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Equality of Opportunity and the Distribution of Long-Run Income in Sweden

Anders Björklund
Markus Jäntti
John E. Roemer

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Forschungsinstitut
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Institute for the Study
of Labor

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Anders Björklund
SOFI, Stockholm University
and IZA

Markus Jäntti
SOFI, Stockholm University

John E. Roemer
Yale University

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

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Equality of opportunity is an ethical goal with almost universal appeal. The interpretation taken here is that a society has achieved equality of opportunity if it is the case that what individuals accomplish, with respect to some desirable objective, is determined wholly by their choices and personal effort, rather than by circumstances beyond their control. We use data for Swedish men born between 1955 and 1967 for whom we measure the distribution of long-run income, as well as several important background circumstances, such as parental education and income, family structure and own IQ before adulthood. We address the question: in Sweden, given its present constellation of social policies and institutions, to what extent is existing income inequality due to circumstances, as opposed to 'effort'? Our results suggest that several circumstances, importantly both parental income and own IQ, are important for long-run income inequality, but that variations in individual effort account for the most part of that inequality.

JEL Classification: D31, D63, J62, C14

Keywords: equality of opportunity, family background, inequality, long-run income

Corresponding author:

Anders Björklund
Swedish Institute for Social Social Research (SOFI)
Stockholm University
SE-10691 Stockholm
Sweden
E-mail: anders.bjorklund@sofi.su.se

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1 Introduction

Equality of opportunity is an ethical goal with almost universal appeal. There are, however, myriad interpretations of what the phrase should mean. In one contemporary interpretation, a society has achieved equality of opportunity if it is the case that what individuals accomplish, with respect to some desirable objective, is determined wholly by their choices and personal effort, rather than by circumstances beyond their control (Arneson, 1989; Cohen, 1989; Roemer, 1993, 1998). Roemer (1998) proposed a way of formalizing this concept, as follows. Suppose that the objective in question, achieved by individuals, is a function $u(x,e,t)$, where x is the value of a policy chosen by the state, e is the effort the individual expends towards achieving the goal, and t is an index defining the circumstances of the individual. We suppose that the society is partitioned into a finite number of *types*, t, where each type comprises individuals with the same circumstances. For example, suppose u measures the income of a worker, t indexes his family background, and e is his level of education. The policy could be one of educational finance, where the policy space is X, and $x \in X$ describes some allocation of educational resources to students in the society (before they become workers earning income), perhaps as a function of their circumstances.

The function u is not an individual utility function: indeed, generally it is the case that the effort e enters negatively into individual preferences – but it enters *positively* into u. The role of individual preferences is suppressed in the present formulation. Instead, we take as data the following: given any policy x, there will ensue in each type t a distribution of effort, which we denote $G_x^t(e)$. This distribution is, of course, determined by the maximization of preference orders by individuals, but all that we need is summarized in the 'reduced form' of these distributions. We equalize opportunities for achievement of the objective measured by u in this society when we choose the policy x that makes the distribution of outcomes u as insensitive as possible to circumstances, measured by t. That is, outcomes should be sensitive to effort, but not to circumstances.

A familiar example of this approach is prevalent in the intergenerational mobility literature. A familiar ethical goal is that the rows of the intergenerational mobility matrix be equal: that is, distribution of income of children should be independent of their parents' income.

Denote by $\varphi_x^t(\pi)$ the inverse function of G_x^t, where $\pi \in [0,1]$ is the quantile of the distribution of effort in his type at which an individual sits, when the policy is x. Then we may write the value of the objective for a particular individual as a function:

$$v^t(\pi;x) = u(x, \varphi_x^t(\pi), t). \tag{1}$$

Note that the function $v^t(\cdot;x)$ is simply the inverse function of the (cumulative) distribution of the objective in type t at policy x. This is a useful formulation, because it shows that the outcome for the individual depends upon his circumstances through two channels: first, the 'direct' effect of his circumstances, through the third argument of u, and second, an indirect effect, through the effect of his circumstances on the distribution of effort in his type (the second argument of u). With regard to this indirect contribution, it is generally the case that one's circumstances affect one's preferences (and hence one's choices of effort), and if a person is not to be held responsible for his circumstances, then he should not be held responsible for the *distribution* of preferences, and hence of effort, in his type. Thus, an equal-opportunity policy should hold people only partially responsible for their choices: they are responsible, in a word, for where on the distribution of effort in their type they sit, but not for the properties of the distribution itself (such as its median, mean, and variance).

Thus, we measure the ethically relevant degree of a person's effort by the value of π, not the value of e. The function v is the one that is useful in this theory. To equalize opportunities means to choose the policy x which renders the functions $v^t(\cdot;x)|t = 1,2,...,T$ as close to each other as possible. If we could render these functions identical, then a person's prospects for achieving the objective would depend only on his or her effort choice, not circumstances. Inequalities due to differential effort, as defined here, are not considered undesirable by this ethic.

The literature contains a number of measures of the closeness of these functions (see Roemer, 2004). The simplest version is to attempt to equalize the means of these functions across t, or more generally, to maximize the minimum of ("maximin") these means. That is, the equal opportunity policy x^* is that one which solves the following program:

$$\max_x \min_t \int_0^1 v^t(\pi;x)d\pi. \tag{2}$$

We now describe our project in the present paper. We are not, here, interested in choosing an equal-opportunity policy, but in asking: in Sweden, given its present constellation of social policies and institutions, to what extent is existing income inequality due to circumstances, as opposed to 'effort'? That is, to what extent has Sweden succeeded in equalizing opportunities for income acquisition? While there is a growing literature on computing equal-opportunity policies, with respect to various objectives, and in various countries, it is usually the case that the set of circumstances chosen is quite small, and the number of types into which the population is partitioned is likewise small. This is due to the paucity of good data during adolescence. Thus, in these studies, probably too much of existing inequality is observed as being due to effort, and too little to circumstances, because the set of circumstances observed is only a small proper subset of the true set of circumstances. Sweden, on the contrary, possesses a longitudinal data set, described in section 2, which permits us to observe many circumstances for the male population during childhood. We are able to partition the population into types defined by parental income during childhood (4 levels), parental education (3 levels), own IQ during adolescence (4 levels)[1], number of siblings (3 levels), body mass index during adolescence (4 levels) and family structure (2 kinds): thus, a partition of the population into 1152 types. Call these five characteristics of a person's environment the direct circumstances affecting him or her. The objective we choose is the income of the individual, and we define effort as the residual determinant of income after these circumstances are accounted for. Since our data consist of more than one third of the total population of Swedish males, we have enough observations in all 1152 cells to construct meaningful functions $v^t(\cdot)$, where we now suppress x, since we are observing these outcomes at one existing 'policy'. In terms of the theory explained above, we are interested in knowing how close these functions are to each other, across t.

Rather than using some metric on the space of functions to answer this question, we take a less abstract approach. Consider a measure of income inequality, such as the Gini coefficient. We can consider this inequality as due to the contributions of the various circumstances, and the contribution of effort, the residual. Note, however, that it is important to measure this residual after the effect of circumstances upon the error term in an econometric regression of income upon the circumstances has been taken into account. Thus we must include as one circumstance, the effect of the direct circumstances upon the residual. Let us call the residual, sterilized of the effect of the direct circumstances upon it, the sterilized residual. We view the Gini coefficient (and several other measures of inequality)

[1]There is much debate on whether IQ, tested during adolescence, is due to nature or nurture. We need take no position on the nature-nurture issue; see Björklund et al. (2007) for some Swedish evidence on that issue. The question we need to address is if IQ can properly be considered a circumstance, something for which we should not hold the individual responsible. As we discuss below, this is potentially controversial. We take here the view that even if it may reflect some prior effort, we should still not hold individuals responsible to their characteristics at such a young age and thus treating IQ as a circumstance is justified.

as created by contributions of the direct circumstances, the effect of the direct circumstances on effort, and the sterilized residual, and we model this construction of the Gini as a cooperative game; the Shapley value of this game assigns to each circumstance, and to sterilized effort, its relative contribution to total inequality.

The paper proceeds as follows. In Section 2 we describe the data we use, and in Section 3 we describe our empirical approach. Section 4 reports the results for both our full sample as well as two different cohorts of men. In the concluding section, we summarize our findings, and compare the results to what has been found by other authors.

2 Data

In order to examine the role of circumstances and effort on the distribution of long-run income, we must define the data and variables that allow such an analysis. Thus, we start with a sample of Swedish men who have been linked to their parents, with rich data on the incomes, education and other socio-economic characteristics of both generations. The key concept is that of *circumstance*. Circumstances are captured by partitioning the population (and sample) into discrete *types*, each of which has a particular set of circumstantial background characteristics. The key idea is that an individual should not be held accountable for outcomes that vary because of type.

Samples and source registers In order to achieve our goals, we exploit a combination of Swedish administrative register data sets. A first and basic source is Statistics Sweden's so-called Multi-generational register. This is a register of all persons who were born 1932 and onward, and who have ever received a unique national registration number from 1961 and onward.[2] For the Swedish population defined in this way, the register contains information about biological (and adoptive) parents and their national registration number. From this information, one can also infer which individuals are related as siblings; full siblings are those who have the same father and mother, half siblings are those who only have one parent in common. Our analysis sample is a 35 percent random sample of the Swedish male population born 1955-67 defined in this register. We also use the Multi-generational register to identify parents and siblings.

[2]The requirement that the persons must have been registered in Sweden from 1961 and onward implies that persons 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 second source is the set of bidecennial censuses conducted from 1960 to 1980. We can identify our main sample of sons in the households of these censuses as well as other persons in the household. Thus we can determine whether our offspring generation lived with their biological parents or not in the fall of these census years.

The third source is Statistics Sweden's income register, which in turn come from the Swedish tax assessment procedure. A limitation is that such data are available only from 1968 onwards. From that year the income register provides data on total income from all sources of income, from work, self employment, capital, real estate as well as some transfers (from 1974 onward). We use such income data for both parents and sons. The earlier data for parents stem from their own compulsory tax assessments. In later years, when we measure sons' incomes, the source of the data is compulsory reports by employers to the tax authorities.

The fourth source is the Swedish Military Enlistment Battery, which provides a measure of intellectual capacity. The purpose of these tests is to classify Swedish men to different military positions with different demands on general intellectual capacity. For the cohorts who now are adults, military service was compulsory in Sweden with only few exceptions. Generally, the tests were done during the year when men turned 18 years of age. The Enlistment Battery contained four cognitive tests: instructions, synonyms, metal folding and technical comprehension. The subtests were designed to measure the primary IQ factors Induction, Verbal Comprehension, Spatial Ability and Technical Comprehension respectively. We use a summary measure of intellectual ability based on the four tests provided by the military organization that runs the tests.[3] The Enlistment Battery also provides measures of height and weight, which we use to calculate the body mass index, BMI.

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 As our outcome variable for sons we use a measure of total market income before taxes provided by Statistics Sweden. It includes income from all sources, that is, labor, business, capital, realized capital gains as well as some taxable social transfers such as unemployment insurance, sickness pay, parental

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

leave payment, and pensions. We use the average of real total income over the years when sons were 32-38 years of age. At these ages, we are likely to get a good estimate of long-run income (see Böhlmark & Lindquist, 2006). Further, averaging over as long a period as seven years is likely to eliminate most transitory income variation that is not relevant for our purposes.

Our 5 background characteristics are

1. parental income quartile group (4 groups)
2. parental education group (3 groups)
3. family structure/type (2 groups)
4. number of siblings (3 groups)
5. IQ quartile groups (4 groups)
6. body mass index quartile group (4 groups)

the combination of which gives us $T = 1152$ types.

For *parental income* we apply the same income concept as for sons. We use a multi-year average of the sum of the two biological parents' incomes during the years when the son was 13-17 years old. 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. This measure we divide into four quartile groups of equal size.

To measure *parental education*, we make use of the fact that the 1970 census made special effort to collect information about education. We use the educational level of the biological parent who has the highest educational level according the information in the census. This level in turn, we split into three groups: only compulsory school, more than compulsory school but no college, and at least some college.

We also use the censuses to construct a *family type* indicator. This is equal to one if the son 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 son 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, 1-2 or 3+ siblings.

For *IQ*, we split the summary measure of intellectual ability from the Military Enlistment Battery into four quartile groups The use of own IQ as a circumstance, as opposed to effort, is potentially controversial, for several reasons. First, cognitive test scores at age 18 are very likely affected by educational choices up to that age. Moreover, to some extent such choices, and performance within the chosen educational path, reflect effort on the part of the young individual making them. However, the key here is the following. We define as a circumstance factors that affect socio-economic outcomes, but for which we do not hold the individual *responsible*. Your actions and effort prior to the age of 18, even if they in part reflect your ambitions and motivations, are not something we would hold you responsible for.

Body Mass Index is calculated from height and weight as measured at military enlistment, and broken down into quartile groups.

The definitions imply that we need to make some sample restrictions. Importantly, our reliance on military enlistment data necessitates an exclusive focus on men. We acknowledge that by so doing we exclude one important circumstance, namely gender. We also focus on those persons born in Sweden, as the information on the parents of foreign-born inhabitants can be quite sketchy and unreliable. We also only include persons for whom both the biological mother and biological father are non-missing in the Multigeneration register.

Descriptives Table 1 shows the number of observations, the mean, standard deviation and maximum of sons' long-run incomes for each birth cohort and the whole sample. Table 2 shows the the same statistics for parental income for each cohort of sons. We should note that for the 1960 cohort is small due to a high attrition in the military data for this cohort.[4] Moreover, the 1967 cohort contains some outliers, which with the result that their standard deviation jumps quite substantially and is more than twice as high as that for any other cohort.[5]

Table 3 shows the distribution of types across cohorts. We do have some "drift" across cohorts across the distribution of parental income and education, in that the younger cohorts enjoy disproportionately higher income and education. The fact that the IQ type distribution is quite skewed is explained by the fact that we use the military test results scaled on the "stanine" scale, i.e., discrete

[4]Cesarini (2009) investigates if this attrition is selective, and finds that it is not. We have experimented with eliminating the entire 1960 cohort from the analyzes altogether, and the results were not substantially different.

[5]The most likely explanation for those high numbers is realized capital gains during the end of the period.

Table 1 Descriptives, sons' long-run incomes

birthyear	N	Mean	Std	Min	Max
1955	16197	234323	153036	0	$1.20e+07$
1956	16821	234624	140900	0	$9.73e+06$
1957	16505	235187	149659	0	$1.23e+07$
1958	16480	236790	139746	0	$9.18e+06$
1959	16307	236880	143962	0	$5.10e+06$
1960	2442	243834	173219	0	$3.70e+06$
1961	14469	248740	168657	0	$5.34e+06$
1962	16791	259540	242082	0	$1.38e+07$
1963	17953	274663	353906	0	$2.35e+07$
1964	19187	282622	407151	0	$3.76e+07$
1965	18988	286325	448066	0	$4.06e+07$
1966	18477	290906	222853	0	$7.39e+06$
1967	18346	308531	1263642	0	$1.68e+08$
ALL	208963	262090	452580	0	$1.68e+08$

Table 2 Descriptives, parental long-run incomes

birthyear	N	Mean	Std	Min	Max
1955	16197	299131	200042	712	6126417
1956	16821	300450	180593	241	3987879
1957	16505	311492	177863	241	3043500
1958	16480	322165	215743	157	13788115
1959	16307	331482	197420	365	9853299
1960	2442	335869	171774	4462	2497343
1961	14469	351258	213342	478	14552906
1962	16791	358252	177239	510	7428959
1963	17953	358926	203160	1326	14344192
1964	19187	355404	168743	241	7025543
1965	18988	351733	169366	273	6260280
1966	18477	349116	155384	1060	2742221
1967	18346	345727	184995	196	13079620
ALL	208963	336939	187924	157	14552906

Table 3 Marginal distribution of types

	ParentIncType			
	1	2	3	4
1955	38.2	27.3	17.2	17.3
1956	37.0	26.7	18.4	17.9
1957	33.0	27.2	19.9	19.9
1958	30.2	26.3	22.3	21.3
1959	26.2	26.9	23.7	23.2
1960	24.5	25.4	25.6	24.6
1961	20.7	24.8	26.9	27.6
1962	18.9	23.5	27.3	30.3
1963	18.8	23.0	28.0	30.2
1964	17.9	23.8	29.0	29.3
1965	18.4	23.8	29.1	28.7
1966	18.3	24.5	29.7	27.5
1967	18.7	25.3	29.7	26.3
Overall	24.4	25.2	25.3	25.1

	ParentEducType		
	1	2	3
1955	52.0	37.1	10.9
1956	51.0	37.9	11.1
1957	49.2	38.9	11.9
1958	47.4	40.3	12.3
1959	45.7	41.4	12.9
1960	45.6	41.2	13.2
1961	43.0	43.4	13.6
1962	40.6	45.2	14.2
1963	39.0	46.8	14.2
1964	36.5	49.2	14.3
1965	34.2	51.5	14.3
1966	32.0	53.2	14.8
1967	30.1	55.1	14.8
Overall	41.4	45.3	13.3

	FamilyType	
	1	2
1955	21.3	78.7
1956	21.5	78.5
1957	20.7	79.3
1958	21.4	78.6
1959	22.1	77.9
1960	25.7	74.3
1961	26.4	73.6
1962	26.3	73.7
1963	26.4	73.6
1964	28.2	71.8
1965	30.1	69.9
1966	30.1	69.9
1967	30.4	69.6
Overall	25.6	74.4

	IQType			
	1	2	3	4
1955	35.5	19.4	31.6	13.4
1956	36.1	19.5	31.4	12.9
1957	37.1	19.7	31.2	11.9
1958	37.1	19.9	31.1	11.9
1959	36.2	19.6	32.1	12.0
1960	36.6	19.5	31.8	12.2
1961	35.7	20.0	31.8	12.5
1962	36.9	23.9	28.2	11.0
1963	35.1	24.6	29.0	11.3
1964	35.5	23.5	28.0	13.0
1965	33.9	24.1	29.6	12.5
1966	32.5	24.1	30.2	13.3
1967	32.2	24.5	30.3	13.0
Overall	35.3	22.0	30.3	12.4

	BMIType			
	1	2	3	4
1955	28.5	26.3	24.1	21.0
1956	28.1	25.7	24.0	22.3
1957	27.4	25.5	24.6	22.5
1958	26.7	25.1	24.8	23.4
1959	25.9	24.7	24.8	24.7
1960	22.4	24.3	26.7	26.7
1961	24.3	24.1	25.3	26.2
1962	24.9	24.7	25.0	25.4
1963	24.1	24.1	25.3	26.5
1964	23.6	24.8	25.9	25.8
1965	23.8	24.9	25.1	26.2
1966	23.0	24.9	25.2	27.0
1967	22.2	24.2	26.1	27.5
Overall	25.1	24.9	25.1	25.0

	SibType		
	1	2	3
1955	15.1	61.2	23.8
1956	14.6	62.0	23.4
1957	14.4	62.4	23.2
1958	13.7	64.0	22.3
1959	13.7	64.9	21.4
1960	12.7	65.8	21.5
1961	14.0	66.6	19.4
1962	13.9	67.2	18.8
1963	13.3	69.1	17.6
1964	13.7	70.1	16.2
1965	13.3	71.4	15.3
1966	14.7	71.5	13.8
1967	14.5	73.1	12.4
Overall	14.1	67.2	18.8

integers from 0-9, which generates a very lumpy distribution. In particular, the first and third quartiles include scale values 4 and 7 respectively, which leads to disproportionate mass in those quartile groups.

Next, we show the cumulative distribution of income, our $v^t(\pi)$, for a few selected types. For each figure, we have set the other characteristics in the middle category, and display the separate CDF for types that vary only across the selected characteristic.[6] We show 3 such figures, one for types by parental education, parental income quartile group, and own IQ quartile group.

From the Figures 1 to 3, we see something interesting. Except for Figure 3, which varies IQ type, it's the case that median income for the various types is almost the same. Look, e.g., at Figure 2, which varies parental education. The divergence of the CDFs occurs mainly in the upper part of the income distribution. For IQ, this is not so – divergence occurs even at low levels of 'effort.'

It is not easy to tell why these patterns occur. Perhaps 'social connections' of the parents are important for 'high parental income' and 'high parental education', which have big payoffs at the upper end of child distribution of income. In other words, social connections of high-status parents can increase child's income, but either only a fraction of high-status parents use their social connections, or social connections are effective only if the child has certain (industrious) qualities. But IQ, which is most closely tied to merit (in the sense of ability) has a more or less continuous effect on the individual's income.

Our speculation on the importance of parental connections is inspired, in part, by work by Corak & Piraino (2011) that examines the extent to which sons in Canada have worked in the same firm as their fathers. While the fraction of father-son pairs who have shared the same employer (defined in a few alternative ways) is surprisingly high overall, this probability increases sharply once the focus is on fathers in the upper end of the income distribution. This is consistent with a few different explanations, but social connections and nepotism is prominent among them. A comparison of Canada and Denmark suggests remarkably similar patterns in the two countries (Bingley et al., 2010), which leads us to speculate this might also be the case in Sweden.

Moreover, Björklund et al. (2010) find that the intergenerational elasticity of father-son income increases sharply at the very top of the income distribution, results that are consistent with patterns of the more general convex relationship between the ln of income of father's and son's in Denmark, Finland and Norway

[6] Specifically, we choose FamilyType=1, IQType=3, ParentEducType=2, ParentIncType=3, SibType=2 and BMIType=3.

Figure 1 Income distribution (CDF) among example types ($v^t(\pi)$): by level of parental education (labels: 1=only compulsory; 2=more than compulsory, no college; 3=at least some college)

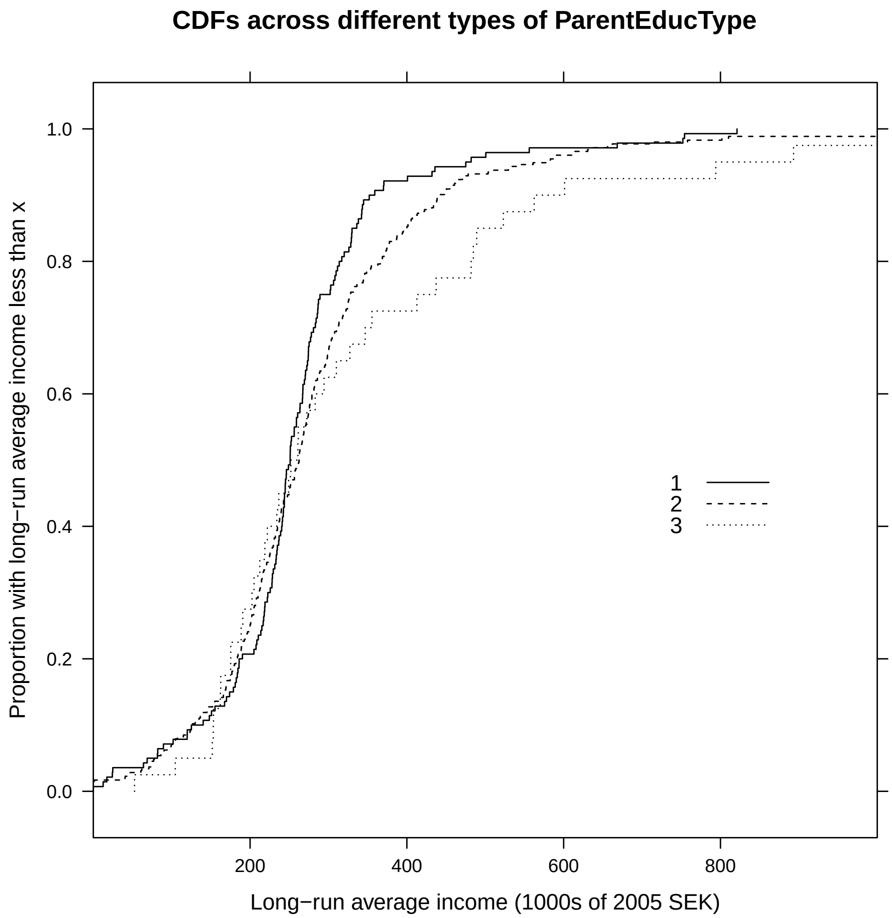


Figure 2 Income distribution (CDF) among example types ($v^t(\pi)$): by level of parental income (labels indicate quartile group of a multi-year average of parental income)

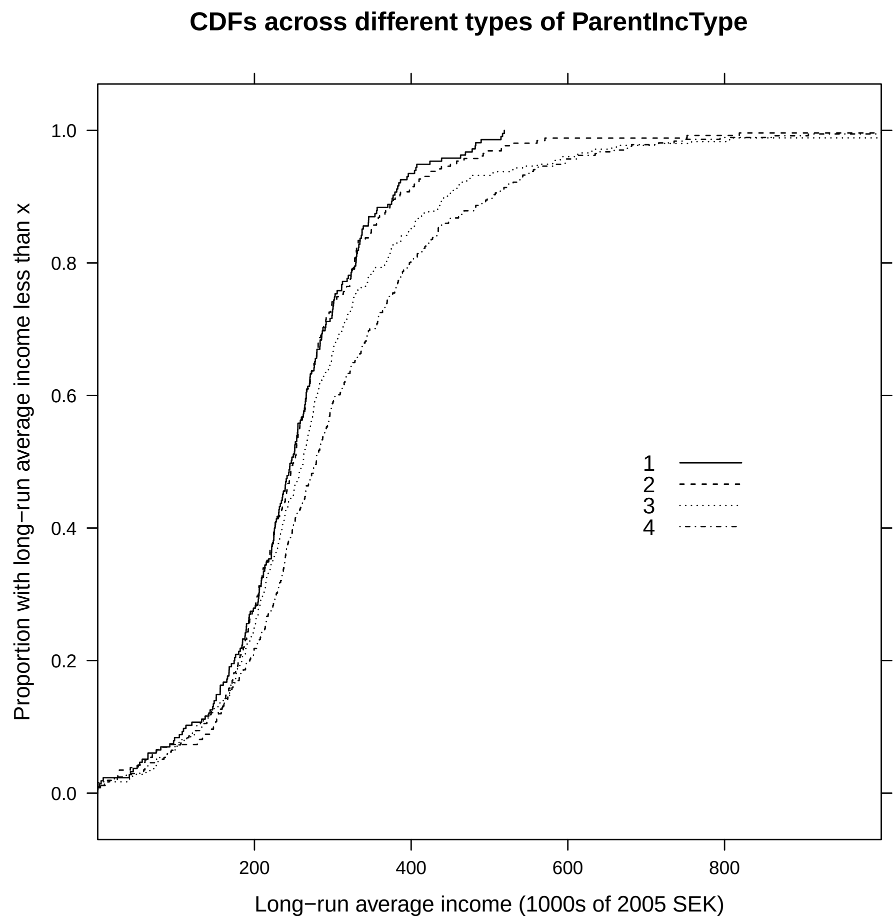
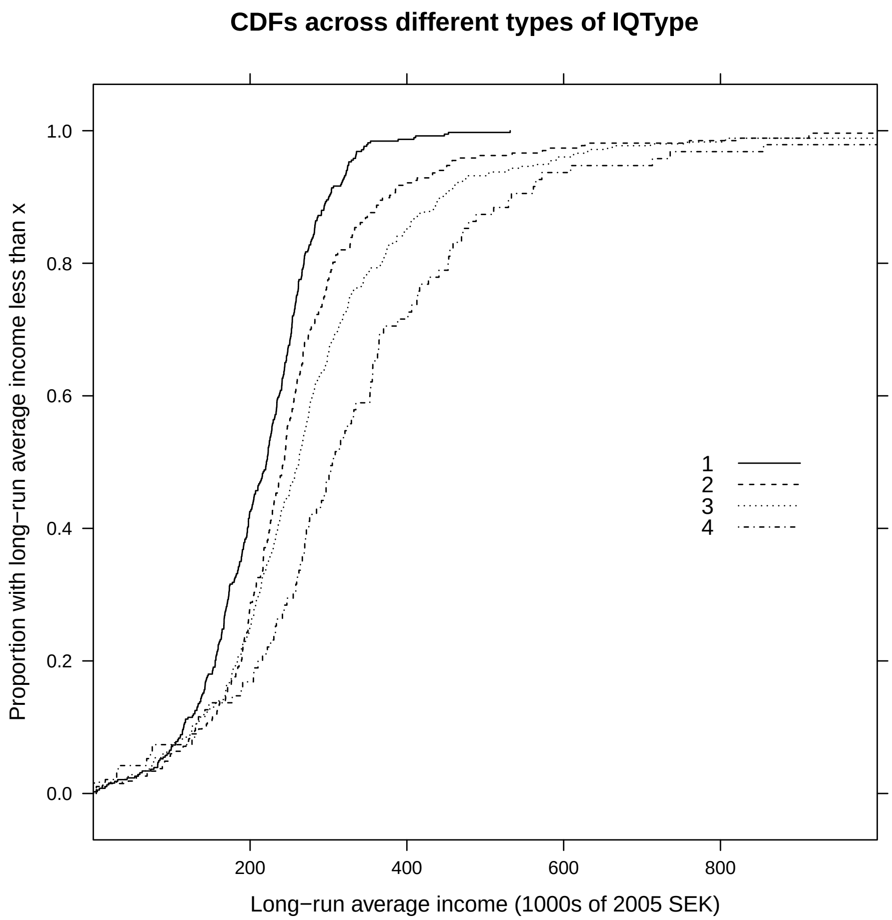


Figure 3 Income distribution (CDF) among example types ($v^t(\pi)$): by level of own IQ (labels indicate quartile group of military enlistment cognitive test result)



(Bratsberg et al., 2007).

Thus, the evidence in Figures 1 and 2 of little dependence of long-run income on parental socio-economic status at the lower end of the distribution, and close to equal median incomes, but large income advantages toward the low end, is consistent with several pieces of recent evidence on intergenerational socio-economic transmission.

The continuity of IQ is also interesting, since it operates across the whole distribution in a close to homogenous way. Taken with the graphs that distinguish between parental income types, the connection of IQ with the outcomes appears to be much more straightforward as the advantage bestowed by having higher IQ (or traits that are highly correlated with it that are rewarded in the labour markets) operates throughout the income distribution.

3 Methods

The approach we take is based on Keane & Roemer (2009), Betts & Roemer (2007) and Lee (2008). We are interested in what fraction of the inequality of long-run income, Y, which has distribution F_Y, can be attributable to *circumstances* and what can be attributable to *effort*. Circumstances are captured by partitioning the population (and sample) into discrete *types*, each of which has a particular set of circumstantial background characteristics. The key idea is that an individual should not be held accountable for outcomes that vary because of type.

Denote each of the J background characteristics by X_j, which can take K_j specific values (see Section 2). Each type t consists of a particular cell or collection of value $t \in \mathcal{T}$, where the set $\mathcal{T}$ consists of elements $\mathbf{X}^t = (X_1 = x_1^t, X_2 = x_2^t, X_3 = x_3^t, X_4 = x_4^t, X_5 = x_5^t, X_6 = x_6^t)$. The type of a particular sample member is $\mathbf{X}_i^t$.

We now outline a version that takes effort to be the deviation of long-run income from the expected income of a person of type t, $\mathrm{E}[Y|\mathbf{X}^t]$ from actual income of that person. We measure effort by the residual of a regression of $\ln Y$ on $\mathbf{X}^t$:[7]

$$\begin{aligned} \ln Y_i^t &= \mu + \sum_t \mathrm{Ind}[i \text{ is of type } t]\beta^t + \varepsilon_i^t \Leftrightarrow \\ \ln Y_i^t &= \mu + \sum_j \mathbf{X}'_{ji}\beta_j + \varepsilon_i^t, \end{aligned} \tag{3}$$

[7]Note that 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.

where the second row uses the more conventional notation with each separate characteristic being a set of dummy variables. The two formulations are interchangeable, but the latter is what we actually use in regressions.

We next measure the role of each circumstance, and of effort, by a Shapley-value decomposition of the inequality index $I(F_Y)$. The above implementation takes the "raw" residual from an empirically estimated version of equation (3) as a measure of effort.

The problem with this is that the distribution of ε_i^t may vary across types, that is, it can be heterogeneous. Each type is characterized by an expected/average income, captured in equation (3) as the deviation of that type's income from the overall average (i.e., $\mathrm{E}[\ln Y|\mathbf{X}^t] = \mu + \mathrm{Ind}[i \text{ is of type } t]\beta^t$. Each type may in addition be characterized by a different distribution of effort ε^t, F_ε^t. As a person should not be held accountable for her circumstances (captured by type), and F_ε^t is a consequence of being of type t, variations in ε and therefore realized income Y that are attributable to differences in F_ε^t are also part of what a person can not be held accountable for.

The solution to this in Betts & Roemer (2007) is to measure effort by being at a particular quantile p in the distribution of effort among type t, and standardize the distribution of effort to be the same across all types. That solution is not available to us in this accounting exercise. How, then, should we take into account differences in the *distribution* of effort?

The heterogeneity takes the form of heteroscedasticity. That is, each type t has its own variance $\sigma_t^2 = \mathrm{Var}[\varepsilon^t|\mathbf{X}^t]$. We address this by adding and subtracting to the regression equation a residual term that has a homogenous variance. The most natural candidate for standardizing the distribution across types is to choose the overall variance, which, since the expectation of the residual is zero in all groups is given by the weighted average of the variance within types as $\sigma^2 = \sum_t f_t \sigma_t^2$. This allows us to distinguish between a residual whose variance varies across types, and one that does not. It is this latter residual that we associate with individual effort. Thus, we add one more background characteristic, namely the effect of type on the variation of effort to our list of characteristics. Thus, we work with a regression equation of the form

$$\begin{aligned}\ln Y_i^t &= \mu + \sum_j \mathbf{X}'_{ji}\beta_j + \varepsilon_i^t \\ &= \mu + \sum_j \mathbf{X}'_{ji}\beta_j + \varepsilon_i^t - \underbrace{\varepsilon_i^t/k\sigma_t}_{u_i} + \underbrace{\varepsilon_i^t/k\sigma_t}_{u_i} \\ &= \mu + \sum_j \mathbf{X}'_{ji}\beta_j + \widetilde{\varepsilon}_i^t + u_i,\end{aligned} \tag{4}$$

where $k = (1/\sum_t f_t\sigma_t^2)^{-1/2} = 1/\sigma$. Thus, u_i has variance $1/k^2 = \sigma^2$ across all types. This separates between standardized effort u_i that is measured in terms of a common distribution, and that part of effort $\widetilde{\varepsilon}_i^t = \varepsilon_i^t - u_i$ that captures the influence of type on the conditional variation of income around the expected value for each type.

Implementing this is quite straightforward and involves estimating in the first step 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 and/or very small estimated variances, leading to very large standardized residuals u_i. For this reason, in our baseline case, we regress the estimated variances on the background characteristics, and use the fitted values from that regression as the basis for $\varepsilon_i^t/k\sigma_t$. This procedure smooths out the more extreme values.

After we have run the regressions, we proceed with examining the importance of each of the circumstances as well as effort on the distribution of income. A circumstance, such as parental education, is turned "on" or "off". When it is "on", the circumstance takes on its actual variation in the population and affects long-run income through its associated regression coefficients. When it is "off", we eliminate variation due to the circumstance by replacing for every observation its actual variation with the mean value – which equals mean of the average proportion in each category of the circumstance multiplied by the estimated coefficient. The importance of a circumstance is measured by comparing the inequality of long-run income (measured in levels, not natural logarithms) when the circumstance is "off" to when it is "on".

Formally, from equation (3) a circumstance j contributes $\mathbf{X}'_{ji}\beta_j$ to income. We compare inequality when we allow the circumstance to contribute $\mathbf{X}'_{ji}\widehat{\beta}_j$ 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 $\overline{\mathbf{X}}'_j\widehat{\beta}_j$, thus eliminating variation across individuals from that circumstance.

The contribution of a circumstance to inequality in the above sense may depend on the order in which inequality from that source is measured. This is a well-known problem in inequality decompositions. We use here the Shapley-value decomposition. Specifically, with J circumstances, and type-specific as well as homogeneous effort, we have $J+2$ factors whose impact on inequality we want to measure. We proceed as follows. We generate the powerset of the $J+2$ factors. For each element in the powerset, we have a set of circumstances that vary, and the rest are constant (except of course the empty set, with no circumstances that vary, and the set of all circumstances, in which case all vary). We calculate our inequality indices for each of the sets, by constructing the level of income for each observation allowing the $J+2$ factors either to vary or not from the regression and taking the antilog of the counterfactual ln income.

Then, for each of the circumstances, 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 circumstance. The importance of a circumstance is measured as the normalized average of all such comparisons.[8] The Shapley-value decomposition approach (Shorrocks, 1999) has several benefits. Among others, it results in an additive decomposition of inequality, i.e., the sum of all contributions is the value of overall inequality.

This method is based on a discrete number of types. Yet, three of our variables describing circumstances, namely parental income, IQ and BMI, are continuous. In order to fit these variables into our framework of discrete types, we have divided them into groups (in this case four groups each). It might be argued that this approach ignores some within-type variation in circumstances and thus underestimates the importance of circumstances and overestimates the role of effort. However, our use of types implies that our underlying regression model has a quite flexible functional form. We acknowledge that it is a challenging task for future research to develop the analysis of equality of opportunity to the case of continuous circumstances, see O'Neill et al. (2000) for an approach to do so in a different setting than ours.

4 Results

Main results We provide three sets of results, distinguished by how they deal with heterogeneity across types. Our baseline case allows heterogeneity across

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

types, but in estimating it, we regress the residual standard deviation of each type on each circumstance (not including interactions) and use the fit from that regression as our estimate of the standard deviation of each type. In one sensitivity analysis, we use instead the type-specific residual standard deviation (except for cells with fewer than 10 observations, for which we use the regression fit). We further examine the results of making no allowance for type-specific heterogeneity.

The results from the underlying regressions are reported in Table A 1. The estimates are reasonable and some of them are substantial in magnitude. For example, the coefficients on the four IQTypes go from zero (the omitted case) to .325 with small differences across cohorts. Further, the coefficients on the four ParentIncTypes go from zero to .206, also with small differences across cohorts. The two family structure variables (parental separation and number of siblings) also have sizeable coefficients; growing up with both biological parents is associated with an income advantage of .071 log points. What is somewhat surprising is that the coefficients on parental education are so small, in some cases even insignificant and for the oldest cohort even with the “wrong” sign. As a sensitivity analysis, we dropped parental income and re-estimated the equations. The coefficients for parental education became quite large, were strongly significant and had the “correct” sign. Thus, we conclude that parental income subsumes the impact of education in the preferred regression.

The Shapley-value decomposition of inequality in our baseline case for all cohorts as well as the “old” (1955-1959) and “young” (1963-1967) cohorts are shown in Table 4. We measure inequality using four inequality indices, namely the Gini coefficient, two members of the Generalized Entropy-class of measures (GE(0) and GE(1), corresponding to the log mean deviation and the so-called Theil(1) measure of inequality, as well as the squared coefficient of variation CV2. which in turn is $2 \times$ GE(2). Each panel shows the value of the inequality index in the top row, followed by the percentage contribution of each factor in the subsequent rows.

Focusing on the shares of each factor in overall inequality, it appears that the three most important contributors to inequality of opportunity are parental income, IQ, and the type heterogeneity of effort. The relative importance of each of these varies across measures and this most likely varies in importance across the distribution of income. For instance, parental income accounts for 7.1 percent of the Gini coefficient, while IQ type and type heterogeneity (i.e., differences in the variance of the residual) account for 11.5 and 5.1 percent, respectively. Compare this to the CV2, for which parental income accounts for 5.4, IQ for 3.8 and type

Table 4 Contribution of types to overall inequality of long-run average income – for all cohorts (Panel A) and for cohorts born 1955-1959 (Panel B) and 1963-1967 (Panel C) – heterogeneous effort controlled using smoothed residual variance

A. All (born 1955-1967)

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.257	0.150	0.159	2.196
Relative contributions				
ParentIncType	7.1	2.8	3.2	5.4
ParentEducType	0.4	0.1	0.1	0.1
IQType	11.5	4.9	4.9	3.8
SibType	0.9	0.2	0.3	0.6
FamilyType	1.7	0.5	0.3	−2.2
BMIType	0.8	0.1	0.2	0.4
Type heterogeneity	5.1	2.6	7.3	24.5
Residual	72.6	88.7	83.8	67.4

B. Cohorts born 1955-1959

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.228	0.120	0.104	0.320
Relative contributions				
ParentIncType	7.2	2.8	3.2	2.1
ParentEducType	0.0	−0.2	−0.2	−0.2
IQType	11.1	4.6	5.4	4.5
SibType	0.7	0.2	0.2	0.1
FamilyType	1.8	0.6	0.7	0.8
BMIType	0.9	0.2	0.2	0.4
Type heterogeneity	4.3	0.8	2.2	3.8
Residual	74.1	91.0	88.4	88.6

C. Cohorts born 1963-1967

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.270	0.166	0.189	3.034
Relative contributions				
ParentIncType	5.7	2.1	1.7	0.1
ParentEducType	0.3	0.1	0.1	0.0
IQType	12.6	5.3	4.5	−0.6
SibType	0.8	0.2	0.3	0.6
FamilyType	2.3	0.7	0.7	1.1
BMIType	0.7	0.1	0.1	0.2
Type heterogeneity	6.4	4.1	12.1	32.0
Residual	71.3	87.4	80.7	66.6

variation for 24.5 percent of the total. For the GE(0), by contrast, parental income accounts for 2.8, IQ for 4.9 and type variation for 2.6 percent of the total. As the GE(0) is sensitive to income differences at the low end, the Gini to the middle and the CV2 to the top, these differences suggest that type variation is quite important at the high end of the distribution of outcomes, while IQ may matter more at the low end and middle of the distribution. On this interpretation, parental income may be relatively important throughout the distribution. The residual, which is supposed to capture effort, is very important, accounting for between 2/3 (CV2) and almost 90 (GE(0)) percent of the inequality of long-run income.

In Panels B and C of Table 4, we show the results for cohorts born between 1955-59 and 1963-67, to capture change across time in the importance in circumstances. The results suggest that parental income is an important circumstance in both cohorts, as is IQ. An exception to this is the CV2 in the later cohort, for which parental income matters very little and for which IQ gives a negative contribution. This may be driven by a few outlying observations in the very youngest cohorts – see Table 1 – which have a very large influence on the CV2. Indeed, the point estimate for the CV2 increases by a factor of ten between the two cohorts. Moreover, almost one third of this very large increase is captured by the heterogeneity across types. For the older cohorts, type variation captured between 0.8 to 4.3 percent of the inequality of long-run income, while own IQ accounted for between 4.5 and 11.1 percent, and parental income accounted for between 2.1 and 7.2 percent of inequality. On the whole, type heterogeneity is more important for the younger cohort. We have not been able to come up with an explanation for this result.

Sensitivity analysis We show, below, results from varying our treatment of heterogeneity. In particular, it clearly is worthwhile to pay attention to the heterogeneity in the distribution of effort across types.

Using actual rather than regression-smoothed standard deviations to measure heterogeneity across types does not change our results very much (cf. Table 4 and 5). The roles of heterogeneity, parental income and IQ are largely similar to that found in our baseline case. Things look quite different when we examine the old and young cohorts separately, in Panels B and C of Table 5. As earlier, heterogeneity across types is relatively unimportant in the older cohorts, born between 1955 and 1959, although heterogeneity across types contributes negatively to GE(1). But for the younger cohorts, heteoregeneity across types has a much smaller contribution than in the corresponding analysis using the smoothed standard deviations (cf Table 4) and the contribution is negative for both the GE(0) and GE(1). We interpret this as being driven by several extreme residual variance estimates within quite small cells and, rather than tinkering with the size of cells for which we use the regression smooths (currently n=10) we prefer the use of the smoothed estimates altogether.

If, instead, we ignore heterogeneity across types, parental income and own IQ are still the most important circumstances, and appear so quite robustly both in the full set of cohorts and in the young and old cohorts separately (see Table 6). Of course, effort, as captured by the now quite heterogeneous regression residual, captures a greater share of the variation. However, as we saw, accounting for variations in the distribution of effort, by distinguishing between hetero- and homoscedastic residual variation, captures a substantial part of the variation that is now ascribed to variations in individual effort.

5 Conclusions

The single starkest finding of our analysis is that at least two thirds, and generally over 70 percent of the income inequality in Sweden is due to our residual term, which we have called 'effort,' and this is so even after we have accounted for a set of circumstances that is about as complete as one can expect to compile, given existing data sets. Importantly, we have sterilized the error term of the effect of direct circumstances upon it.

The important role of 'effort' in explaining inequality is a mark of the high level of development of Sweden. If we conceive of economic development as a process which enhances the degree of distributive justice in a society, and if equality of opportunity, as here conceived of, comprises justice, then Sweden has moved a great distance towards distributive justice. The recent work by de Barros et al. (2009) computes the degree to which circumstances explain inequalities of various kinds in 28 Latin American countries: it is not unusual for circumstances to account for between 30 and 50% of inequality, and this is so even though their data do not permit measurement of the extensive set of circumstances which we have been able to define for Sweden. So if, with our 1152 types, only at most one third, and in general less, of inequality is due to circumstances in Sweden, that is a great social accomplishment. de Barros et al. (2009) do not have access to own IQ, which turned out to be important in our study. On the other hand, as do we, they did have access to family structure variables, which are typically missing in

Table 5 Contribution of types to overall inequality – heterogeneous effort controlled using the actual residual variance for all cohorts and for cohorts born 1955-1959 and 1963-1967

A. All (born 1955-1967)

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.257	0.150	0.159	2.196
Relative contributions				
ParentIncType	6.8	2.8	3.1	4.9
ParentEducType	0.4	0.1	0.1	0.1
IQType	11.0	4.9	4.9	3.5
SibType	0.9	0.2	0.3	0.6
FamilyType	1.6	0.5	0.3	−1.8
BMIType	0.8	0.1	0.2	0.4
Type heterogeneity	6.6	1.7	5.4	29.4
Residual	72.0	89.6	85.7	63.0

B. Cohorts born 1955-1959

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.228	0.120	0.104	0.320
Relative contributions				
ParentIncType	6.8	2.8	3.1	1.8
ParentEducType	0.0	−0.2	−0.2	−0.1
IQType	10.5	4.6	5.4	4.3
SibType	0.7	0.2	0.2	0.1
FamilyType	1.7	0.6	0.7	0.7
BMIType	0.9	0.2	0.2	0.3
Type heterogeneity	6.2	0.0	−0.9	4.1
Residual	73.3	91.9	91.5	88.8

C. Cohorts born 1963-1967

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.270	0.166	0.189	3.034
Relative contributions				
ParentIncType	5.4	2.1	1.7	0.2
ParentEducType	0.3	0.1	0.1	0.0
IQType	11.9	5.3	4.3	−1.2
SibType	0.8	0.2	0.2	0.6
FamilyType	2.2	0.7	0.8	1.4
BMIType	0.7	0.1	0.1	0.2
Type heterogneity	6.2	−0.7	−1.3	9.9
Residual	72.5	92.2	94.1	88.8

Table 6 Contribution of types to overall inequality – no heterogeneity of effort correction for all cohorts and for cohorts born 1955-1959 and 1963-1967

A. All (born 1955-1967)

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.262	0.156	0.175	2.970
Relative contributions				
ParentIncType	7.9	3.5	4.7	7.2
ParentEducType	0.5	0.2	0.2	0.2
IQType	12.5	5.8	7.2	11.7
SibType	1.0	0.3	0.3	0.7
FamilyType	1.6	0.3	0.3	0.9
BMIType	0.9	0.1	0.2	0.5
Residual	75.6	89.8	87.0	78.8

B. Cohorts born 1955-1959

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.231	0.122	0.111	0.379
Relative contributions				
ParentIncType	8.0	3.4	5.0	7.4
ParentEducType	−0.1	−0.2	−0.4	−0.6
IQType	12.0	5.1	6.5	5.8
SibType	0.8	0.2	0.2	0.2
FamilyType	1.7	0.4	0.5	0.7
BMIType	1.0	0.1	0.1	0.2
Residual	76.6	90.9	88.0	86.3

C. Cohorts born 1963-1967

	Gini	GE(0)	GE(1)	CV2
Index value				
	0.276	0.175	0.219	5.074
Relative contributions				
ParentIncType	6.5	2.8	3.8	6.1
ParentEducType	0.3	0.2	0.2	0.5
IQType	13.9	6.7	8.3	13.1
SibType	0.9	0.2	0.3	0.7
FamilyType	2.2	0.5	0.5	1.4
BMIType	0.8	0.1	0.2	0.3
Residual	75.3	89.4	86.8	77.9

related studies.[9]

Moreover, if we take the longer historical view, it is clear that time's arrow points in the direction of increasing equality of opportunity. Capitalism destroyed one great cause of inequality of opportunity, feudal relations, and replaced it, at least to some degree, with meritocracy. As we have seen, the meritocracy is highly imperfect, especially in countries at low levels of development. Even in Sweden, however, parental income remains a significant correlate of child success. One might surmise that the effect of parental income is, nevertheless, meritocratic, in the sense that high-resource families imbue their children with skills which are valuable in a market economy. Our earlier remarks on Figures 1, 2 and 3 suggest that this is not the entire story – that social connections of parents, which are more akin to feudal remnants, remain important for child success. We believe this is an important issue to pursue in further research.[10]

That IQ is the most significant circumstance for explaining income in Sweden is no surprise: for among the circumstances we have listed, IQ is the one which most clearly measures merit, that is, capacities which are valuable in income-producing activities. In market economies, it will be extremely difficult, if not impossible, to eliminate the correlation between IQ and income – especially the correlation with pre-tax income, which is what we have measured here. Redistributive taxation, and counting public goods as a contribution to income, would naturally reduce the effect of IQ on disposable income.

It is also philosophically contentious to assert that a person's income should not, ethically speaking, be correlated with his or her intellectual capacity. Naturally, there is the usual economic argument about markets being necessary to achieve efficiency; but there is also the philosophical belief, held by many, that a person deserves to benefit from his inborn traits (which IQ partially or substantially reflect). This view has come to be known as self-ownership, and is most prominently espoused by Nozick (1974). The equal-opportunity view, however, maintains that a person deserves to benefit only by virtue of his freely chosen effort, and hence, although it may be nearly impossible to eliminate the correlation between IQ and income (since markets are surely necessary in complex economies), that only means that the extent to which complex societies can achieve distributive justice is limited. If the reader protests that there is no such thing as freely chosen effort – if he or she is, in philosophical lingo, an incompati-

[9]See e.g. Checchi & Peragine (2010) and Bourguignon et al. (2007).

[10]See also Roemer (2004) for a discussion about cases when parental income is not necessarily a circumstance.

bilist[11] – then equality of opportunity reduces to full outcome equality. We doubt, however, that there is any society today that ascribes to this principle. Every society reserves a role for personal responsibility, and its theory of equal opportunity should be consonant with that view.

It is noteworthy that one of the most important circumstances, in our analysis, is what we have called the type variation of effort: namely, the effect of circumstances on the distributions of effort within types. In Table 5, Panel A, this accounts for 5.1% of Gini inequality: it accounts for 19% of total circumstantial inequality (5.1/27.4). In other words, a substantial part of 'choice' should not be considered voluntary, but is due to factors that are clearly beyond the control of persons. For social policy, this is of great importance. It is also one of the most difficult ideas for ordinary citizens to understand. Conservative social policy is often justified by the view that individuals from disadvantaged types have bad habits and exert low effort, and to some extent, this is surely true, politically incorrect as it may be to say so. (A recent example is the prevalence of obesity among poor people in many advanced countries.) The correct ethical posture towards such behaviors must be based upon an understanding of the extent to which they are due to circumstances.

Even among those who ascribe to the general view of 'responsibility – sensitive egalitarianism,' of which the ethic promoted in this paper is an instance, there is disagreement on this issue. Dworkin (1981) and Fleurbaey (2009) advocate the view that if an adult 'identifies with his preferences' then he should be held responsible for the consequences of exercising them. Thus, these writers would probably not agree to consider the type-variation in effort a circumstance. But we find their view untenable. If one's preferences are themselves influenced by disadvantage during the period of their formation, any sophisticated theory of psychology should not hold the individual responsible for their consequences. Of course, what these authors fear is that there is a danger of sacrificing liberalism: one could argue that a slippery slope leads from including the effect of circumstances on effort as a circumstance to denying people freedom of choice. To say we must be aware of the slippery slope is not the same as saying that we should assign the person complete responsibility for his preferences once he reaches the age of consent. Slippery slopes should be treated with care, not abolished.

The measurement of the importance of family background based on sibling

[11] Incompatibilism is the view that a materialist view of causation is inconsistent with the existence of free will. Many (most?) political philosophers are compatibilists: they believe in materialist causation, yet also in responsibility.

correlations is similar to the approach in this paper. A sibling correlation provides a lower bound on the importance of family and neighbourhood characteristics in the variance of income in that it captures all influences that the siblings share. Some of those influences can be observed directly, like the types used in this paper, but some can not, but still lead to brothers' income being positively correlated (see Solon, 1999). Part of what siblings may share is a propensity to exert effort – e.g. because they were brought up to be ambitious. Thus, examination of sibling correlations does address, although less explicitly, similar issues as our approach here based on observable types. Interestingly, Björklund et al. (2009) estimate that roughly one third of the variance in the log of long-run earnings in Sweden can be attributed to family influences, a number quite similar to what we find for the CV2.

The two comments just offered – with respect to the contentious inclusion of IQ and type-heterogeneity of effort as circumstances – are both made in the interests of defending our analysis against an accusation that we have gone too far. But there is another view, recently developed by Lefranc et al. (2009) that would argue we have not gone far enough. These authors object to the procedure of declaring the residual, after circumstances have been accounted for, as effort. They maintain the residual reflects the effects of effort and luck. The point is well-taken. What we cannot measure could just as well be due to luck as to effort. The solution to this problem is to attempt to measure effort by a series of behaviors, and then to ascribe the remaining residual to luck. Lefranc et al. (2009) attempt to do so with French data. While we find this an interesting approach, the Swedish register data that we use do not offer rich possibilities to explore it further.

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Table A 1 Regression results

		All (1955-1967)	1955-1959	1963-1967
(Intercept)		11.992 (0.006)	11.990 (0.008)	12.042 (0.009)
BMIType(omitted: 1)	2	0.038 (0.004)	0.041 (0.005)	0.029 (0.006)
	3	0.048 (0.004)	0.037 (0.006)	0.045 (0.006)
	4	0.037 (0.004)	0.031 (0.006)	0.027 (0.006)
FamilyType(omitted: 1)	2	0.071 (0.003)	0.070 (0.005)	0.089 (0.005)
IQType(omitted: 1)	2	0.114 (0.004)	0.096 (0.006)	0.122 (0.006)
	3	0.192 (0.004)	0.163 (0.005)	0.222 (0.006)
	4	0.325 (0.005)	0.281 (0.007)	0.363 (0.008)
ParentEducType(omitted: 1)	2	0.013 (0.003)	−0.006 (0.005)	0.004 (0.005)
	3	0.009 (0.005)	−0.020 (0.008)	0.012 (0.008)
ParentIncType(omitted: 1)	2	0.071 (0.004)	0.062 (0.005)	0.064 (0.007)
	3	0.118 (0.004)	0.096 (0.006)	0.101 (0.007)
	4	0.206 (0.005)	0.189 (0.007)	0.190 (0.007)
SibType(omitted: 1)	2	0.030 (0.004)	0.012 (0.006)	0.038 (0.007)
	3	−0.008 (0.005)	−0.019 (0.007)	0.002 (0.008)
n		208351	82172	92594
k		15	15	15
σ		0.629	0.57	0.662
Adj R^2		0.0602	0.0547	0.0612