken the military enlistment test.[12] Second, we need to make a strong assumption, which is that a brother’s IQ and non-cognitive ability are equally good measures of his sister’s abilities as they are of his brother’s abilities. That is, we assume that the measurement error is similar for mixed and same-sex siblings. Bouchard and McGue (1981) suggest that brother–brother and brother–sister correlations in IQ are

[9] The algorithm is implemented in the statistical programming language **R** (Ihaka and Gentleman 1996) using a few standard libraries and is available from Markus Jäntti on request.

[10] We use the so-called mean-equalized Shapley-value decomposition, which can be contrasted with the zero-equalized decomposition. In our case, the latter would be implemented by not using the mean fraction of each category of a factor, but setting them all to zero, effectively making the omitted category the “default” value after elimination of a factor in generating the counterfactual income. See Sastre and Trannoy (2002) for a discussion and Sect. 5.2, footnote 18 for a comparison of the two approaches.

[11] See O’Neill et al. (2000) for an approach to do so in a different setting than ours.

[12] This restriction forces us to leave out singletons from our main analysis. The results here and in other research using Swedish data suggest this particular selection issue does not matter much. For instance, intergenerational income elasticities in Sweden vary very little with number of children, nor does family size appear important for other measures of the importance of family background (Lindahl 2010; Björklund et al. 2010; Björklund and Jäntti 2012).

very similar. In addition, using a large Swedish register dataset, Grönqvist et al. (2016) find that the brother–sister correlations in IQ and non-cognitive ability amount to 92 and 93% of the brother–brother correlations. These findings lend plausibility to the assumption that the measurement error is similar for mixed and same-sex siblings.

Third, our estimated regression coefficients will suffer from attenuation bias. We correct for this bias by comparing the coefficient estimates for men when using their own versus their brothers' characteristics and applying the difference between the two sets of estimates to each coefficient for women. We also correct for this bias when using brother proxies for men.

Finally, the Shapley-value decomposition can also be biased, for two distinct reasons. First, in the Shapley-value decomposition, the estimated regression coefficients suffer from attenuation bias. This source of bias we do correct for as described above. However, the Shapley-value decomposition will also biased because of classification errors. Recall that we divide our circumstances into groups. When using proxy measures, we classify some individuals into other IQ and non-cognitive ability groups than we would have based on their own characteristics. We do not adjust for this bias.

4 Data

Samples and source registers

We now proceed to describe the data we use. The data have been constructed by combining information from several Swedish administrative registers. A first and basic source is Statistics Sweden's so-called Multi-generational register. This is a register of all individuals who were born 1932 and onward, and who have ever received a unique national registration number from 1961 and onward.[13] For the Swedish population defined in this way, the register contains information about biological and adoptive parents along with their national registration number. Our analysis sample is based on a 35% random sample of the Swedish population born 1952–1964 as defined in this register. The multi-generational register is used to identify parents and siblings.

The second source is the set of quinquennial censuses conducted from 1960 to 1980. We identify our main sample children in the households of these censuses as well as other individuals in the household. Thus, we can determine whether the individuals in the child generation lived with their biological parents in the census years.

The third source is Statistics Sweden's income register, which in turn comes from the Swedish tax assessment procedure. Such data are available starting in 1968. The income register provides data on total income from all sources of income—from work, self employment, capital, real estate—and from 1974 onward, some transfers. These incomes are used for both parents and children. The parents' data stem from their self-reported compulsory tax assessments. The childrens' data stem in part from compulsory reports by employers to the tax authorities.

[13] The requirement that the individuals must have been registered in Sweden from 1961 and onward implies that individuals who died between 1932 and 1960 are not included. For our purposes, however, this is not a problem since we want to observe outcomes in the 1990s and 2000s.

The fourth source is the Swedish Military Enlistment Battery, which provides data on cognitive (IQ) and non-cognitive ability. For the cohorts we examine, military service was mandatory only for men. Thus, enlistment data are unavailable for women.[14] The purpose of these tests is to classify Swedish men to different military positions with different demands on general intellectual and non-cognitive capacity. Generally, the tests were done during the year the men turned 18. In our main specification, we measure IQ and non-cognitive ability of both men and women using the information of their brothers.

To construct our analysis sample, we make use of the fact that all four data sources contain the unique Swedish national registration number, by means of which we can merge the information from the four sources.

Variables

Our outcome variable is total market income before taxes as provided by Statistics Sweden. It includes income from all sources, that is, labour, business, capital, realized capital gains as well as some taxable social transfers such as unemployment insurance, sickness pay, parental leave payment, and pensions. We use the average of real total income over the years when sons and daughters were 37–43 years old. This age interval is based on the findings in Böhlmark and Lindquist (2006), who study life-cycle variations in the associations between current and lifetime income for Swedish men and women. Böhlmark and Lindquist (2006) show that life-cycle bias is a more serious problem for women than for men, because there is greater heterogeneity in women's labour supply and income profiles over the life-cycle. For the cohorts born closest to ours—born 1948–1950—they find that measuring women's incomes around the age of 40 provides the best available estimate of their long-run income. Therefore, we center our age interval at 40. Further, the results in Böhlmark and Lindquist (2006) suggest that averaging over an appropriately chosen age interval eliminates much of transitory income variation while also eliminating much of the life-cycle bias. While the result is not necessarily a good measure of permanent income, it is as far as we an tell, the best available. Following earlier research in Sweden using a similar approach, we call this long-run income. In Sect. 5.3, we test the robustness of our results to measuring income at ages other than 37–43.

Next, we turn to our background characteristics, the *circumstances* that define our types (when characteristics are continuous, we divide them into groups). Apart from gender, we have six circumstances, namely

1. Parental income (4 groups).
2. Parental education (3 groups).
3. Family structure (2 groups).
4. Number of siblings (3 groups).
5. IQ (4 groups).
6. Non-cognitive ability (4 groups).

[14] A very small number of women enlisted voluntarily, but since this is a very selected and tiny sample, we do not use their enlistment data.

the combination of which gives us 1152 distinct types or, when combined with gender, 2304 distinct types.

For *parental income* we use the same income concept as for children. We use the multi-year average of the sum of the two biological parents' incomes in the years the child was 13–17. We treat an income observation of SEK 100 or lower (in 2005 prices) as missing, so the over-time average is only taken for non-zero income. We split the measure of parental income into four quartile groups of equal size, where one denotes the lowest and four the highest parental income group.

We measure *parental education* by the educational level, as measured by the census, of the biological parent who has the highest educational level. This level we split into three groups: only compulsory school (group 1), more than compulsory school but no college (group 2), and at least some college (group 3).

We also use the censuses to construct a *family structure* indicator. This is equal to one if the child lived with both biological parents during its first three censuses in life. For example, for the cohort born in 1955 this implies that we require that the child lived with both biological parents in the 1960, 1965, and 1970 censuses. If this condition is not fulfilled, the indicator takes on the value zero.

We use data from the Multi-generational register to compute the *number of full biological siblings*. We split the observations into three groups: 0 siblings, 1–2 siblings and 3 or more siblings.

IQ is measured by the summary measure of intellectual ability provided in the enlistment data, which is based on four different cognitive tests: instructions, synonyms, metal folding and technical comprehension. The subtests are designed to measure the primary IQ factors induction, verbal comprehension, spatial ability and technical comprehension.[15] We split the summary measure of intellectual ability into four quartile groups.

Non-cognitive ability is measured based on a structured interview during military enlistment, which was mandatory for Swedish men aged 18–20. The approximately 25-min interviews are conducted by a psychologist charged with rating an individual's suitability for military service. The conscript's overall suitability for military service is given a score from 1 to 9. The psychologist determines the score based on a number of specific characteristics such as level of responsibility, independence, outgoing character, persistence, emotional stability, power of initiation and social skills (Lindqvist and Vestman 2011). We split the measure of non-cognitive ability into four quartile groups.

It is important to note that we treat non-cognitive ability and IQ as circumstances since we do not hold individuals responsible for their actions (including their effort) before the age of 18. As Björklund et al. (2012) point out, to classify IQ as a circumstance is potentially controversial, because these IQ test scores can depend on earlier educational choices and performance, which in turn may depend on individual effort. A similar reasoning may apply to non-cognitive ability. Ultimately, what counts as circumstances is a matter for the social planner. In Sect. 5.3, we check the

[15] Mårdberg and Carlstedt (1998) and Carlstedt (2000) provide more information on the cognitive tests we use. See also Björklund et al. (2010) for additional information.

robustness of our results by excluding IQ and non-cognitive ability from the vector of circumstances.

The variable definitions imply that we need to make some sample restrictions. We focus on individuals born in Sweden as there is limited information on the parents of foreign-born inhabitants and only include individuals for whom both the biological mother and biological father are non-missing in the Multigenerational register. Furthermore, we limit our main analysis samples to individuals who have at least one brother with non-missing information on both IQ and non-cognitive ability. Thus, we eliminate singletons from our main analysis samples. In case an individual has more than one brother, we take the average across all brothers as the measures of IQ and non-cognitive ability.

As mentioned in Sect. 3, find that the brother-brother correlation in IQ and non-cognitive ability is slightly higher than the brother–sister correlation. While, by contrast, Bouchard and McGue (1981) find no such difference in brother-brother and brother-sister correlations, this would suggest greater measurement errors for women than for men. On the other hand, conditional on having a brother, women have, on average, more brothers than men. This difference will make the proxy measures more precise for women than for men as we average across more brothers for women than for men. It is not clear which of these effects dominates.

Descriptive statistics

In Table 1 we show some descriptive statistics for our main analysis sample. This sample contains more than 180,000 women and more than 180,000 men with a total sample of about 370,000 individuals roughly but not quite uniformly distributed across birth years 1952–1964; the share tends to increase toward later years indicating increased cohorts sizes.

In the offspring generation, the average income of men is about SEK 100,000 higher than that of women but with a substantially higher dispersion—a Gini of 0.30 as opposed to 0.24 for women. In the parental generation, the difference between men's and women's income is larger; the average income of fathers is more than SEK 150,000 higher than that of mothers. Moreover, in the parental generation, the income dispersion is smaller for fathers than for mothers. The Gini is 0.29 for fathers and 0.44 for mothers. In the first rows of Table 1, we show the share of fathers and mothers in each education group. On average, fathers have slightly higher education than mothers. Looking across the columns, we see that parental income and education are roughly equal for men and women, as we would expect them to be.

5 Results

We begin this section by showing results first for men only, comparing results using own IQ and non-cognitive ability to those obtained using their brothers' characteristics as proxies for their own. This is followed by our main analysis. In order to investigate whether there are gender differences in the level and structure of inequality of opportunity, we start by analyzing men and women separately, measuring in both cases IQ and non-cognitive ability by those of their brothers. Next we pool men and women

Table 1 Descriptive statistics

Born in	Female	Male	All
1952	5.5e+00	5.5e+00	5.5e+00
1953	6.1e+00	6.1e+00	6.1e+00
1954	6.5e+00	6.4e+00	6.5e+00
1955	7.2e+00	7.2e+00	7.2e+00
1956	7.6e+00	7.6e+00	7.6e+00
1957	7.8e+00	7.8e+00	7.8e+00
1958	8.1e+00	8.2e+00	8.1e+00
1959	8.5e+00	8.5e+00	8.5e+00
1960	8.7e+00	8.5e+00	8.6e+00
1961	8.6e+00	8.6e+00	8.6e+00
1962	8.4e+00	8.4e+00	8.4e+00
1963	8.4e+00	8.5e+00	8.4e+00
1964	8.7e+00	8.6e+00	8.7e+00
N	1.8e+05	1.9e+05	3.8e+05

	Female	Male	All
Education level, mother			
Only compulsory	62.7	62.7	62.7
Beyond compulsory, no college	29.9	29.9	29.9
At least some college	7.4	7.4	7.4
Education level, father			
Only compulsory	57.5	57.2	57.3
Beyond compulsory, no college	32.0	32.2	32.1
At least some college	10.5	10.6	10.6
Average yearly income, offspring			
Mean	209,793.3	310,498.2	261,216.4
Std	146,129.1	414,132.2	317,111.8
Gini	0.241	0.303	0.296
Average yearly income, mother			
Mean	98,427.5	98,458.1	98,443.1
Std	83,112.2	83,739.5	83,432.3
Gini	0.445	0.447	0.446
Average yearly income, father			
Mean	262,436.7	263,325.4	262,890.0
Std	178,756.4	177,967.7	178,354.8
Gini	0.286	0.287	0.286

The upper panel shows the percent of offspring individuals in the sample born each year along with the overall sample size. The lower panel presents descriptive statistics of parental education and income and offspring income. We measure income by total market income (in SEK) before taxes. For the offspring generation, income is averaged over ages 37-43. For fathers and mothers, income is averaged over the years when the child was 13-17 years old and add gender to the circumstance vector. This analysis provides us with an estimate of inequality of opportunity in the overall population and allows us to compare the importance of gender to that of the other circumstances in accounting for income inequality. We close the section with two sets of robustness checks to check if the results are sensitive to the age at which income is measured and if the conclusions regarding the role of gender are robust to excluding IQ and non-cognitive ability from the circumstance vector.

5.1 Regression results

The two sets of regression coefficients for men, shown in Table 7, have largely expected signs but differ in that men's own IQ and non-cognitive ability are used in the circumstance vector in the left column, while in the right column, those of their brothers. Income increases with parental income, parental education, IQ and non-cognitive ability, and decreases with the number of siblings. Individuals who did not live with both their biological parents have, on average, a lower income than those who did. As expected, the influence of IQ and non-cognitive ability on long-run income is larger when using the men's own characteristics than when letting those of their brothers act as proxies.[16]

In Table 8, we show the regression coefficients for women (middle column) when using their brothers' IQ and non-cognitive ability as proxies for their own. The left column for men repeats the right column of Table 7 but is included to facilitate comparison. The female regression coefficients are generally smaller than the male ones. This is particularly true for the coefficients on IQ and non-cognitive ability. The gender difference in the coefficients on IQ and non-cognitive ability is compatible with two different explanations. First, it may be that women have lower returns to IQ and non-cognitive ability than men.[17] Second, the measurement error caused by using brothers' IQ and non-cognitive ability as proxies may be larger for women than for men. Although we assume that the measurement error is similar for men and women, we cannot test this with our data. The regression results for the male and female samples pooled, including gender among the circumstances and brothers' characteristics as proxies, are shown in the last column of Table 8. The coefficients suggest that being a man offers a 0.33 log point advantage in comparison to being a woman.

[16] To determine if the differences are statistically significantly different from zero, we need to know not only the variance matrix of each estimator, but also their covariance. While that can, in principle, be worked out and estimated using asymptotics, we opted instead to use bootstrapping. Specifically, we first use bootstrapping to estimate the covariance of the parameter estimators for the model using own IQ and non-cognitive ability scores, on the one hand, and brothers' IQ and non-cognitive ability, on the other. We then ran a second bootstrap procedure, in which, for each bootstrap draw, we calculated the bootstrap χ^2-statistic corresponding to the Wald statistic that measures the distance of the difference from zero. The empirical distribution of this statistic suggests that difference in the two columns, are, indeed, statistically significant.

[17] It has previously been found that these skills count differently for men and women, see for instance Heineck and Anger (2010), Bowles et al. (2001) and Heckman et al. (2006).

5.2 Decomposition of inequality

Men using own and brothers' IQ and non-cognitive ability

Turning to the decomposition of long-run income inequality into components due to circumstances and effort, we first compare the results for men using their own and their brothers' characteristics. Starting with results obtained using the men's own IQ and non-cognitive ability, the first row of panel A of Table 2, shows the estimated values of our four inequality measures; the Gini coefficient (Gini), the mean log deviation (GE[0]), the Theil index (GE[1]), and the squared coefficient of variation (CV^2). For instance, the estimated Gini coefficient for men's income is 0.297.

The following rows show the contribution of each of the circumstances, measured as their share (in percent) of the inequality index as obtained by the Shapley-value decomposition. Parental income, parental education, number of siblings, family structure, IQ and non-cognitive ability measure direct effects, i.e., shifters of the conditional expectation (of log income). Indirect contributions of circumstances arise because of differences in the distribution of effort across types. Under the label "Type heterogeneity", we report the joint indirect contribution of all circumstances (these could, in principle, be broken down by specific factors but we do not do so here). The last row shows the share of income inequality that remains once all circumstances have been accounted for. It is this (homogeneous) residual that we associate with individual effort.

Starting with the Gini coefficient we see that 66.3% of income inequality remains when all circumstances have been accounted for. This means that 33.7% of income inequality is accounted for by circumstances, so 33.7% of income inequality in men's income can be attributed to inequality of opportunity. IQ, non-cognitive ability, parental income and type heterogeneity are the most important contributors to inequality, accounting for 9.3, 8.3, 6.4 and 6.4% of income inequality.

Comparing the results across columns, circumstances typically account for a lower share of income inequality when using other indices than the Gini; between 71.0 and 82.3% of income inequality remains after taking all circumstances into account so between 17.7 and 29.0% of income inequality can be attributed to circumstances. Using the other inequality indices also slightly alters the relative importance of circumstances and type heterogeneity. In particular, for indices other than the Gini, type heterogeneity is more important than parental income. These results are in line with the results of Björklund et al. (2012)—who only include men—but we provide evidence on the importance of non-cognitive ability which they do not.[18]

Results obtained using the men's brothers' IQ and non-cognitive ability as proxies for their own are shown in panel B of Table 2. As expected, the contributions of IQ

[18] As discussed in Sect. 3, footnote 10, the mean-equalized decomposition we use can be contrasted with a zero-equalized decomposition. The latter involves eliminating a factor by setting all its categories save the omitted one (which is subsumed by the intercept) to zero (rather than replacing variation due to a factor with its implied mean values). We compared the two approaches for our baseline case. The results from these two alternative decomposition approaches suggest essentially no differences in the importance of effort or of the contribution of individual factors to the importance of circumstances, suggesting the choice of zero- vs. mean-equalization does not matter in this application.

Table 2 Contribution of circumstances and effort to inequality of long-run average income for men w/o bias correction—own characteristics (panel A), brothers' characteristics without bias correction (Panel B) and brothers' characteristics with bias correction (panel C)

	Gini	GE(0)	GE(1)	CV2
(A) Own characteristics				
Index value				
Ineqest	0.297	0.189	0.215	1.454
Relative contributions				
ParentInc	6.4	3.3	3.9	2.8
ParentEduc	1.7	1.0	1.3	0.9
Sib	0.6	0.0	0.0	0.3
Family	1.0	0.2	0.1	−0.4
IQ	9.3	5.0	5.6	5.5
NC	8.3	4.4	5.0	4.5
Type heterogeneity	6.4	3.7	7.9	15.5
Residual	66.3	82.3	76.1	71.0
(B) Brothers' characteristics				
Index value				
Ineqest	0.297	0.189	0.215	1.454
Relative contributions				
ParentInc	7.8	3.8	4.5	3.2
ParentEduc	3.4	1.8	2.3	1.8
Sib	0.7	0.1	0.1	0.5
Family	1.2	0.2	0.2	−0.5
IQB	4.0	1.8	2.2	3.2
NCB	4.1	1.8	2.2	2.5
Type heterogeneity	5.9	3.3	7.3	16.1
Residual	72.9	87.1	81.3	73.4
(C) Brothers' characteristics with bias correction				
Index value				
Ineqest	0.303	0.197	0.226	1.754
Relative contributions				
ParentInc	6.2	3.2	3.7	3.3
ParentEduc	1.7	1.0	1.2	0.9
Sib	0.5	0.0	0.0	0.3
Family	0.9	0.2	0.1	−0.2
IQB	8.8	4.6	5.1	6.0
NCB	7.9	4.0	4.4	4.3
Type heterogeneity	5.1	2.9	6.5	14.8
Residual	69.0	84.1	78.9	70.6

and non-cognitive ability are substantially smaller that when using the men's own characteristics (estimates of the contributions of IQ and non-cognitive ability in panel B are about half the size of those in panel A). The total share of inequality than can be attributed to circumstances therefore decreases.

Note also that, as in Björklund et al. (2012), the number of siblings contributes little to inequality. This is in line with other evidence for Sweden (e.g. Björklund et al. 2010) and suggest that the fact that we restrict our main analysis below to men and women with at least one brother is of little consequence for our conclusions.

As detailed above, we adjust for the bias from the use of proxy measures using the estimated difference in the regressions that use own and brothers' characteristics; these results are displayed in panel C of Table 2.[19] Comparing results in panels A–C, we see that correcting for the bias leads to results that are substantially closer to those obtained using men's own characteristics. In particular, measuring inequality by the Gini, IQ and non-cognitive ability now account for 8.8 and 7.9% of income inequality, in comparison to 9.3 and 8.3% when using men's own characteristics (panel A) and 4.0 and 4.1% when using the brothers' but not correcting for the bias (panel B). Moreover, 69.0% of the Gini coefficient remains after taking the circumstances into account. This number should be compared to 66.3% when using the own characteristics and 72.9% when using brothers' as proxies uncorrected for bias. We conclude that the bias correction seems to work well. Relying on the assumption that the brother-sister and brother-brother correlations are roughly equal, we apply this bias correction to women's data.

Separate analyses for the male and female samples

We now turn to our main results, investigating first the presence of gender differences in the level and structure of inequality of opportunity. The results, for both men and women using brothers' IQ and non-cognitive ability and adjusting for the bias, are shown in Table 3.[20] For women, between 75.0 and 90.7% of income inequality, depending on the index, remains when all circumstances have been accounted for (see panel B). This means that the contribution of all circumstances, including type heterogeneity, ranges from 9.3 to 25.0% of income inequality. When measuring inequality by the Gini or the mean log deviation (GE[0]), the three most important circumstances among women are parental income, IQ and non-cognitive ability. When instead measuring inequality by the Theil index (GE[1]) or the squared coefficient of variation (CV^2), the most important circumstances are IQ, non-cognitive ability and type heteroegenity.

Comparing the results for men and women (panels A and B), the same circumstances seem to be most influential for men and women, but they generally account for a

[19] The inequality indices are slightly different in panel C as compared to the panels A and B. The reason for this is that in panels A and B, we restrict the sample to men for whom there is enlistment data both for themselves and for at least one brother. Doing this, we can compare the results when using the men's own characteristics, to those when using their brothers' as proxies. In panel C, on the other hand, we only require that there is enlistment data for at least one of the men's brothers. We choose to restrict the sample in panel C in this way because we then impose the same sample restrictions on the male and female samples.

[20] Note that panel A for men is identical to panel C in Table 2.

Table 3 Contribution of circumstances and effort to inequality of long-run average income using brothers' characteristics with bias correction—men (panel A), women (panel B), and both men and women (panel C)

	Gini	GE(0)	GE(1)	CV2
(A) Men				
Index value				
Ineqest	0.303	0.197	0.226	1.754
Relative contributions				
ParentInc	6.2	3.2	3.7	3.3
ParentEduc	1.7	1.0	1.2	0.9
Sib	0.5	0.0	0.0	0.3
Family	0.9	0.2	0.1	−0.2
IQB	8.8	4.6	5.1	6.0
NCB	7.9	4.0	4.4	4.3
Type heterogeneity	5.1	2.9	6.5	14.8
Residual	69.0	84.1	78.9	70.6
(B) Women				
Index value				
Ineqest	0.240	0.136	0.122	0.476
Relative contributions				
ParentInc	5.3	2.1	3.0	4.0
ParentEduc	0.8	0.3	0.5	0.6
Sib	0.3	0.1	0.1	0.1
Family	0.2	0.0	0.0	0.0
IQB	7.5	3.1	4.2	4.8
NCB	6.8	2.7	3.6	4.6
Type heterogeneity	4.1	1.0	3.1	8.6
Residual	75.0	90.7	85.5	77.2
(C) All				
Index value				
Ineqest	0.296	0.186	0.204	1.450
Relative contributions				
Gender	13.1	7.7	8.5	8.1
ParentInc	4.9	2.6	3.3	3.4
ParentEduc	2.5	1.4	1.8	1.1
Sib	0.8	0.2	0.2	0.3
Family	1.6	0.5	0.4	0.0
IQB	5.2	2.6	3.0	3.4
NCB	4.1	1.7	1.8	1.9
Type heterogeneity	4.9	3.1	7.3	19.7
Residual	62.9	80.1	73.5	62.1

somewhat smaller share of income inequality among women. The total share of income inequality that can be attributed to inequality of opportunity is thus slightly larger for men. This holds across the four inequality measures. For instance, measuring inequality by the Gini, 75.0% of income inequality among women, in comparison to 69.0% among men, remains after accounting for all circumstances. Thus, the results suggest that there are slightly more equal opportunities among women than among men.[21]

One potential explanation for this finding is that women work part time to a much larger extent than men do. According to the labour force survey, just under 30% of women in ages similar to those we study work part time, as compared to 7% of the men (Statistics Sweden 2016) . If variation in hours worked is less related to circumstances than is variation in hourly wages, circumstances are less important for women's than for men's income, even in the absence of gender differences in the importance of circumstances for hourly wages.[22] Another possible explanation for the result that circumstances are less important among women than men is that women are absent from the labour market for other reasons which also are less related to circumstances than hourly wages are. In particular, we expect a substantially larger fraction of women to be on parental leave.[23]

As our data do not allow us to analyze the consequences of gender differences in part-time work and parental leave take-up for our results, the finding that there are more equal opportunities among women than among men should be interpreted with caution. Note, however, that this finding is in line with previous studies estimating sibling correlations to analyze the role of family and community background. Sister correlations in income are lower than the corresponding correlation for brothers, both in Sweden (Björklund et al. 2004, 2010; Björklund and Jäntti 2012) and elsewhere (Björklund et al. 2004; Schnitzlein 2014; Jäntti and Jenkins 2015).

Gender as a circumstance

In order to estimate inequality of opportunity in the overall population and to compare the importance of gender to that of the other circumstances, we pool men and

[21] An alternative interpretation is that circumstances that we do not include are more important for women than for men. However, we fail to come up with any obvious candidates. Moreover, the measurement error caused by using brothers' IQ and non-cognitive ability may be larger for women than for men. However, as explained in Sect. 3, we believe that measurement error is roughly similar for men and women. In addition, in Sect. 5.3, we make a robustness check excluding IQ and cognitive ability, the results of which suggest circumstances still play a smaller role for women's than for men's income.

[22] To get an idea of the importance of gender differences in part time work for our results, we conducted a preliminary analysis using data from the 2010 wave of the Swedish Level-of-Living Survey. In contrast to our register data, the survey contains information on both gross hourly wage and gross monthly wage. Using parental education and occupation as circumstances, we find that parental characteristics are more important for men than for women in both hourly and monthly wages, as measured by the share of ln variance explained, but that the gender difference in R^2 is essentially the same for hourly and monthly wages. This, in turn, suggests that circumstances or at least family background characteristics are important for wages but not for hours worked. This analysis does not support the hypothesis that women's part time work explains why circumstances are less important for women than for men.

[23] Men belonging to the cohorts we study took out about 10% of overall parental leave days (Försäkringskassan 2014).

women and include gender as one of the circumstances; results are shown in Table 3, panel C. For men and women combined, between 62.1 and 80.1% of income inequality remains after taking all circumstances into account. For all inequality measures, these shares are lower than they are for the male and female samples. This means that the share of income inequality that can be attributed to circumstances is higher for the overall population than for men and women separately.

The most striking result for the (pooled) overall population is that gender accounts for a substantial part of income inequality. When measured by the Gini, gender accounts for 13.1% of income inequality, which makes gender the most important circumstance. In fact, the contribution of gender to income inequality is almost as large as the joint contribution of the next three most important circumstances, namely parental income, IQ and type heterogeneity. Again, gender differences in part-time work and parental leave take-up are potentially important mechanisms behind the importance of gender in accounting for income inequality. The four most important circumstances are the same for all inequality measures. Measuring inequality by the mean log deviation (GE[0]) or the Theil index (GE[1]), gender is still the single most important contributor to inequality. When using (half) the squared coefficient of variation (CV^2, i.e., $2 \times$GE[2]]), however, type heterogeneity accounts for a larger share of income inequality than does gender.

Results that do not adjust the coefficients for attenuation bias, shown in Table 4, are roughly similar to those reported above, but suggest less inequality attributable to circumstances. Moreover, now IQ and non-cognitive ability are less important, while parental income and education are more important circumstances in inequality of opportunity.

5.3 Robustness checks

We examine the robustness of our results in two ways. First, we measure the income of both men and women at alternative ages. We then examine if our main conclusions regarding the role of gender change when we exclude IQ and non-cognitive ability from the circumstance vector.

Measuring income at other ages

So far, we have used total market pretax income averaged over ages 37–43 as outcome variable. Now, we examine whether our results are robust to using ages 32–38 or 40–46, shown in the left and right panels of Table 5. Focusing first on the separate analyses of the male and female samples, we see that parental income, IQ, non-cognitive ability and type heteroegenity are still the most important circumstances for both men and women, regardless of the age at which income is measured. Furthermore, women still seem to have more equal opportunities than men (see panels I.A–II.B).

Turning to the results for the pooled samples, and looking first at the results when measuring income at ages 32–38, the main difference is that gender now accounts for a larger share of income inequality than in the main analysis. Measuring inequality by the Gini, gender accounts for 16.7% of income inequality when measuring income at ages 32–38, in comparison to 13.1% when measuring income at ages 37–43. Measuring

Table 4 Contribution of circumstances and effort to inequality of long-run average income using brothers' characteristics *without* bias correction—men (panel A), women (panel B), and both men and women (panel C)

	Gini	GE(0)	GE(1)	CV2
(A) Men				
Index value				
Ineqest	0.303	0.197	0.226	1.754
Relative contributions				
ParentInc	7.7	3.8	4.5	4.1
ParentEduc	3.3	1.8	2.2	1.8
Sib	0.8	0.1	0.1	0.4
Family	1.4	0.3	0.2	−0.2
IQB	4.0	1.8	2.2	2.9
NCB	4.3	1.9	2.2	2.5
Type heterogeneity	5.3	2.9	6.5	15.3
Residual	73.4	87.5	82.1	73.3
(B) Women				
Index value				
Ineqest	0.240	0.136	0.122	0.476
Relative contributions				
ParentInc	7.2	2.6	3.8	5.0
ParentEduc	2.6	1.0	1.5	1.8
Sib	0.4	0.1	0.1	0.1
Family	0.6	0.1	0.1	0.0
IQB	1.9	0.6	0.9	1.3
NCB	2.5	0.8	1.2	1.9
Type heterogeneity	4.4	1.0	3.0	8.5
Residual	80.3	93.9	89.4	81.4
(C) All				
Index value				
Ineqest	0.296	0.186	0.204	1.450
Relative contributions				
Gender	14.3	8.2	8.9	8.3
ParentInc	6.0	3.0	3.8	3.7
ParentEduc	2.4	1.3	1.7	1.6
Sib	0.5	0.1	0.1	0.2
Family	0.9	0.2	0.2	−0.1
IQB	2.4	1.1	1.4	1.9
NCB	2.9	1.2	1.6	1.9
Type heterogeneity	5.3	3.3	7.6	19.7
Residual	65.3	81.7	74.8	62.8

Table 5 Robustness check measuring income at alternative ages: Contribution of circumstances and effort to inequality of long-run average income using brothers' characteristics with bias correction—men (Panel A), women (panel B), and both men and women (panel C)

	I. Ages: 32–38; born: 1955–1967				II. Ages: 40–46; born: 1949–1961			
	Gini	GE(0)	GE(1)	CV2	Gini	GE(0)	GE(1)	CV2
(A) Men								
Index value								
Ineqest	0.262	0.156	0.172	2.895	0.317	0.212	0.251	1.961
Relative contributions								
ParentInc	5.7	2.6	3.2	4.1	6.0	3.2	3.9	4.0
ParentEduc	0.5	0.3	0.4	1.0	1.8	1.1	1.4	1.1
Sib	0.5	0.0	0.0	−0.2	0.6	0.0	0.0	0.3
Family	1.0	0.2	0.2	1.2	0.9	0.2	0.1	−0.2
IQB	7.6	3.5	3.7	0.2	9.0	4.7	5.1	5.4
NCB	8.8	4.2	4.8	6.2	7.5	3.8	4.2	4.0
Type heterogeneity	6.3	3.2	7.9	24.4	4.9	2.6	5.7	13.6
Residual	69.7	86.0	79.7	63.0	69.4	84.3	79.6	71.8
(B) Women								
Index value								
Ineqest	0.233	0.132	0.113	0.500	0.239	0.134	0.122	0.500
Relative contributions								
ParentInc	4.8	1.7	2.5	4.0	4.6	1.9	2.7	3.3
ParentEduc	0.7	0.3	0.4	0.5	1.2	0.6	0.8	0.8
Sib	0.4	0.1	0.1	−0.3	0.4	0.0	0.0	0.2
Family	0.2	0.0	0.1	0.2	0.8	0.1	0.2	−0.1
IQB	6.2	2.3	3.2	4.4	8.1	3.5	4.4	4.5
NCB	7.1	2.6	3.6	5.0	6.6	2.7	3.4	3.8
Type heterogeneity	3.6	1.2	3.4	11.5	4.4	1.5	4.3	13.3
Residual	76.9	91.8	86.7	74.7	73.9	89.8	84.2	74.1
(C) All								
Index value								
Ineqest	0.273	0.163	0.167	2.286	0.301	0.191	0.217	1.590
Relative contributions								
Gender	16.7	10.2	11.1	9.7	10.8	6.1	6.9	6.8
ParentInc	4.4	2.1	2.9	4.6	4.9	2.7	3.5	3.9
ParentEduc	1.9	1.0	1.5	3.8	2.3	1.3	1.7	1.1
Sib	0.9	0.3	0.3	0.8	0.7	0.1	0.2	0.3
Family	1.8	0.6	0.7	2.1	1.9	0.6	0.5	0.1
IQB	4.3	2.0	2.3	0.8	5.6	2.8	3.1	3.2
NCB	4.6	1.8	1.9	0.1	4.0	1.7	1.8	2.1
Type heterogeneity	4.0	2.0	5.1	17.2	5.8	3.9	8.8	21.2
Residual	61.4	80.0	74.2	61.0	64.0	80.7	73.6	61.2

income at ages 40–46, instead, the corresponding figure is 10.8%. Thus, a smaller share of income inequality can be attributed to gender when income is measured later on in life. In addition, when measuring income at ages 40–46 and measuring inequality by the Theil index (GE[1]), type heteroegenity accounts for a larger share of income inequality than gender does, while the opposite is true in the main analysis. To conclude, the share of income inequality that can be attributed to gender varies slightly when income is measured at alternative ages. The finding that gender matters more at younger ages may be because these ages are more likely to coincide with parental leave take-up. The main conclusion—namely that gender appears to be the most important circumstance—holds true for all age intervals.[24]

Excluding IQ and non-cognitive ability from the circumstance vector

Here, we examine if our broad conclusions are robust to excluding IQ and non-cognitive ability from the circumstance vector. There are two reasons for conducting this robustness check. First, although we believe that measurement error arising from using brothers' characteristics as proxies is likely to be similar for men and women, we cannot test this with the data at hand. Thus, we want to make sure that our main conclusions regarding the role of gender in generating inequality of opportunity are not driven by the potential gender difference in the measurement error. Second, as discussed in Sect. 4, whether IQ and non-cognitive ability should be regarded as circumstances or not, is ultimately a decision that should be made by the social planner, not researchers. Therefore, we also provide results excluding these characteristics from the circumstance vector.

When performing this robustness check, we use the same sample as in the main analysis. That is, we restrict the sample to men and women for whom there is data on IQ and non-cognitive ability for at least one brother. The results in Table 6 show that after excluding IQ and non-cognitive ability from the circumstance vector, a larger share of income inequality remains when all circumstances have been accounted for. Measuring inequality by the Gini coefficient, this residual share of income inequality is 77.5% among men, 82.7% among women and 67.9% for men and women combined. Just as in the main analysis, there seem to be somewhat more equal opportunities among women than among men. Moreover, when analyzing men and women separately, the three most important circumstances are parental income, parental education and type heterogeneity. Turning to the results from the overall population (panel C), gender is still the most important circumstance except when using (half) the squared coefficient of variation (CV^2), just as in the main analysis. For the Gini, gender accounts for 14.7% of income inequality, in comparison to 13.1% in our main analysis (including IQ and non-cognitive ability in the circumstance vector).

[24] When we measure income at alternative ages, we also change cohorts. Thus, we cannot disentangle the variations across age intervals from cohort effects. However, we suspect that the declining importance of gender as a circumstance is related to the declining likelihood of parental leave take-up with age. We are unable to explore this further in our data but a combination of family (rather than individual) income and information of leave periods can in future research help shed light on this.

Table 6 Robustness check excluding IQ and non-cognitive ability: contribution of circumstances and effort to inequality of long-run average income—men (panel A), women (panel B), and both men and women (panel C)

	Gini	GE(0)	GE(1)	CV2
(A) Men				
Index value				
Ineqest	0.303	0.197	0.226	1.754
Relative contributions				
ParentInc	9.6	4.5	5.4	4.6
ParentEduc	5.5	2.7	3.3	2.3
Sib	1.2	0.1	0.2	0.9
Family	1.9	0.3	0.2	−0.7
Type heterogeneity	4.4	2.7	4.5	−1.4
Residual	77.5	89.7	86.4	94.4
(B) Women				
Index value				
Ineqest	0.240	0.136	0.122	0.476
Relative contributions				
ParentInc	8.4	2.9	4.3	5.9
ParentEduc	3.9	1.4	2.0	2.2
Sib	0.7	0.1	0.2	0.3
Family	1.0	0.1	0.1	−0.1
Type heterogeneity	3.4	1.4	3.0	6.3
Residual	82.7	94.1	90.4	85.3
(C) All				
Index value				
Ineqest	0.296	0.186	0.204	1.450
Relative contributions				
Gender	14.7	8.2	9.1	8.9
ParentInc	7.3	3.4	4.4	4.4
ParentEduc	3.9	1.9	2.5	2.2
Sib	0.8	0.1	0.1	0.4
Family	1.2	0.2	0.2	−0.2
Type heterogeneity	4.3	3.2	6.5	14.7
Residual	67.9	82.9	77.2	69.6

It thus appears that even after excluding IQ and non-cognitive ability from the circumstance vector, our two main conclusions regarding gender and equality of opportunity still hold true. Namely, women have more equal opportunities than men and, of the circumstances we examine, gender is the most important contributor to inequality in long-run income in Sweden.

6 Conclusions

In this paper, we explore equality of opportunity in long-run income for Swedish men and women by analyzing to what extent income inequality can be attributed to circumstances that individuals cannot be held accountable for. The key idea is that a society has achieved equality of opportunity if circumstances have no influence on income.

Our main contribution is to provide insights into the role of gender in inequality of opportunity. Relative to previous studies on equality of opportunity in income, we have the advantage of using a large register dataset with incomes of both men and women along with detailed background information. This dataset allows us to examine the role of gender in two different ways. First, by conducting separate analyses for men and women, we investigate gender differences in the share of income inequality that can be attributed to circumstances. This analysis also shows if the relative importance of each of the circumstances is similar for men and women. Second, and more importantly, we pool men and women and treat gender as a circumstance. Doing this, we analyze inequality of opportunity in the overall population and compare the importance of gender to that of the other circumstances.

Apart from using a large and detailed dataset and analyzing the role of gender in generating income inequality, one advantage of our study is that we examine both the direct and the indirect contributions of circumstances to income. The indirect contribution arises because the distribution of effort may vary with circumstances. As the distribution of effort is a consequence of an individual's circumstances, we regard income differences due to differences in the distribution of effort as due to circumstances rather than to effort.

The individuals in our sample were born between 1952 and 1964 and we use total market pretax income averaged over seven years as the outcome variable. Our circumstances consist of parental income, parental education, number of siblings, family structure, IQ and non-cognitive ability. Analyzing men and women separately, we find that circumstances account for up to 31% of income inequality among men and up to 25% among women. This implies that there are slightly more equal opportunities among women than among men. Parental income, IQ, non-cognitive ability and differences in the distribution of effort are important contributors to income inequality for both men and women. Pooling men and women and including gender as an additional circumstance, we find that circumstances account for up to 38% of income inequality in the overall population. In other words, up to 38% of income inequality in long-run income in Sweden can be attributed to inequality of opportunity. Of the circumstances considered in this paper, gender turned out to be the most important determinant of inequality of opportunity, accounting for 13% of income inequality. Given the significant role played by gender, it seems important to include both men and women in the analysis sample and to treat gender as a circumstance in order to get as complete a picture as possible of inequality of opportunity in a society. In future research, it would be interesting to look further into potential mechanisms behind the importance of gender as a circumstance. It seems particularly useful to investigate the roles of gender differences in part time work and parental leave take-up.

Our results for the male sample are in line with those of Björklund et al. (2012), but differ from theirs slightly since they did not include non-cognitive ability. To the best of our knowledge, the only two previous studies that report how important gender is relative to other circumstances are Ferreira and Gignoux (2011) and de Barros et al. (2009). Our findings on the importance of gender stand in stark contrast to theirs. While we find that gender is the most important contributor to income inequality in Sweden, they conclude that in Latin America, gender is less important than family background variables such as parental education. However, we cannot draw any firm conclusions from the comparison of these studies since they differ along several dimensions, such as the empirical approach, outcome variable and the circumstances considered. These differences point to the need for more studies on this topic. Moreover, for international comparisons of the role of gender in generating inequality of opportunity, it seems particularly important to take differences in female labour force participation into account.

While we do account for the indirect contribution of circumstances to income inequality arising from differences in the distribution of effort, we do not analyze to what extent each of the circumstances contributes to the differences in the distribution of effort. That is, when we report the importance of each of the circumstances, we only report their direct contributions. In addition to the direct contributions, we also report the joint indirect contribution of all circumstances. Part of the differences in the distribution of effort are likely driven by gender, because of, for example, differences in the variation of hours worked between men and women. Thus, when we conclude that gender accounts for up to 13% of income inequality, we underestimate the total contribution of gender to income inequality since this number does not include the indirect contribution.

Our choice of outcome variable also merits further discussion. First, we use individual income despite the fact that family income may be a better measure of standard of living, especially for women. However, Swedish register data do not for the period we study provide a good measure of family income as we can only observe if individuals live together if they are married or if they have children together. Therefore, we base our analysis on individual income. Second, we use total income rather than wages since total income better reflects standard of living. The use of disposable income, which includes all public transfers and deducts direct taxes, might be better still, but we do not have access to that.

To estimate the share of income inequality in Sweden that is due to inequality of opportunity, we would ideally want to observe all the relevant background factors of individuals. Since we can only observe a subset of these factors, we are likely to overestimate the role of effort in generating income inequality. For instance, if individuals inherit their labour-leisure preferences from their parents, it is an open question to what extent they should be held accountable for income differences stemming from differences in labour supply. But we do not observe parental preferences, so we cannot include them as circumstances in the analysis. Moreover, one may question the fact that we interpret all of the residual as effort, as the residual also contains income differences due to differences in luck (Lefranc et al. 2009). While both the role of inherited labour supply preferences and of luck merit further investigation, doing so with the data at hand is very difficult and must be left for future study.

Appendix

See Tables 7 and 8

Table 7 Regression results for men using own and brothers' characteristics

		Men—own IQ and NC	Men—brother's IQ and NC
(Intercept)		12.13 (0.00)	12.17 (0.00)
Family (omitted: 1)	2	0.06(0.01)	0.08 (0.01)
IQB (omitted: 1)	2	0.08 (0.00)	0.05 (0.00)
	3	0.13 (0.00)	0.08 (0.00)
	4	0.25 (0.00)	0.13 (0.00)
NCB (omitted: 1)	2	0.13 (0.00)	0.07 (0.00)
	3	0.17 (0.00)	0.11 (0.00)
	4	0.24 (0.00)	0.15 (0.00)
ParentEduc (omitted: 1)	2	0.00 (0.00)	0.03 (0.00)
	3	0.08 (0.01)	0.13 (0.01)
ParentInc (omitted: 1)	2	0.07 (0.00)	0.08 (0.00)
	3	0.12 (0.00)	0.13 (0.00)
	4	0.21 (0.01)	0.24 (0.01)
Sib (omitted: 1)	2	−0.03 (0.01)	−0.04 (0.01)
		−0.06 (0.01)	−0.09 (0.01)
n		166,918	192,650
k		15	15
σ		0.64	0.66
Adj R^2		0.096	0.062

Table 8 Regression results for men and women using brothers' characteristics

		Men	Women	All
(Intercept)		12.17 (0.00)	11.94 (0.00)	11.89 (0.00)
Family (omitted: 1)	2	0.08 (0.01)	0.03 (0.01)	0.06 (0.00)
Gender (omitted: female)	Male			0.33 (0.00)
IQB (omitted: 1)	2	0.05 (0.00)	0.02 (0.00)	0.04 (0.00)
	3	0.08 (0.00)	0.03 (0.00)	0.06 (0.00)
	4	0.13 (0.00)	0.06 (0.00)	0.09 (0.00)
NCB (omitted: 1)	2	0.07 (0.00)	0.04 (0.00)	0.06 (0.00)
	3	0.11 (0.00)	0.06 (0.00)	0.08 (0.00)
	4	0.15 (0.00)	0.08 (0.00)	0.11 (0.00)
ParentEduc (omitted: 1)	2	0.03 (0.00)	0.03 (0.00)	0.03 (0.00)
	3	0.13 (0.01)	0.08 (0.01)	0.10 (0.00)
ParentInc (omitted: 1)	2	0.08 (0.00)	0.05 (0.00)	0.06 (0.00)
	3	0.13(0.00)	0.10 (0.00)	0.12 (0.00)
	4	0.24 (0.01)	0.18 (0.00)	0.21 (0.00)
Sib (omitted: 1)	2	−0.04 (0.01)	−0.00 (0.01)	−0.02 (0.00)
		−0.09 (0.01)	−0.04 (0.01)	−0.06 (0.00)
n		192,650	184,628	377,278
k		15	15	16
σ		0.66	0.62	0.65
Adj R^2		0.062	0.029	0.1

References

Albrecht J, Björklund A, Vroman S (2003) Is there a glass ceiling in Sweden? J Labor Econ 21(1):145–177

Almås I (2008) Equalizing income versus equalizing opportunity: a comparison of the United States and Germany. Res Econ Inequal 16:129–156

Almås I, Cappelen A, Lind J, Sørensen E, Tungodden B (2011) Measuring unfair (in)equality. J Public Econ 95(7–8):488–499

Altonji JG, Blank RM (1999) Race and gender in the labor market. Handb Labor Econ 3:3143–3259

Arulampalam W, Booth AL, Bryan ML (2007) Is there a glass ceiling over Europe? Exploring the gender pay gap across the wage distribution". Industrial and Labor Relations Review 60(2):163–186

Betts JR, Roemer JE (2007) Equalizing opportunity for racial and socioeconomic groups in the United States through educational finance reform. In: Woessmann L, Peterson PE (eds) Schools and the equal opportunity problem, Chap. 9. MIT Press, Cambridge, pp 209–238

Böhlmark A, Lindquist MJ (2006) Life-cycle variations in the association between current and lifetime income: replication and extension for Sweden. J Labor Econ 24(4):879–896

Björklund A, Freeman R (1997) Generating equality and eliminating poverty, the Swedish way. In: Freeman R (ed) Welfare state in transition. Chicago University Press, Chicago

Björklund A, Hederos Eriksson K, Jäntti M (2010) IQ and family background: are associations strong or weak? BE J Econ Anal Policy. doi:10.2202/1935-1682.2349. http://www.bepress.com/bejeap/vol10/iss1/art2 (**Contributions; Article 2**)

Björklund A, Jäntti M (2012) How important is family background for laboureconomic outcomes? Labour Econ 19(4):465–474

Björklund A, Jäntti M, Roemer JE (2012) Equality of opportunity and the distribution of long-run income in Sweden. Soc Choice Welf 39(2–3):675–696

Björklund A, Lindahl L, Lindquist MJ (2010) What more than parental income, education and occupation? An exploration of what Swedish siblings get from their parents. BE J Econ Anal Policy: doi:10.2202/1935-1682.2449 (**Contributions; Article 102**)

Björklund A, Eriksson T, Jäntti M, Raaum O, Österbacka E (2004) Family structure and labor market success: the influence of siblings and birth order on the earnings of young adults in Sweden. In: Corak M (ed.) Generational income mobility in North America and Europe, Chap. 9. Cambridge University Press, Cambridge, pp 207–225

Blau FD, Kahn LM (2003) Understanding international differences in the gender pay gap. J Labor Econ 21(1):106–144

Bouchard TJ, McGue M (1981) Familial studies of intelligence: a review. Science 212:1055–1059

Bourguignon F, Ferreira FH, Menéndez M (2003) Inequality of outcomes and inequality of opportunities in Brazil. World Bank Policy Research Working Paper 3174

Bowles S, Gintis H, Osborne M (2001) The determinants of earnings: a behavioral approach. J Econ Lit 39:1137–1176

Carlstedt B (2000) Cognitive abilities: aspects of structure, process and measurement". Ph.D. thesis. Gothenburg University

Chantreuil F, Trannoy A (2013) Inequality decomposition values: the trade-off between marginality and efficiency. J Econ Inequal. doi:10.1007/s10888-011-9207-y

Checchi D, Peragine V (2010) Inequality of opportunity in Italy. J Econ Inequal 8(4):429–450

Checchi D, Peragine V, Serlenga L (2010) Fair and unfair income inequalities in Europe. Discussion Paper 5025. IZA, Bonn. http://ftp.iza.org/dp5025.pdf

Devooght K (2008) To each the same and to each his own: a proposal to measure responsibility-sensitive income inequality. Economica 75(298):280–295

Ferreira FHG, Gignoux J (2008) The measurement of inequality of opportunity: theory and an application to Latin America. Policy Research Working Paper Series 4659. The World Bank

Ferreira FHG, Gignoux J (2011) The measurement of inequality of opportunity: theory and an application to Latin America. Rev Income Wealth 57(4):622–657

Ferreira FH, Peragine V (2016) Equality of opportunity: theory and evidence". In: Adler MD, Fleurbaey M (eds) Oxford handbook of well-being and public policy, Chap. 25. Oxford University Press, Oxford

Fleurbaey M, Peragine V (2013) Ex ante versus ex post equality of opportunity. Economica 80:118–130

Försäkringskassan (2014) Föräldraförsäkringen och den nya föräldranormen

Gottschalk P, Smeeding TM (1997) Cross-national comparisons of earnings and income inequality. J Econ Lit 32(2):633–686

Grönqvist E, Öckert B, Vlachos J (2016) The intergenerational transmission of cognitive and non-cognitive abilities. J Human Res. doi:10.3368/jhr.52.4.0115-6882R1

Heckman JJ, Stixrud J, Urzua S (2006) The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. J Labor Econ 24(3):411–482

Heineck G, Anger S (2010) The returns to cognitive abilities and personality traits in Germany. Labour Econ 17(3):535–546

Ihaka R, Gentleman R (1996) R: a language for data analysis and graphics. J Comput Graph Stat 5(3):299–314

Jenkins SP (1994) Earnings discrimination measurement: a distributional approach. J Econom 61(1):81–102

Jenkins SP, Van Kerm P (2009) The measurement of economic inequality. In: Salverda W, Nolan B, Smeeding TM (eds) Oxford Handbook of Economic Inequality, Chap. 3. Oxford University Press, Oxford, pp. 40–70

Jäntti M, Jenkins SP (2015) Income mobility. In: Atkinson AB, Bourguignon F (eds) Handbook of income distribution, Chap. 10. Elsevier, Amsterdam, pp 807–935

Keane MP, Roemer JE (2009) Assessing policies to equalize opportunity using an equilibrium model of educational and occupational choices. J Public Econ 93(7–8):879–898. doi:10.1016/j.jpubeco.2009.04.002

Lee W (2008) Empirical estimation of the share of observed income inequality due to unequal circumstance (**memo to authors**)

Lefranc A, Pistolesi N, Trannoy A (2009) Equality of opportunity and luck: Definitions and testable conditions, with an application to income in France. J Public Econ 93(11–12):1189–1207

Lindahl L (2010) A comparison of family and neighborhood effects on grades, test scores, educational attainment and income—evidence from Sweden. J Econ Inequal. doi:10.1007/s10888-010-9144-1
Lindqvist E, Vestman R (2011) The labor market returns to cognitive and noncognitive ability: evidence from the Swedish enlistment. Am Econ J Appl Econ 3(1):101–128
Mårdberg B, Carlstedt B (1998) Swedish enlistment battery (SEB): construct validity and latent variable estimation of cognitive abilities by the CAT-SEB. Int J Sel Assess 6(2):107–114
Niehues J, Peichl A (2014) Lower and upper bounds of unfair inequality: theory and evidence for Germany and the US. Soc Choice Welfare 43(1):73–99
Nilsson W (2005) Equality of opportunity, heterogeneity and poverty. Ph.D. thesis. Umeå University
O'Neill D, Sweetman O, Van de Gaer D (2000) Equality of opportunity and kernel density estimation: an application to intergenerational mobility. Adv Econ Res Ann 14:259–274
Peichl A, Ungerer M (2016) Accounting for the spouse whenmeasuring inequality of opportunity. Soc Choice Welf 47(3):607–631
Ramos X, Van De Gaer D (2016) Approaches to inequality of opportunity: principles, measures and evidence. J Econ Surv 30:855–883
Roemer JE, Trannoy A (2015) Equality of opportunity. In: Atkinson A, Bourguignon F (eds) Handbook of income distribution, Chap. 4. Elsevier, Amsterdam, pp. 217–300
Roemer JE, Trannoy A (2016) Equality of opportunity: theory and measurement. J Econ Lit 54(4):1288–1332
Sastre M, Trannoy A (2002) Shapley inequality decomposition by factor components: some methodological issues. J Econ 77(1):51–89 (**ISSN: 1617-7134**)
Schnitzlein DD (2014) How important is the family? Evidence from sibling correlations in permanent earnings in the USA, Germany, and Denmark. J Popul Econ 27(1):69–89
Shorrocks A (2013) Decomposition procedures for distributional analysis: a unified framework based on the Shapley value. J Econ Inequal 11(1):99–126
Statistics Sweden (2016) Labour force statistics—labour force participation among 20-64 year old population by region, education level and gender 2006–2014. Statistical database. http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__AM__AM9906__AM9906B/RegionIndU1b/?rxid=a1791966-f2cc-4f5f-9448-93472a137e1c (**visited on 10 December 2016**)
de Barros RP, Ferreira FHG, Vega JM, Chanduri JS (2009) Measuring inequalities of opportunities in Latin America and the Caribbean. World Bank Publications, Washington, D.C