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# Long-term evolution of inequality of opportunity[†]

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**Abstract**

The main goal of this paper is to document and analyze the long-term evolution of inequality of opportunity and thus extend the recent empirical literature, which is mainly concerned with its measurement at a specific point in time. Using repeated cross-section surveys for five European countries (France, Germany, Great Britain, Italy, and Switzerland), the evolution of inequality of opportunity is measured for a period of about two decades for the whole populations, as well as for different birth cohorts. Relative inequality of opportunity represents an important portion of total income inequality, with values ranging from 30 to 50 percent according to the standard deviation of logs (and reaching a lower share in case of mean log deviation) and, for all the countries, it shows a stable or declining time trend. When the birth cohorts are followed across time, inequality of opportunity decreases with age: the effect of circumstances seems to weaken over the life cycle. This is a quite different age profile from that of inequality of outcomes (income or consumption), which generally increases with age. A decomposition of the relative inequality of opportunity allows highlighting some key drivers of its time evolution. In all the countries, there has been a clear enhancement of equality of educational opportunity (as captured by a downward trending intergenerational education persistence) and a reduction of the returns to education. However, for some countries, notably Italy, these trends have failed to translate into decreasing inequality of opportunity in the income distribution because of the increasing role of parental networking (an additional channel through which parental background affects the incomes of offspring).

**Keywords:** Inequality of Opportunity, Decomposition methods, Education mobility, Returns to Education, Family Networking, Cohort Analysis.

**JEL Classification:** D31, D63, E24, I24, J62.

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## 1. Introduction

The recent empirical literature on equality of opportunity (EOp) has provided a significant body of evidence on the extent of inequality of opportunity in different countries. See Brunori et al. (2015) for a first assessment of the existing evidence and Ferreira and Peragine (2016), Ramos and Van de Gaer (2016) and Roemer and Trannoy (2015) for methodological and conceptual issues related to the measurement of EOp.

A common feature of the existing literature is the static approach. Almost all empirical analyses use income distribution at a given point in time as the relevant distribution of individual advantages and are limited to computation of inequality of opportunity as a snapshot for a given country or set of countries.[1]

This paper instead is concerned with the evolution of inequality of opportunity, i.e. with a dynamic approach. In addition, the time variation of EOp allows to study its main determinants. By so doing, we move the research on EOp a step forward and propose and test a (simple) empirical model that can explain the generation of inequality of opportunity in a given economy.

There are three different ways to analyze the evolution of inequality of opportunity, which correspond to three different concepts of inequality dynamics: (i) inequality measured across repeated snapshots of the population (repeated cross-sectional analysis); (ii) inequality measured along life courses (longitudinal analysis); (iii) inequality measured across generations (cohort analysis).

While analysis (ii) requires the availability of a rich longitudinal data set containing information of individual incomes and circumstances over the entire life cycle of the individuals, the analyses (i) and (iii) can be potentially carried out by using repeated cross-section surveys, hence are much less data intensive. This is the reason why in the present paper we focus on analyses (i) and (iii). See Aaberge et al. (2011) for an analysis of long-term inequality of opportunity along the lines of concept (ii).

## 2. The model

### 2.1 Canonical models of inequality of opportunity

The conceptual basis for the definition of inequality of opportunity is provided by the distinction, among the factors influencing the individual achievements, between individual efforts and pre-determined circumstances – defined as those which lie outside the realm of individual responsibility. The EOp approach considers that inequality due to the former is not ethically offensive, whereas it suggests that differences in individual outcomes due to the latter represent a violation of the principle of equality of opportunity and should be removed. In what follows we will follow the simple framework introduced by Checchi and Peragine (2010) to measure inequality of opportunity.

Consider a distribution of income $Y$ in a given population. Suppose that all determinants of $Y$, including the different forms of luck, can be classified into either a set of circumstances $C$ that lie beyond individual responsibility, belonging to a finite set $\Omega$, or as responsibility characteristics,

[1] Also the cross-country comparability is a relevant issue, given the potentially different definitions of outcome and circumstances involved in the analysis.

summarized by a variable $e$, denoting effort,[2] belonging to the set $\Theta$. The outcome of interest is generated by a function $g: \Omega \times \Theta \to \mathbb{R}$ such that:

$$Y = g(C, e) \tag{1}$$

This can be seen as a reduced-form model in which income is exclusively determined by circumstances and effort, such that all individuals having the same circumstances and the same effort obtain the same income. Roughly speaking, the source of unfairness in this model is given by the effect that circumstance variables (which lie beyond individual responsibility) have on individual outcomes.

A parametric implementation of the model above,[3] which has been extensively used in the literature (see Bourguignon et al. 2007), considers estimating by OLS the following equation

$$Y_i = a + bC_i + \epsilon_i \tag{2}$$

and computes inequality of opportunity as the value of a given inequality measure $I(\cdot)$ applied to the distribution of the predicted values $\hat{Y}_i$, where $\hat{Y}_i = \hat{a} + \hat{b}C_i$. Hence the value of absolute inequality of opportunity is given by $I(\hat{Y})$ while the value of relative inequality of opportunity is given by $I(\hat{Y})/I(Y)$.

A dynamic version of the model can be obtained by introducing the time dimension in alternative ways. We could consider a first expression, in which income is assumed to vary with time, while circumstances are assumed to be time invariant:

$$Y_{it} = a + bC_i + \epsilon_{it} \tag{3}$$

Model (3) assumes that circumstances impact income in an identical way over the entire life. A variant of the same model considers the possibility of time-varying effects, possibly distinguishing between fixed and time-varying circumstances:

$$Y_{it} = a_t + b_t C_i + c_t C_{it} + \epsilon_{it} \tag{4}$$

Both models (3) or (4) are highly demanding in terms of data, because their longitudinal structure requires repeated observations of the same individual, possibly under alternative sets of circumstances which are independent from her will. In addition, implementing models (3) or (4) would provide a picture of the evolution of EOp over the life cycle of the specific birth cohorts that are present at the start of the analysis.

A less demanding approach in terms of data exploits the availability of repeated cross sections from the same population. If one is interested in understanding whether a society is experiencing changes in the EOp of its citizens, the relevant model considers

$$Y_{it} = a_t + b_t C_{it} + \epsilon_{it} \tag{5}$$

where $Y_{it}$ is the income of individual $i$ sampled in survey $t$. The data generating process is allowed to change over time among random draws from the (same country) population. The implicit

[2] Effort could also be treated as a vector. However, we follow the literature and treat it as a scalar.
[3] In this paper we follow the ex ante approach. See Fleurbaey and Peragine (2013) for a comparison between the ex ante and ex post approaches to equality of opportunity.

assumption is the over-time stability of the population, such that changes in EOp can be attributed to changes in the relevant parameters $a$ and $b$. Model (5) is specular to cross-country analysis, once $t$ is interpreted as a country indicator, but has the advantage of greater comparability of the underlying populations, originating from the same country.

If the number of cross-sections available for the same country is large enough, and their time span covers a sufficient number of years, one could interpret them as a pseudo-panel, in order to get as close as possible to model (3). In such a case the relevant model becomes

$$Y_{i\tau t} = a_{t\tau} + b_{t\tau} C_{i\tau t} + \epsilon_{i\tau t} \tag{6}$$

where $Y_{i\tau t}$ is the income of individual $i$ born in year $\tau$ and sampled in survey $t$. In such a case, EOp can be repeatedly measured along three dimensions: in a specific year of survey $t$, repeated observations refer to different birth cohorts $\tau$'s; for a specific birth cohort $\tau$, repeated observations refer to different dates of survey $t$'s; for a specific age cohort $(t - \tau)$, repeated observations refer to different life cycles. Section 2.2 initially adopts the approach described by model (5). It uses repeated cross-section surveys of the population of a specific country and estimates, for each year, the relevant parameters of the model. An extension which uses the cohort structure of model (6) is also considered. Both these *dynamic* approaches provide interesting and distinct insights on the evolution of EOp.

### 2.2 Our empirical model

This section presents a decomposition of measured inequality of opportunity into its constituting components in the same vein as what Solon (2004) did for intergenerational mobility of incomes. In the empirical literature (Ferreira and Peragine 2015), circumstances have included gender, age, ethnicity, region of birth, parental background (in terms of educational attainment and occupational status). For simplicity of exposition, let us consider circumstances as consisting of a single variable, parental education, indicated with $E_{\theta-1}$ where $\theta$ denote generations.[4]

We assume that parental background affects the income opportunity of the child through two main channels: *educational investment* and *family networking*.[5] The first channel can be simply described by the intergenerational persistence of educational attainment (Black and Devereux 2011)

$$E_{i\theta} = \delta + \eta E_{i\theta-1} + \epsilon_{i\theta} \tag{7}$$

where $E_{i\theta}$ is the education of the child, $E_{i\theta-1}$ is the education of the parents, $\eta$ is a measure of intergenerational persistence and $\epsilon$ captures any unobservable component (like ability as well as effort). This intergenerational correlation can be justified on various grounds: *cultural dependency* (more educated parents value education more and press their children to follow in their footsteps), *financial resources* (more educated parents hold better jobs and earn higher salaries which allow larger resources to be invested in education); *teaching practices* (more educated parents are capable to support their children during their schooling career).

[4] One could easily add additional circumstances (like gender, age and foreign citizenship, as we do in the empirical section) but the line of argument would remain unaffected.

[5] Since parental background includes many other dimensions beyond education (like parental income, access to educational resources, family wealth, neighborhood), our model is observationally equivalent to many other models of intertemporal transmission of social status. See for example DeFraja (2002),

Education is valued in the labor market. Following the *Mincerian* approach, we assume that individuals choose optimally the amount of schooling by balancing costs (foregone incomes) and benefits (higher wages expected in the future – see Heckman et al 2005). As a consequence, the earnings of people with different educational attainments will differ by an amount that will be proportional to the years of schooling, as in the following equation (where we abstract from the usual demographic information):

$$\log(Y_{i\theta}) = \alpha + \beta E_{i\theta} + \omega_{i\theta} \tag{8}$$

where $Y_{i\theta}$ is the income of the child, $\beta$ is the standard return to education and $\omega$ is a random error (capturing unobservable components – ability, effort – but also unpredictable components – luck). Besides helping providing education, parents may influence children's outcomes by other means. To consider this additional influence, we adopt an *extended mincerian equation* as follows

$$\log(Y_{i\theta}) = \alpha + \beta E_{i\theta} + \gamma E_{i\theta-1} + \omega_{i\theta} \tag{9}$$

The inclusion of parental education can be justified as proxy for family networking in non-competitive labor markets, where connection referrals matter to obtain good jobs (Kramarz and Nordström 2014); it is also consistent with intergenerational transmission of financial assets through bequests. By replacing equation (7) into equation (9) we obtain:

$$\log(Y_{i\theta}) = y_{i\theta} = [\alpha + \delta\beta] + [\gamma + \eta\beta]E_{i\theta-1} + [\omega_{i\theta} + \beta\epsilon_{i\theta}] \tag{10}$$

If we now denote with $I(\cdot)$ any inequality measure, we get

$$I(y_\theta) = I([\alpha + \delta\beta] + [\gamma + \eta\beta]E_{\theta-1} + [\omega_\theta + \beta\epsilon_\theta]) \tag{11}$$

where we can notice that income inequality will be a function of the distribution of parental education (circumstances) and unobservable components (effort, ability and/or luck), as well as of the structural parameters of the income generating process.

For consistency with most of the literature on earnings inequality, we have chosen the *standard deviation of logs* as our inequality indicator.[6] In such a case

$$sd(y_\theta) = \sqrt{var(y_t)} = \sqrt{(\gamma + \eta\beta)^2 var(E_{\theta-1}) + var(\omega_\theta) + \beta^2 var(\epsilon_\theta) + 2\beta cov(\omega_\theta, \epsilon_\theta)} \tag{12}$$

As previously mentioned, a relative measure of inequality of opportunity is given by the ratio between the inequality attributable to circumstances and total inequality. In the present case, the income attributable to circumstances is given by the predicted values $\hat{y}_{i\theta} = (\hat{\alpha} + \hat{\delta}\hat{\beta}) + (\hat{\gamma} + \hat{\eta}\hat{\beta})E_{i\theta-1}$ , obtainable from the estimation of equations (7) and (9). The relative IOp is thus given by the following equation:

[6] Analytic and empirical results are almost identical if we replace the standard deviation of logs with the mean log deviation.

$$IOp = \frac{\sqrt{var(\hat{y})}}{\sqrt{var(y)}} = \frac{(\hat{\gamma}+\hat{\eta}\hat{\beta})\sqrt{var(E_{\theta-1})}}{\sqrt{(\hat{\gamma}+\hat{\eta}\hat{\beta})^2 var(E_{\theta-1})+\hat{\sigma}^2_{\hat{\omega}_\theta}+\beta^2\hat{\sigma}^2_{\hat{\epsilon}_\theta}+2\beta cov(\hat{\omega}_\theta,\hat{\epsilon}_\theta)}} = \\ = \frac{(\hat{\gamma}+\hat{\eta}\hat{\beta})}{\sqrt{(\hat{\gamma}+\hat{\eta}\hat{\beta})^2+\frac{\hat{\sigma}^2_{\hat{\omega}_\theta}+\beta^2\hat{\sigma}^2_{\hat{\epsilon}_\theta}+2\beta cov(\hat{\omega}_\theta,\hat{\epsilon}_\theta)}{var(E_{\theta-1})}}} \quad (13)$$

Equation (13) indicates that, other things constant, relative IOp declines when there is:

1) a reduction in the intergenerational persistence of education $\hat{\eta}$;
2) a reduction in the (private) return to education $\hat{\beta}$;
3) a reduction in the effect of family network in the labor market $\hat{\gamma}$;
4) an increase in the variance and covariance of the non-observable components $\hat{\omega}$ and $\hat{\epsilon}$;
5) a reduction in the variance of the educational attainment of the previous generation.

We will focus mostly on the combination of parameters $(\hat{\gamma} + \hat{\eta}\hat{\beta})$ which summarizes the channels of intergenerational persistence. As it is intuitive, if the educational investment becomes irrelevant (because education yields insignificant returns in the labor market), then parents become unable to transmit privileges to their offspring, and inequality declines as a consequence. Similarly, if parents are unable to actively network on behalf of their children, the disadvantage due to circumstances will decline.

The same approach can be used to assess the role of other circumstances. As a final example, consider the impact of gender: women are better achievers in schooling, but they are discriminated against in the labor market. Equations (7) and (9) are to be modified accordingly:

$$E_{i\theta} = \delta\phi_i + \eta E_{i\theta-1} + \epsilon_{i\theta} \quad (7)'$$
$$\log(Y_{i\theta}) = \alpha\phi_i + \beta E_{i\theta} + \gamma E_{i\theta-1} + \omega_{i\theta} \quad (9)'$$

where now $\phi_i$ is a dummy variable for women, $\delta$ is the mean school gap achieved by women and $\alpha$ is the gender wage gap. Since $var(\phi) = \lambda(1-\lambda)$, where $\lambda$ is the fraction of women in the working population, then we get that relative inequality of opportunity now reads

$$IOp = \frac{\sqrt{var(\hat{y})}}{\sqrt{var(y)}} = \frac{(\hat{\alpha}+\hat{\delta}\hat{\beta})\sqrt{(\lambda(1-\lambda))}+(\hat{\gamma}+\hat{\eta}\hat{\beta})\sqrt{var(E_{\theta-1})}}{\sqrt{(\hat{\alpha}+\hat{\delta}\hat{\beta})^2(\lambda(1-\lambda))+(\hat{\gamma}+\hat{\eta}\hat{\beta})^2 var(E_{\theta-1})+\hat{\sigma}^2_{\hat{\omega}_\theta}+\beta^2\hat{\sigma}^2_{\hat{\epsilon}_\theta}+2\beta cov(\hat{\omega}_\theta,\hat{\epsilon}_\theta)}} \quad (13)'$$

In this case, relative inequality of opportunity also depends on whether the schooling advantage $\delta\beta$ for women exceeds (or falls short of) the labor market disadvantage $\alpha$, as well as from the gender composition of the labor force.

## 3. The data

Consistent estimates of the IOp described by equation (13) impose data requirements that are rather demanding:

a) adequate information on circumstances (in addition to gender and age, some information on parental background and country of origin).

b) a measure of disposable income that is comparable across surveys and across countries (if we intend to benchmark one country against the others).

c) a sufficiently extended time coverage in order to capture meaningful dynamics and/or to apply birth/age cohort decomposition.

Existing sources of publicly available data are rather limited with respect to these three criteria. We resorted to the LIS Cross-National Data Center in Luxembourg (http://www.lisdatacenter.org/), which allowed us to process data from four countries (Italy, Germany, France and Switzerland), while a fifth country was obtained from accessing the original provider (United Kingdom – https://www.understandingsociety.ac.uk/).

The surveys we have used are therefore the following:

**Italy:** Survey on Household Incomes and Wealth (SHIW), collected by the Bank of Italy – 11 surveys, covering the period 1993-2014 (information on parental background is not available before the starting date – originally consisting of 112,690 individuals, which reduces to 107,846 when considering non-missing information.

**Germany:** German Socio-economic Panel (SOEP) – 11 surveys, covering the period 1984-2013 – originally including 156,338 individuals, then reduced to 133,467 in case of non-missing information.

**France:** Household Budget Survey (HBS), conducted by the Banque de France) – 6 surveys, covering the period 1978-2005 – originally consisting of 97,306 individuals, declining to 89,119 when missing information is excluded.

**Switzerland:** Swiss Household Panel (SHP) – 6 surveys, covering the period 1999-2014 – originally consisting of 43,102 individuals, which then decline to 31,273 valid observations.

**United Kingdom:** starts as British Household Panel (BHPS), replaced after 2009 by the Understanding Society-Household Longitudinal Survey (UKHLS) – considers 24 waves over the period 1991-2014 – originally consisting of 434,253 individuals, which then decline to 308,625 valid observations.

Our selection rules include individuals aged 25-80 with a positive disposable income, harmonized according to the LIS procedure (variable DPI).[7] Incomes are converted to constant prices using the national consumer price index. Parental education is typically a categorical variable recording the highest educational attainment in the parental couple. In order to estimate a unique coefficient associated to the intergenerational transmission of education, we have converted them into years of education.[8] Descriptive statistics at survey/country disaggregation are reported in tables 1 to 5 in the Appendix.

Using these data, total inequality, absolute inequality of opportunity (namely inequality computed over incomes predicted according to circumstances) and relative inequality of opportunity (see equation (13)) have been estimated for each country and for each survey/year. These measures are

[7] To avoid negative values associated to logs, we have excluded all individuals with yearly incomes below 10. Data for the United Kingdom were rather volatile with respect to top incomes: in order to avoid confounding factors associated to differences in sampling procedures, we have trimmed them excluding incomes exceeding the 99.5 centile.

[8] In the Italian file, recoding implies the following conversion: [1] illiterate=0 years; [2] primary=5 years; [3] lower secondary=8 years; [4] upper secondary=13; [5] tertiary=18. In the German file, recoding implies the following conversion: [1] school not attended =0 years; [2] no school degree =4; [3] Secondary General School (*Hauptschule*)=9 years; [4] Intermediate School (*Realschule*)=10 years; [5] Technical High School (*Fachoberschule*)=12 years; [6] Upper Secondary School (*Abitur*)=13 years. In the Swiss file, recoding implies the following conversion: [1]1: Primary or first stage of basic education=6 years; [2] 2: Lower secondary or Second stage of basic education=9 years; [3] 3A&B Upper secondary education (preparation for tertiary education & voc.educ)=12 years; [4] 3C: Upper secondary education (entrance into the labor market)=11 years; [5] 4A: Post-secondary education non-tertiary (preparation for an institution for higher education)=13 years; [6] 5B: First stage of tertiary education (professional education)=15 years; [7] 5A/6 tertiary education (general education)=16 years. In the UK file recoding implies the following conversion: [1] no qualification =8 years; [2] some qualification=10 years; [3] post school qualification=12 years; [4] university degree=18 years. Eventually, in the case of France there is no information on parental education, but only on parental occupation. In order to retain the country, we have created a dummy variable corresponding to either [5] intermediate profession (foreman, nurse, etc.) or [6] executive, liberal profession. We interpret this variable as the (likely) completion of secondary or tertiary education.

reported in tables 6 to 10, including two indicators of inequality (standard deviation of logs and mean log deviation), which behave in very similar ways. In addition, to apply the decomposition of relative inequality of opportunity as shown in equation (13), equations (7) (which captures intergenerational persistence in education) and (9) (Mincerian wage equation) have been estimated. Estimations were conducted at the country and year/survey level. For illustrative purposes, the results of these estimations at the country level and for the full sample (i.e. for all the surveys pooled together) are reported in table 11.

One can notice that country samples are rather consistent, according to the impact exerted by the regressors. Education is adequately rewarded in all countries, with an estimated yearly return rate ranging between 5.4% in France and 13.2% in Great Britain. The intergenerational persistence in education is highest in Italy and Germany and lowest in Great Britain. There is also general evidence that parental education exerts an impact beyond favoring educational attainment of the next generation, as the coefficient $\hat{\gamma}$ in equation (9) is estimated positive and statistically significant in all countries (its magnitude being highest for continental countries). In all countries, women are on average penalized in terms of both schooling and incomes, while age exhibits an opposite trend: the younger age cohorts are better educated than the older ones, but incomes increase with age, the net effect being ambiguous. Finally, being born in less developed regions (South of Italy, East Germany) or holding a foreign citizenship is associated to lower incomes (but not necessarily lower schooling).

To study the evolution of inequality of opportunity – the main objective of this paper – the estimation of the models reported in table 11 is performed for year survey/year and the results are graphically reported in figures 1, 3, 5, 7, and 9, and discussed in detail in section 4 below.

Given that the sample sizes are large enough, it is possible to carry out the estimations at a more disaggregated level. By disaggregating the population in birth cohorts, we can estimate inequality of opportunity for each cohort and investigate whether the cohort-specific evolution of inequality of opportunity differs from that of the full population. More in detail, we have partitioned birth years and ages in 5-year intervals, and we have retained only cells gathering at least 400 individuals. In each population subgroup, we have estimated inequality, inequality of opportunity and other structural parameters. This procedure is exemplified in table 12 and figure 11 for the Italian case. Despite having the population distributed over 66 cells (the potential number of cells depending on dates of initial and final surveys – top part of the table), only 53 satisfy a sufficient numerousness and are therefore retained for estimation of (relative) inequality of opportunity (bottom part of table 12). Once we have obtained these measures, if we ask ourselves what the time pattern of IOp is, we can plot these measures by birth cohort, as we have done in figure 11. Looking at the graph, one would be tempted to conclude that during the life course IOp exhibits an inverted U-shaped profile, at least in Italy. However, we would be confusing two different dimensions, namely age and cohort: some birth cohorts (for example the one born around the second world war) have experienced higher IOp at any age, compared to neighboring birth cohorts. Thus, we need a more rigorous method to summarize the information contained in the cells, possibly distinguishing between age and cohort effects.

We have then followed Deaton (1997), and we have regressed the obtained measures onto age, cohort and survey dummies, imposing restrictions on the estimated coefficients for dummies. Results are reported in table 13, and then plotted using a smoothing procedure in figure 12 using the LOWESS command in Stata. Simple inspection of the coefficients indicates that the time profiles of the constrained and unconstrained estimates are rather similar, though the time trend may be different. The same procedure is also applied to the estimated structural parameters, weighting the observations by the inverse of their standard errors.

## 4. The results

Having clarified our statistical procedure, it is now time to review our main results, which are fully summarized by figures 1 to 10. For each country, we report two sets of estimates:
a) The first set contains the analysis by year/survey and reports the estimated values of four different variables: relative inequality of opportunity, return to education ($\hat{\beta}$), parental network ($\hat{\gamma}$) and the intergenerational persistence in education ($\hat{\eta}$) (see figures 1, 3, 5, 7, and 9);
b) The second set contains the same variables calculated at different ages and for different birth cohorts. Hence, it reports respectively the age and the cohort profiles of each of the four estimates mentioned above (see figures 2, 4, 6, 8, and 10).

Instead of reviewing the results twice, first by surveys and second by decomposing age and birth cohorts, we have preferred a thorough discussion by country.

### *4.1 Italy*

Starting with relative IOp, the analysis by survey shows a clear reduction in relative IOp at the beginning of the 2000s and then an increase at the beginning of the 2010s. In sum a rather constant time trend: the value of IOp is the same at the start and at the end of the period, also confirmed by the mean log deviation (MLD). As for the magnitude, it varies between 45% and 50% according to the standard deviation of logs and between 30% and 40% according to MLD (see figure 1).

What is behind this high and rather constant time evolution of inequality of opportunity? The decomposition approach of this paper – and in particular considering the trends of intergenerational persistence of education, returns to education, and parental networking – can help answering this question. The intergenerational persistence of education shows a clear declining trend. This trend is well known and explained by the expansion in education that took place in Italy following the compulsory education reform at the beginning of the 1960s, with some signals of trend reversal in recent years. However, this declining trend has not translated into a declining inequality of opportunity in income. Furthermore, the return to education displays a downward trend, which should also help in reducing inequality of opportunity. Apparently, this reduction is not materializing because of the counterbalancing increasing trend of parental networking. Our suggested interpretation is that the increased equality of educational opportunity (associated to the decrease in intergenerational education persistence) and the reduced "value" of education in the labor market have failed to translate into a decrease of opportunity inequality in income because of the increasing role of parental networking.

This interpretation is substantially confirmed when looking at both the age and the cohort analyses, which however shows some additional interesting facts (see figure 2). As for the age profile, the results show a clear declining pattern in relative inequality of opportunity, which is associated with a consistent declining trend in the return to education and a clear increasing trend in both intergenerational persistence and parental networking. The cohort profile follows a similar path in inequality of opportunity, return to education and parental network, while the intergenerational persistence shows a clear declining pattern, which is explained by the expansion in education level that took place in Italy during the last decades. Thus, the general declining pattern of intergenerational education observed in the analysis by survey seems to be mainly driven by the cohort effect.

### *4.2 Germany*

The analysis by survey shows a clear declining pattern in relative IOp, which takes values between 40% and 55% in the case of standard deviation of logs (between 20% and 50% in case of MLD). This is complemented by a fairly constant pattern of intergenerational education persistence and a weakly increasing trend of parental networking (which however is not statistically significant for

most of the sample period), while the return to education shows a declining trend in the 1980s and then a fairly stable pattern (see figure 3).

As for the age profiles, the results show a clear declining pattern in the value of relative inequality of opportunity, which is associated with an inverted U-shaped trend of the return to education and a flat pattern of both intergenerational persistence of education and parental networking. The cohort profile follows a similar path in the values of inequality of opportunity, parental network, and intergenerational persistence of education, while the return to education is rather stationary across cohorts (see figure 4).

*4.3 France*

The analysis by survey clearly shows a declining pattern in relative IOp, which takes values between 30% and 45% in the case of standard deviation of logs (between 20% and 30% in case of MLD). This is complemented by a decreasing trend in intergenerational education persistence. On the other hand, parental networking shows a pretty flat picture and the return to education a constant pattern with a decline in the last period (the first half of the 2000s). Hence, the declining trend of IOp might be mainly driven by the reduction in intergenerational educational persistence (see figure 5).

As for the age profiles, our results show a clear declining pattern in the value of relative inequality of opportunity, which is associated with a consistent declining trend in the return to education and a clear increasing trend in both intergenerational persistence and parental networking. The cohort profile follows a similar path in the values of inequality of opportunity, although the pattern shows an increase in the very first period, and in the return to education and parental network, while the intergenerational persistence shows a clear declining pattern, which is explained by the expansion in education level that has taken place during the last decades (see figure 6).

*4.4 United Kingdom*

The analysis by survey (see figure 7) shows a declining pattern in relative IOp, which takes values between 30% and 50% in the case of standard deviation of log incomes (between 10% and 35% in case of MLD). On the other hand, it is observed a stable pattern in parental networking and a weakly declining trend in both intergenerational education persistence and return to education. Hence the declining trend of IOp might be mainly driven by the reduction in intergenerational educational persistence.

As for the age profiles, the results show a clear declining pattern in the value of relative inequality of opportunity, which is associated with a declining pattern in the return to education. On the other hand, both parental network and intergenerational persistence of education show an increasing trend. The cohort profile follows a similar path, except for the intergenerational persistence of education, which is more stable, while the return to education shows a more stable path (see figure 8).

*4.5 Switzerland*

The analysis by survey shows a clear declining pattern in relative IOp, which takes values between 30% and 40% in the case of standard deviation of logs (between 15% and 25% in case of MLD). This is complemented by a fairly increasing pattern of both intergenerational education persistence and parental networking, while the return to education shows a decreasing trend (see figure 9).

As for the age profiles, the results show a clear declining pattern in the value of relative inequality of opportunity, which is associated with an inverted U-shape of the return to education, a fairly stable trend of parental networking and an increasing pattern of intergenerational persistence of

education. The cohort profile follows a fairly similar path, except for the return to education that, after an increase for the first cohorts, then remains stable (see figure 10).

*4.6 Summing up*

In general, our empirical results are consistent with theoretical expectations. More precisely, the relationships between the trends of inequality of opportunity in the income space, intergenerational persistence in education, return to education and parental networking are consistent with the conjectures based on equation (13).

In addition, it is possible to highlight the following stylized facts:

*i*) in all the countries and the period considered, inequality of opportunity represents an important portion of total income inequality, with values ranging from 30% to 50% according to standard deviation of logs (and reaching a lower share in the case of mean log deviation);

*ii*) in general, inequality of opportunity shows a stable or declining pattern over the period considered in all countries;

*iii*) on the other hand, in all countries considered, there has been a clear enhancement of equality of educational opportunity (as captured by the intergenerational education persistence);

*iv*) in some countries the egalitarian process taking place in the education system has failed to translate into decreasing opportunity inequality in the space of income because of the increasing role of parental networking and the reduced "value" of education in the labor market. This mechanism seems to be at work notably in Italy;

*v*) in some other countries (France, Germany and Great Britain), where both returns to education and the family networking followed a more constant pattern, inequality of opportunity seems to decrease both in the education and in the income space.

The decomposing of inequality of opportunity trends according to the age and cohort effects allow to identify the following additional facts:

*vi*) in all the countries considered, inequality of opportunity decreases with age: the effect of the circumstances at birth seems to weaken over the life cycle. This pattern is quite different from the age profile of the inequality of outcomes (income or consumption), which generally increases with age;

*vii*) the decreasing pattern of relative inequality of opportunity in France and Italy is associated with a consistent declining trend in the return to education and a clear increasing trend in both intergenerational persistence and parental networking. Great Britain shows an increase in intergenerational education persistence, while Germany is characterized by a stable trend of intergenerational education persistence;

*viii*) the cohort effect, on the other hand, shows a more mixed picture: while for Great Britain and Germany the data show a declining path in the values of inequality of opportunity, with the younger generation experiencing lower IOp levels, both Italy and France are characterized by an inverted U-shape pattern;

*ix*) these trends are associated, in Germany and Great Britain, with a stable or weakly increasing trend of the intergenerational educational persistence, while in Italy and France with a clear declining trend in the intergenerational persistence of education, which is explained by the expansion in education level that has taken place during the last decades.

## 5. Concluding remarks

This paper contributes to the analysis of inequality of opportunity in three respects. First, by using extended samples, it is capable to detect time trends, showing that the role of circumstances (parental background, gender, age, and place of birth) in shaping income distribution has declined over the last two decades in all the countries considered in the present analysis. Depending on the

inequality index we choose, inequality of opportunity accounts for between one-third (MLD) and half (standard deviation of logs) of total inequality in personal disposable incomes, at least for the four largest economies in the European Union.

Second, we exploit the large sample sizes to obtain inequality measures by age group and birth cohorts, thus being able to decompose observed trends in age profiles and birth cohort changes. For the five countries under analysis, the observed inequality of opportunity exhibits an inverted U-shaped pattern over the life cycle. Moreover, the most recent age cohorts have experienced a lower IOp, thus appearing as the main beneficiaries of the overall decline in inequality.

Third, the paper proposes a theoretical framework identifying the variables that affect (positively or negatively) inequality of opportunity. The framework is then estimated, and the data confirm the predicted signs. The analysis has focused on the role of three variables: the intergenerational persistence in educational attainment, the return of education, and the networking activity of parents. While the first two variables exhibit a declining trend, which other things constant should produce a decline in IOp, the third one appears to be rising in many countries, thus counteracting the effects of the first two. Consequently, the fair optimism that descriptive statistics suggest with respect to income inequality should be mitigated by paying attention to educational persistence and labor market segmentation.

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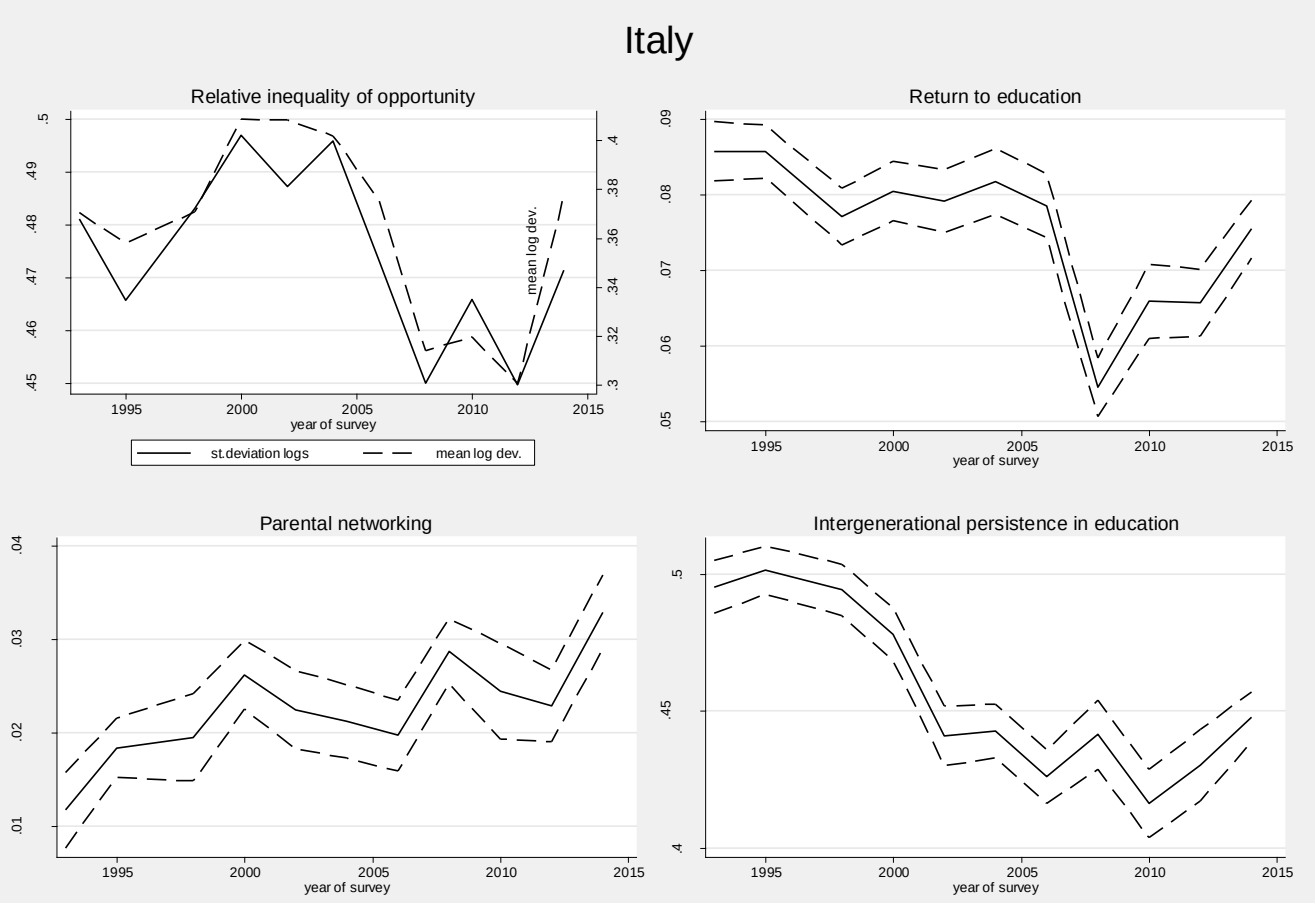
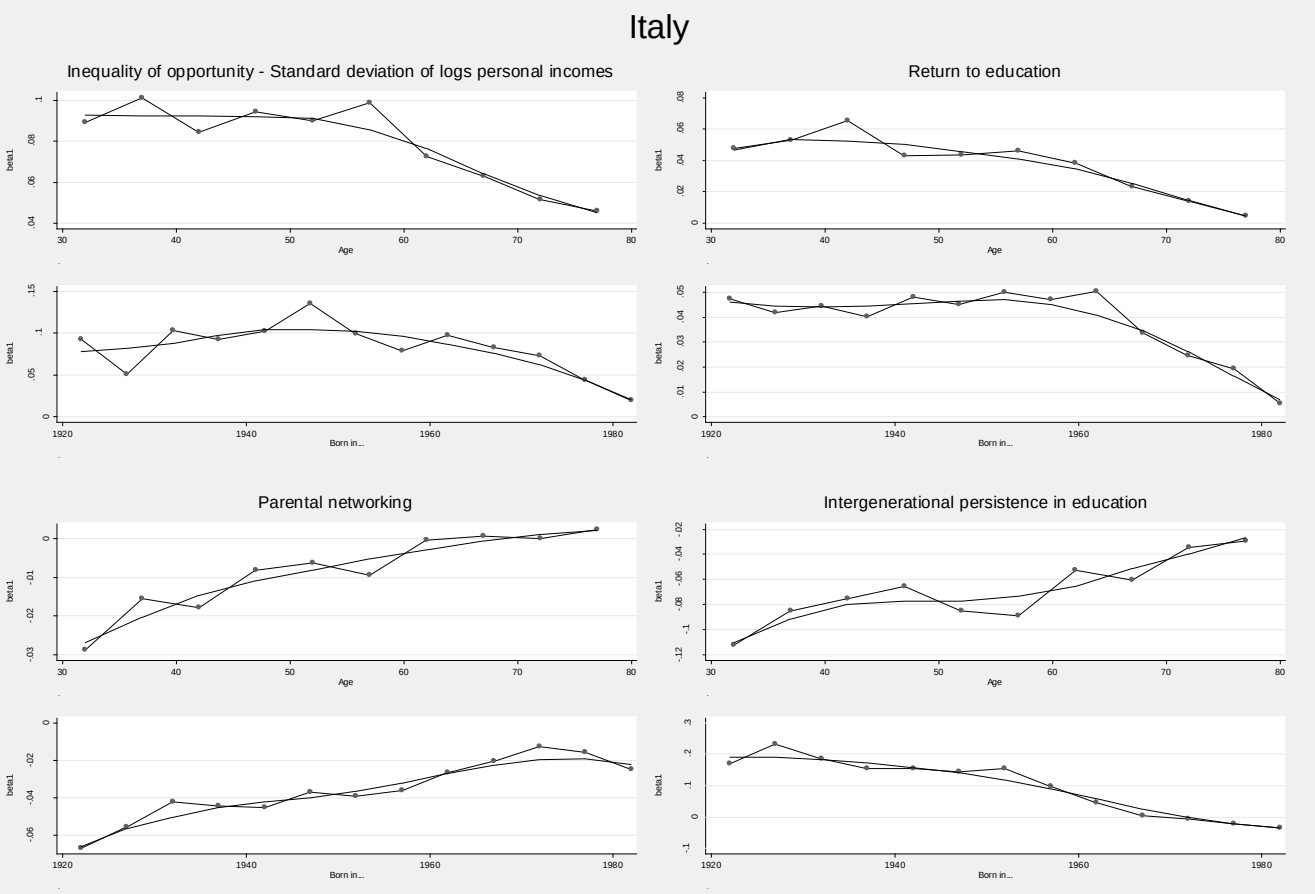
Figure 1 – Italy, by survey



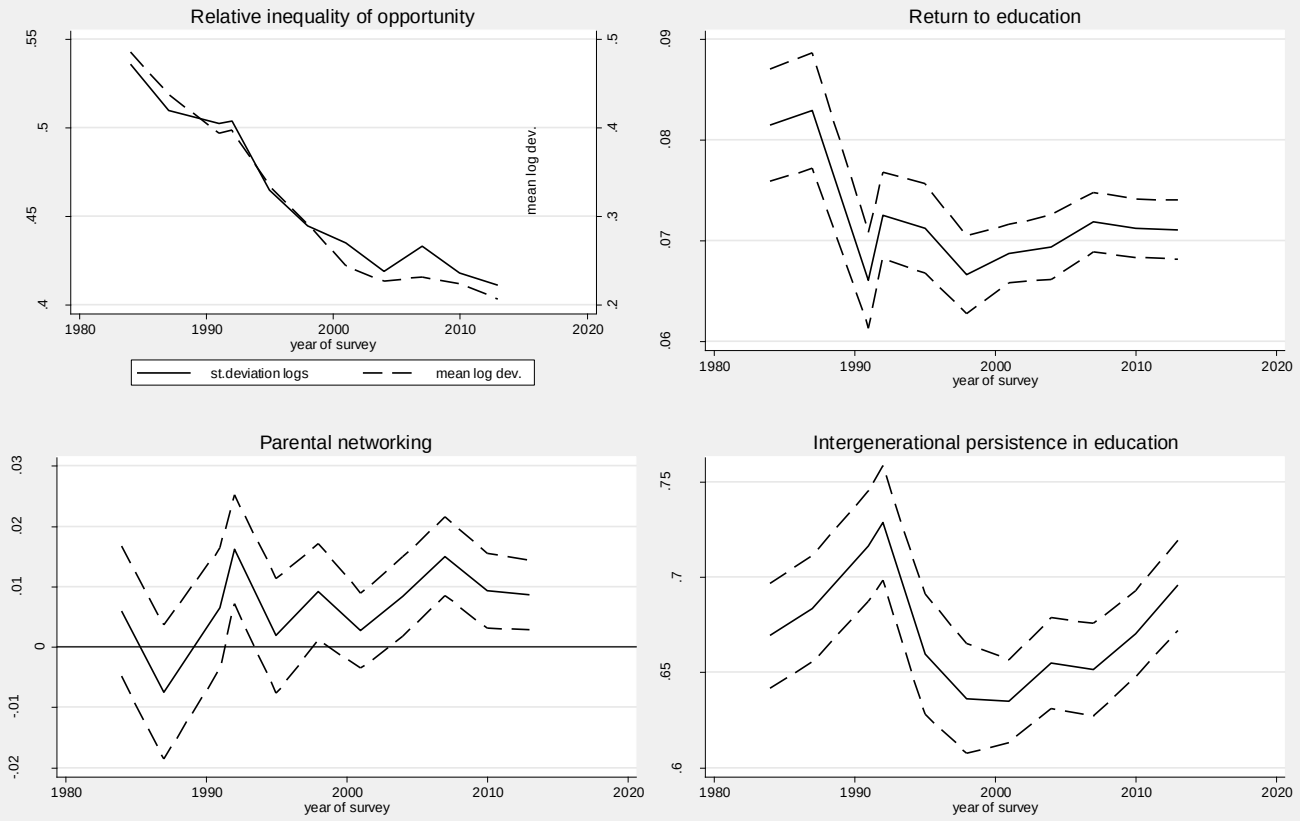

Regressors include gender, age, age², born in South Italy and foreign citizenship

Figure 2 – Italy, age-cohort decomposition



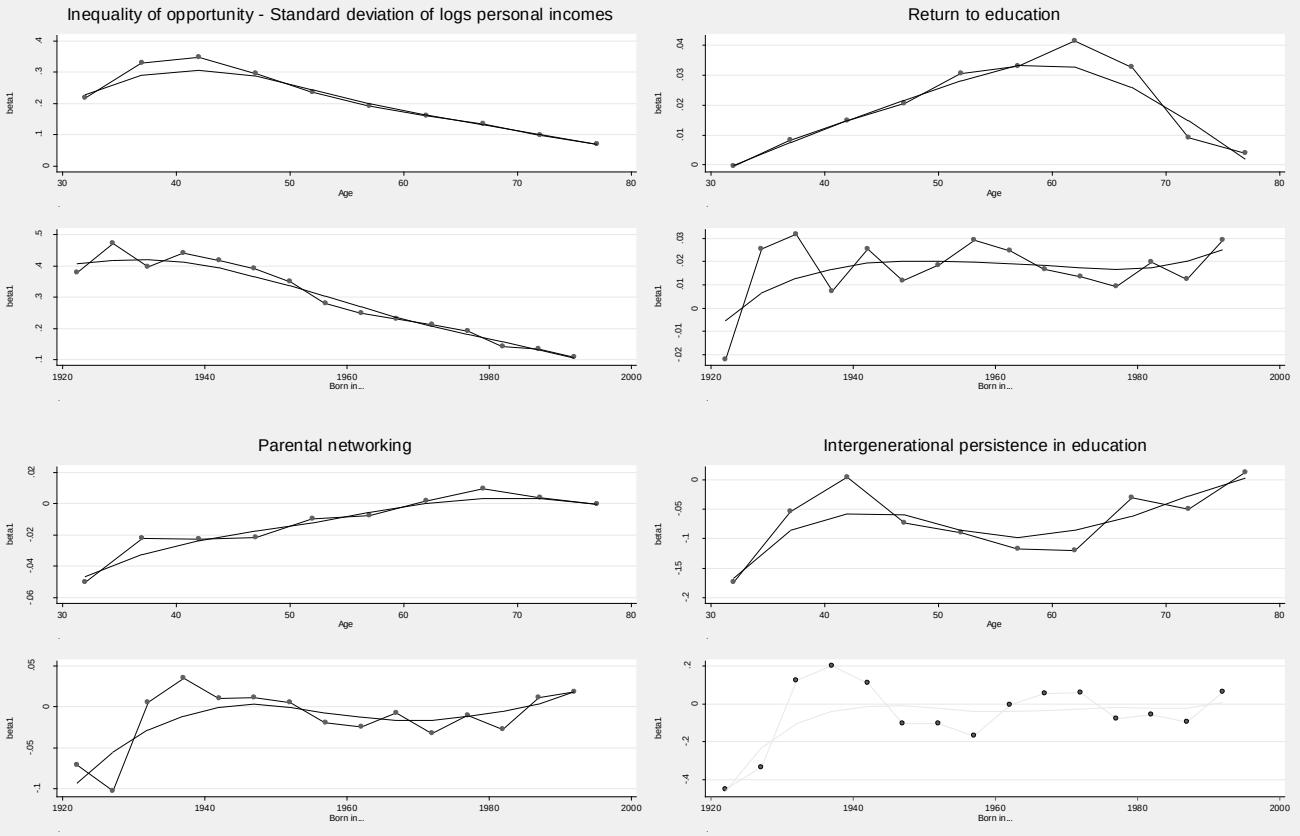

Regressors include gender, age, age², born in South Italy and foreign citizenship - Age and cohort effects obtained from Deaton's decomposition

Figure 3 – Germany, by survey



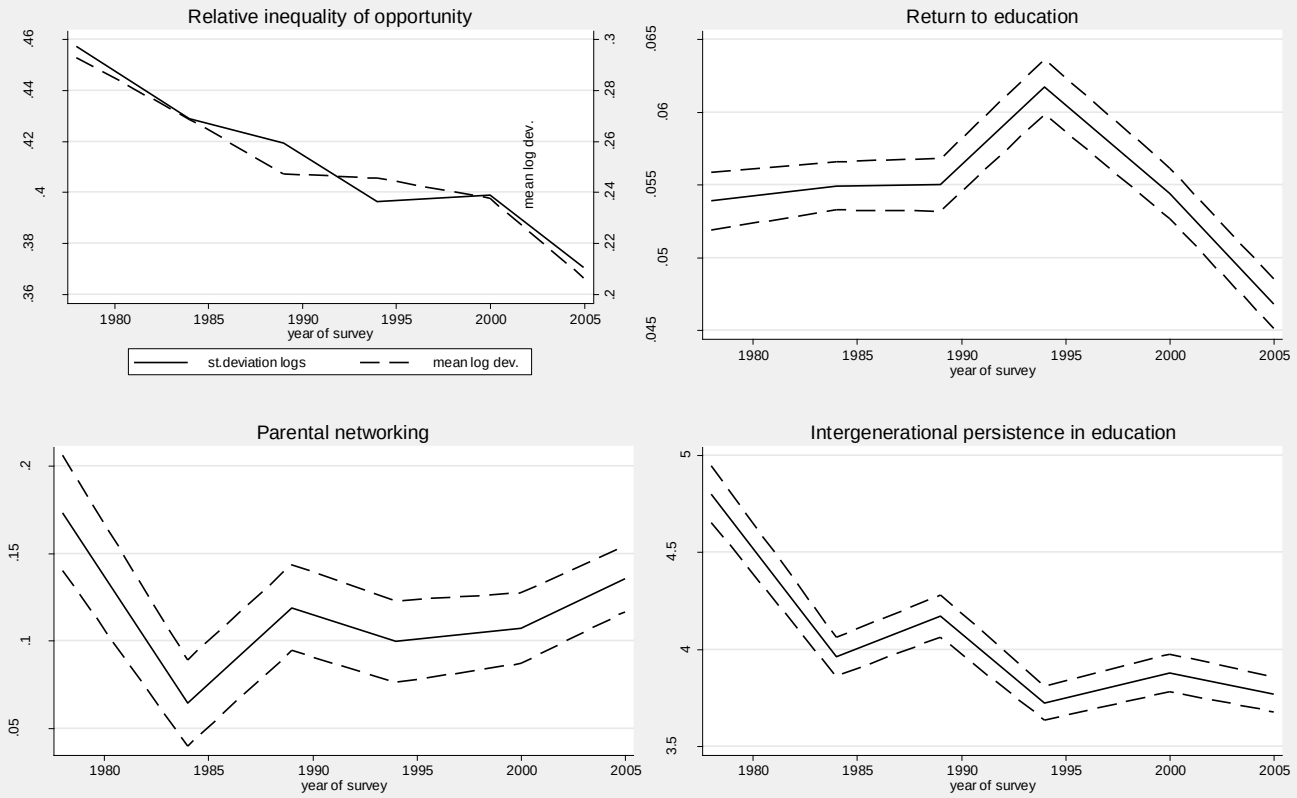

Regressors include gender, age, age², born in East Germany and foreign citizenship

Figure 4 – Germany, age-cohort decomposition



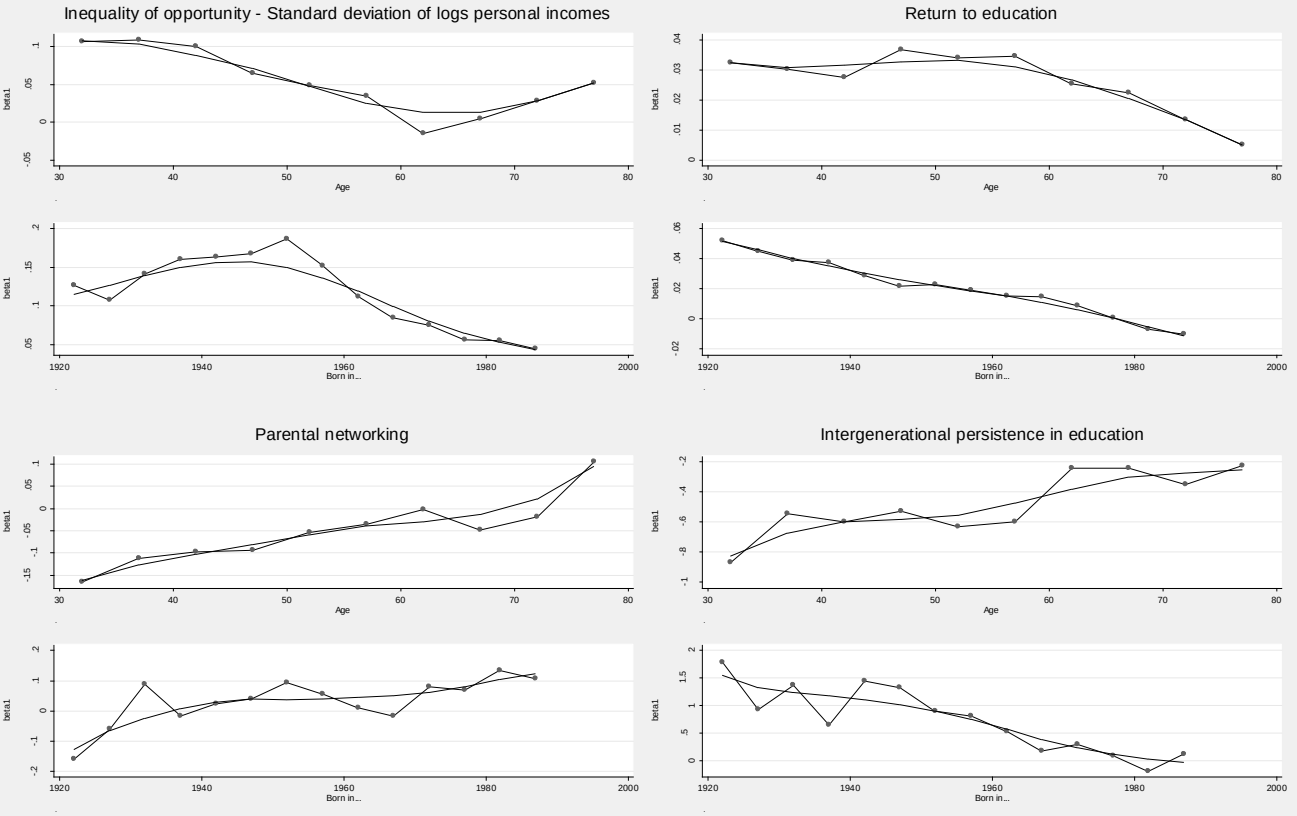

Regressors include gender, age, age², born in East Germany and foreign citizenship - Age and cohort effects obtained from Deaton's decomposition

Figure 5 – France, by survey



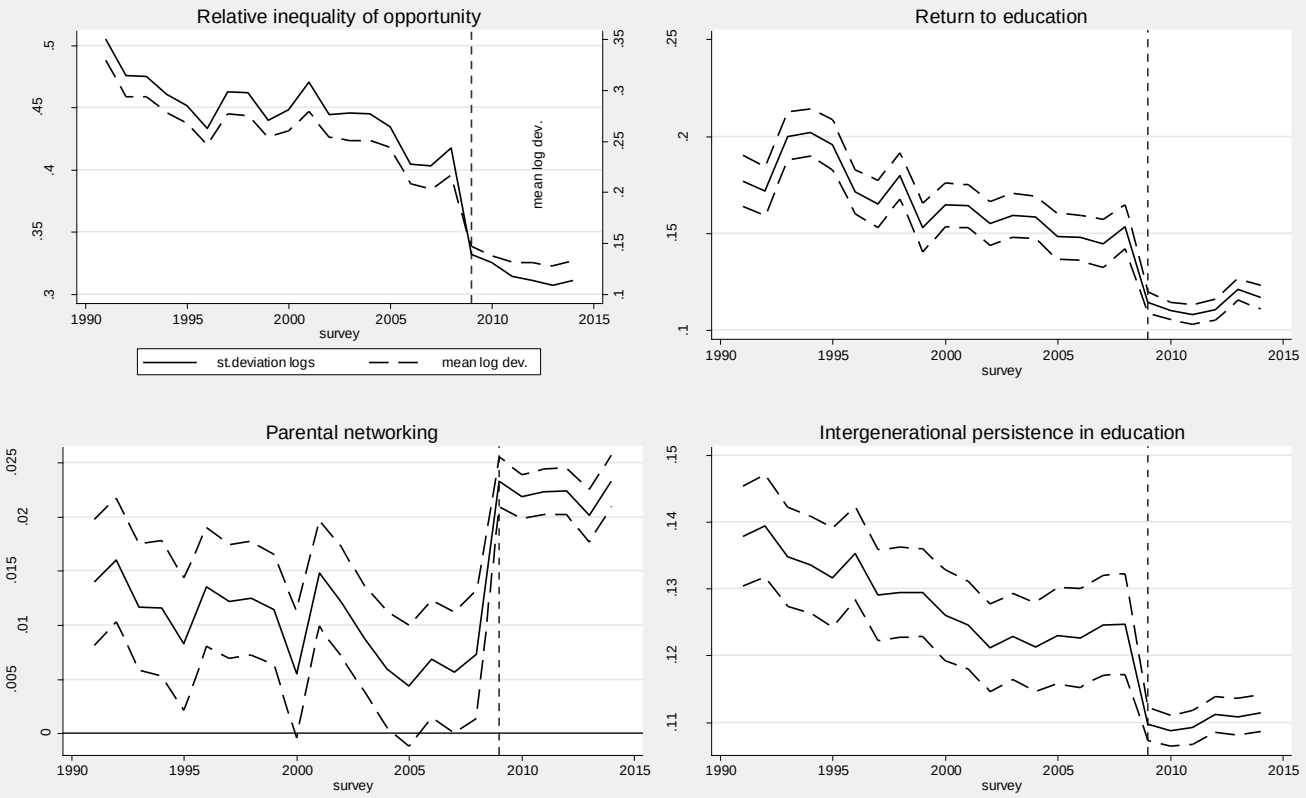

Regressors include gender, age, age² and foreign citizenship
Parental education is absent and is replaced by dummy indicating middle-high parental occupations

Figure 6 – France, age-cohort decomposition



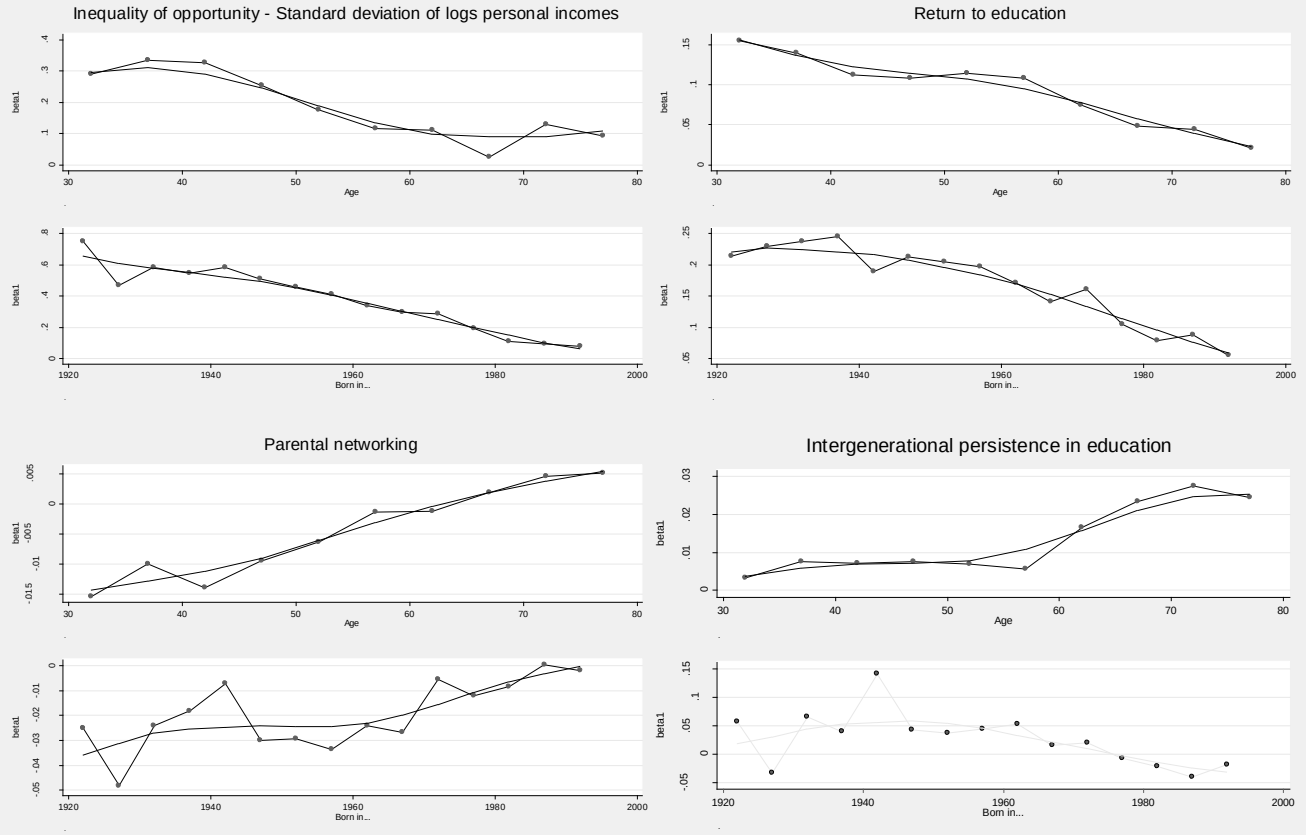

Regressors include gender, age, age² and foreign citizenship - Age and cohort effects obtained from Deaton's decomposition
Parental education is absent and is replaced by dummy indicating middle-high parental occupations

Figure 7 – Great Britain, by survey



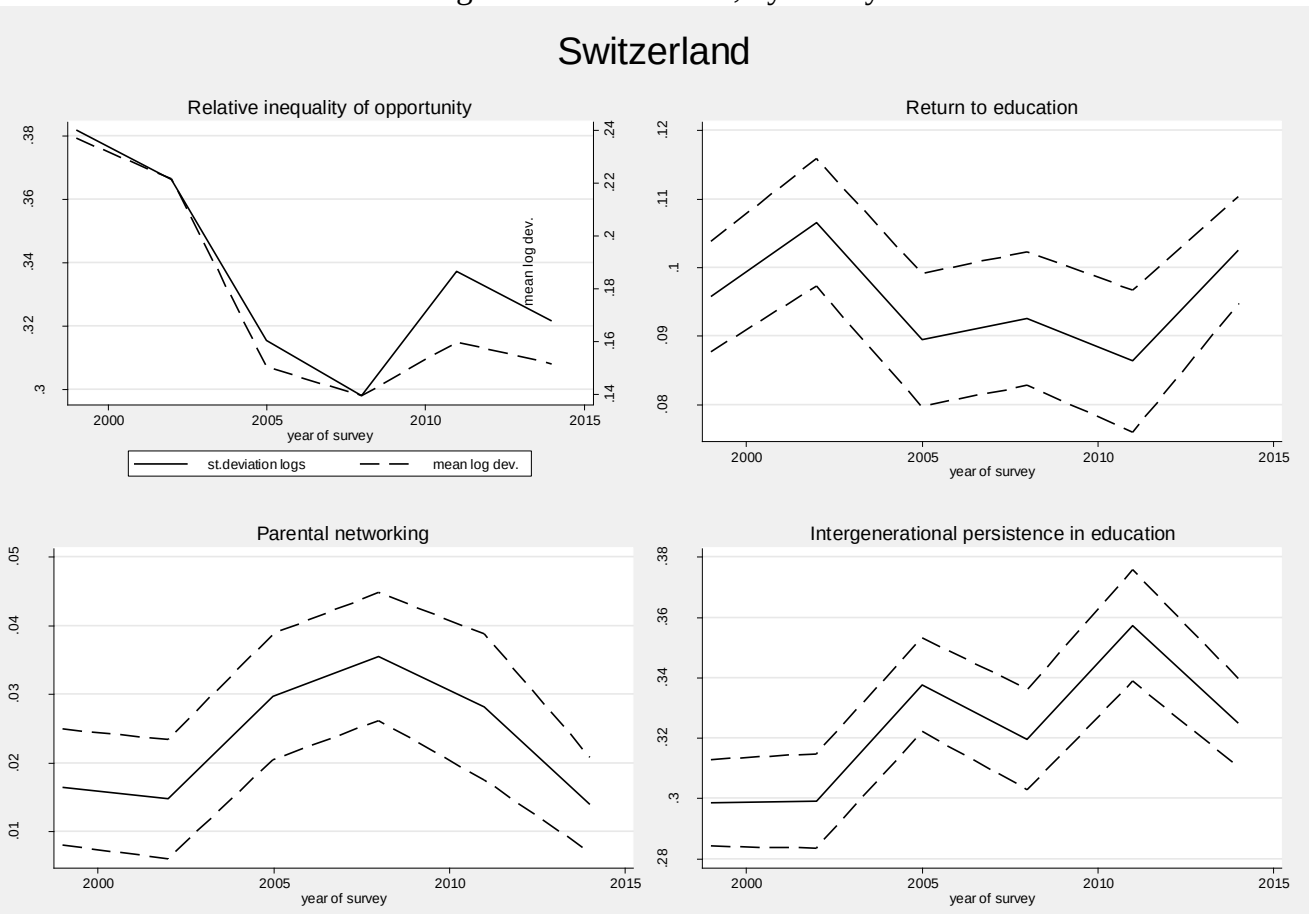

Regressors include gender, age, age², born in England and foreign citizenship
Data trimmed at 99.5th centile - vertical dashed line indicates change of survey

Figure 8 – Great Britain, age-cohort decomposition



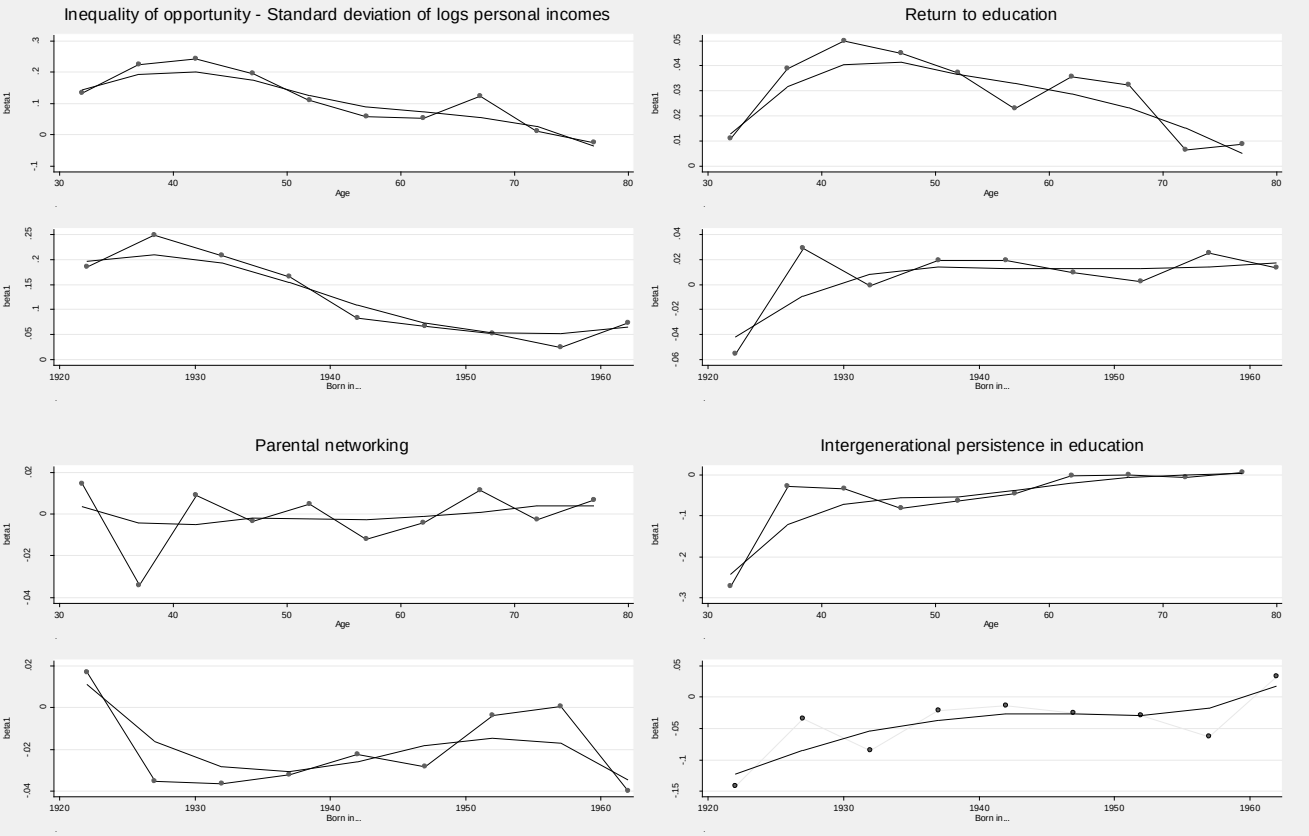

Regressors include gender, age, age², born in England and foreign citizenship - Age and cohort effects obtained from Deaton's decomposition

Figure 9 – Switzerland, by survey




Regressors include gender, age, age² and foreign citizenship

Figure 10 – Switzerland, age-cohort decomposition




Regressors include gender, age, age² and foreign citizenship - Age and cohort effects obtained from Deaton's decomposition

## Appendix

Table 1 – Descriptive statistics - Italy

| survey year | observations | personal disposable income (mean) | personal disposable income (median) | st.deviation logs personal disposable incomes | respondent years of education (mean) | respondent years of education (st.deviation) | highest years of education in the parental couple (mean) | highest years of education in the parental couple (sd.deviation) | fraction of women | fraction of born abroad |
|---|---|---|---|---|---|---|---|---|---|---|
| Italy | | | | | | | | | | |
| 1993 | 12851 | 17491.9 | 15335.0 | 1.21 | 7.90 | 4.32 | 4.52 | 4.17 | 0.52 | 0.00 |
| 1995 | 12875 | 17103.5 | 15019.8 | 1.21 | 8.16 | 4.38 | 4.55 | 4.14 | 0.52 | 0.00 |
| 1998 | 11275 | 18497.0 | 16457.8 | 1.21 | 8.95 | 4.30 | 5.20 | 4.21 | 0.52 | 0.00 |
| 2000 | 11280 | 18827.7 | 16973.7 | 1.19 | 8.94 | 4.25 | 5.04 | 4.13 | 0.51 | 0.00 |
| 2002 | 10161 | 18797.5 | 16839.8 | 1.21 | 8.94 | 4.17 | 5.21 | 4.13 | 0.52 | 0.00 |
| 2004 | 9983 | 19741.8 | 17396.7 | 1.17 | 9.18 | 4.15 | 5.25 | 4.24 | 0.52 | 0.00 |
| 2006 | 9734 | 20611.4 | 18504.9 | 1.15 | 9.55 | 4.01 | 5.53 | 4.11 | 0.52 | 0.02 |
| 2008 | 6239 | 22629.3 | 19974.7 | 0.92 | 9.70 | 4.05 | 5.58 | 4.16 | 0.36 | 0.04 |
| 2010 | 6127 | 22123.2 | 19667.8 | 0.95 | 10.11 | 4.02 | 5.89 | 4.20 | 0.43 | 0.04 |
| 2012 | 6179 | 20435.3 | 18239.1 | 0.94 | 10.22 | 4.02 | 5.96 | 4.26 | 0.43 | 0.07 |
| 2014 | 11142 | 17817.8 | 16666.9 | 1.11 | 9.99 | 3.99 | 5.78 | 4.08 | 0.53 | 0.07 |
| Total | 107846 | 19065.8 | 17129.5 | 1.15 | 9.09 | 4.24 | 5.23 | 4.19 | 0.50 | 0.02 |

Table 2 – Descriptive statistics – Germany

| survey year | observations | personal disposable income (mean) | personal disposable income (median) | st.deviation logs personal disposable incomes | respondent years of education (mean) | respondent years of education (st.deviation) | highest years of education in the parental couple (mean) | highest years of education in the parental couple (sd.deviation) | fraction of women | fraction of born abroad |
|---|---|---|---|---|---|---|---|---|---|---|
| Germany | | | | | | | | | | |
| 1984 | 7034 | 15832.1 | 14558.9 | 1.57 | 10.38 | 3.16 | 8.50 | 2.68 | 0.51 | 0.24 |
| 1987 | 6833 | 17040.5 | 15627.8 | 1.50 | 10.45 | 3.17 | 8.54 | 2.65 | 0.51 | 0.24 |
| 1991 | 9270 | 23964.3 | 19590.6 | 1.23 | 11.18 | 3.47 | 8.82 | 2.31 | 0.52 | 0.17 |
| 1992 | 9118 | 24713.8 | 21100.3 | 1.21 | 11.21 | 3.46 | 8.86 | 2.28 | 0.52 | 0.17 |
| 1995 | 9343 | 25353.1 | 21669.0 | 1.17 | 11.37 | 3.46 | 8.89 | 2.26 | 0.52 | 0.18 |
| 1998 | 10002 | 26218.4 | 22023.8 | 1.09 | 11.49 | 3.48 | 9.03 | 2.14 | 0.53 | 0.15 |
| 2001 | 17188 | 32599.4 | 23837.3 | 1.11 | 12.08 | 3.57 | 9.34 | 1.94 | 0.52 | 0.12 |
| 2004 | 15349 | 31976.3 | 23460.1 | 1.09 | 12.20 | 3.60 | 9.42 | 1.91 | 0.52 | 0.11 |
| 2007 | 14611 | 31331.3 | 22767.6 | 1.05 | 12.33 | 3.62 | 9.52 | 1.85 | 0.52 | 0.09 |
| 2010 | 16010 | 29897.0 | 22305.6 | 1.03 | 12.32 | 3.62 | 9.61 | 1.78 | 0.53 | 0.09 |
| 2013 | 18709 | 30436.0 | 23221.5 | 0.98 | 12.49 | 3.65 | 9.78 | 1.80 | 0.55 | 0.09 |
| Total | 133467 | 27957.3 | 21313.8 | 1.18 | 11.82 | 3.59 | 9.25 | 2.11 | 0.53 | 0.13 |

Table 3 – Descriptive statistics – France

| survey year | observations | personal disposable income (mean) | personal disposable income (median) | st.deviation logs personal disposable incomes | respondent years of education (mean) | respondent years of education (st.deviation) | fraction of parents in top occupations (mean) | fraction of parents in top occupations (st.dev) | fraction of women | fraction of born abroad |
|---|---|---|---|---|---|---|---|---|---|---|
| France | | | | | | | | | | |
| 1978 | 13617 | 22298.4 | 18697.3 | 1.22 | 6.99 | 5.28 | 0.13 | 0.34 | 0.47 | 0.05 |
| 1984 | 15921 | 18460.3 | 16610.8 | 1.10 | 6.71 | 5.01 | 0.14 | 0.35 | 0.50 | 0.04 |
| 1989 | 12411 | 18854.2 | 16599.4 | 1.02 | 7.19 | 5.07 | 0.16 | 0.37 | 0.50 | 0.04 |
| 1994 | 16275 | 20397.3 | 17392.7 | 1.12 | 8.31 | 5.00 | 0.19 | 0.39 | 0.52 | 0.08 |
| 2000 | 15623 | 20749.7 | 17747.5 | 1.02 | 8.74 | 5.02 | 0.21 | 0.41 | 0.53 | 0.10 |
| 2005 | 15272 | 21892.6 | 18936.3 | 0.98 | 9.37 | 5.05 | 0.24 | 0.42 | 0.53 | 0.12 |
| Total | 89119 | 20444.9 | 17646.2 | 1.08 | 7.92 | 5.16 | 0.18 | 0.38 | 0.51 | 0.07 |

Table 4 – Descriptive statistics – Great Britain

| survey year | observations | personal disposable income (mean) | personal disposable income (median) | st.deviation logs personal disposable incomes | respondent years of education (mean) | respondent years of education (st.deviation) | highest years of education in the parental couple (mean) | highest years of education in the parental couple (sd.deviation) | fraction of women | fraction of born abroad |
|---|---|---|---|---|---|---|---|---|---|---|
| Great Britain | | | | | | | | | | |
| 1991 | 4250 | 9628.8 | 7793.0 | 1.05 | 10.80 | 1.33 | 9.86 | 2.55 | 0.56 | 0.06 |
| 1992 | 4344 | 10175.4 | 8418.7 | 1.02 | 10.83 | 1.32 | 9.90 | 2.58 | 0.56 | 0.06 |
| 1993 | 4444 | 10487.5 | 8582.7 | 1.01 | 10.85 | 1.31 | 9.94 | 2.61 | 0.56 | 0.06 |
| 1994 | 4599 | 10748.2 | 8651.2 | 1.01 | 10.87 | 1.31 | 9.99 | 2.62 | 0.56 | 0.05 |
| 1995 | 4752 | 11356.6 | 9149.7 | 1.00 | 10.89 | 1.31 | 10.04 | 2.66 | 0.55 | 0.05 |
| 1996 | 4988 | 11775.5 | 9684.9 | 0.98 | 10.92 | 1.31 | 10.07 | 2.66 | 0.55 | 0.05 |
| 1997 | 5125 | 12343.4 | 10279.9 | 0.99 | 10.93 | 1.30 | 10.11 | 2.68 | 0.55 | 0.05 |
| 1998 | 5276 | 12673.5 | 10487.1 | 0.98 | 10.95 | 1.29 | 10.14 | 2.68 | 0.55 | 0.05 |
| 1999 | 7974 | 12660.5 | 10461.3 | 0.97 | 10.94 | 1.27 | 10.11 | 2.67 | 0.55 | 0.05 |
| 2000 | 8382 | 13478.0 | 11081.8 | 0.95 | 10.95 | 1.26 | 10.13 | 2.67 | 0.55 | 0.05 |
| 2001 | 10457 | 13865.6 | 11349.4 | 0.91 | 10.97 | 1.28 | 10.03 | 2.64 | 0.55 | 0.05 |
| 2002 | 10629 | 14628.7 | 11920.2 | 0.94 | 10.99 | 1.27 | 10.07 | 2.67 | 0.55 | 0.05 |
| 2003 | 11149 | 15243.9 | 12451.8 | 0.92 | 11.02 | 1.27 | 10.11 | 2.68 | 0.54 | 0.05 |
| 2004 | 10339 | 15838.2 | 13100.0 | 0.89 | 11.04 | 1.26 | 10.14 | 2.71 | 0.55 | 0.04 |
| 2005 | 9950 | 16374.9 | 13511.4 | 0.90 | 11.05 | 1.25 | 10.16 | 2.71 | 0.55 | 0.05 |
| 2006 | 9540 | 17001.2 | 13916.2 | 0.87 | 11.06 | 1.25 | 10.17 | 2.71 | 0.55 | 0.04 |
| 2007 | 9000 | 17734.9 | 14355.5 | 0.88 | 11.08 | 1.24 | 10.19 | 2.73 | 0.55 | 0.04 |
| 2008 | 8553 | 18462.5 | 15011.6 | 0.87 | 11.10 | 1.22 | 10.21 | 2.74 | 0.55 | 0.04 |
| 2009 | 28934 | 19932.8 | 15814.4 | 0.99 | 11.26 | 1.28 | 10.62 | 3.05 | 0.56 | 0.16 |
| 2010 | 35477 | 20650.6 | 16680.0 | 0.92 | 11.26 | 1.26 | 10.59 | 3.02 | 0.56 | 0.14 |
| 2011 | 30910 | 21255.4 | 17324.6 | 0.92 | 11.28 | 1.25 | 10.62 | 3.02 | 0.56 | 0.13 |
| 2012 | 28631 | 21792.4 | 17696.6 | 0.92 | 11.31 | 1.24 | 10.68 | 3.05 | 0.56 | 0.13 |
| 2013 | 26803 | 22235.6 | 18004.2 | 0.91 | 11.33 | 1.23 | 10.72 | 3.07 | 0.56 | 0.13 |
| 2014 | 24119 | 23403.6 | 18828.8 | 0.94 | 11.35 | 1.23 | 10.76 | 3.09 | 0.56 | 0.13 |
| Total | 308625 | 18357.2 | 14641.7 | 0.97 | 11.16 | 1.27 | 10.42 | 2.91 | 0.56 | 0.10 |

Table 5 – Descriptive statistics – Switzerland

| survey year | observations | personal disposable income (mean) | personal disposable income (median) | st.deviation logs personal disposable incomes | respondent years of education (mean) | respondent years of education (st.deviation) | highest years of education in the parental couple (mean) | highest years of education in the parental couple (sd.deviation) | fraction of women | fraction of born abroad |
|---|---|---|---|---|---|---|---|---|---|---|
| Switzerland | | | | | | | | | | |
| 1999 | 4327 | 63707.1 | 57579.3 | 1.19 | 12.81 | 2.08 | 11.76 | 2.30 | 0.52 | 0.00 |
| 2002 | 3737 | 62533.1 | 54500.3 | 1.22 | 12.93 | 2.10 | 11.82 | 2.30 | 0.54 | 0.00 |
| 2005 | 5006 | 64389.9 | 54462.5 | 1.22 | 13.09 | 2.11 | 11.93 | 2.31 | 0.55 | 0.15 |
| 2008 | 5373 | 64798.3 | 55044.9 | 1.24 | 13.17 | 2.13 | 11.93 | 2.31 | 0.56 | 0.15 |
| 2011 | 5341 | 70051.9 | 58400.3 | 1.13 | 13.24 | 2.13 | 11.96 | 2.31 | 0.55 | 0.15 |
| 2014 | 7489 | 72643.8 | 60558.3 | 1.15 | 13.40 | 2.18 | 11.98 | 2.48 | 0.53 | 0.16 |
| Total | 31273 | 67087.3 | 57076.7 | 1.19 | 13.15 | 2.14 | 11.91 | 2.35 | 0.54 | 0.12 |

Table 6 – Inequality and inequality of opportunity - Italy

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| survey | st.dev.log incomes | st.dev.log predicted incomes (absolute IOp) | relative inequality of opportunity (2/1) | mean log deviation incomes | mean log deviation predicted incomes (absolute IOp) | relative inequality of opportunity (5/4) |
| Italy | | | | | | |
| 1993 | 1.206 | 0.580 | 0.481 | 0.448 | 0.166 | 0.370 |
| 1995 | 1.206 | 0.562 | 0.466 | 0.440 | 0.158 | 0.358 |
| 1998 | 1.214 | 0.587 | 0.483 | 0.458 | 0.170 | 0.371 |
| 2000 | 1.190 | 0.592 | 0.497 | 0.425 | 0.174 | 0.409 |
| 2002 | 1.207 | 0.588 | 0.487 | 0.418 | 0.171 | 0.408 |
| 2004 | 1.171 | 0.580 | 0.496 | 0.414 | 0.166 | 0.402 |
| 2006 | 1.145 | 0.542 | 0.473 | 0.384 | 0.144 | 0.375 |
| 2008 | 0.921 | 0.415 | 0.450 | 0.267 | 0.084 | 0.314 |
| 2010 | 0.946 | 0.441 | 0.466 | 0.298 | 0.095 | 0.320 |
| 2012 | 0.941 | 0.423 | 0.450 | 0.294 | 0.088 | 0.300 |
| 2014 | 1.108 | 0.523 | 0.471 | 0.363 | 0.137 | 0.377 |
| Total | 1.140 | 0.545 | 0.477 | 0.397 | 0.148 | 0.370 |

Table 7 – Inequality and inequality of opportunity - Germany

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| survey | st.dev.log incomes | st.dev.log predicted incomes (absolute IOp) | relative inequality of opportunity (2/1) | mean log deviation incomes | mean log deviation predicted incomes (absolute IOp) | relative inequality of opportunity (5/4) |
| Germany | | | | | | |
| 1984 | 1.569 | 0.841 | 0.536 | 0.669 | 0.325 | 0.486 |
| 1987 | 1.495 | 0.762 | 0.510 | 0.619 | 0.271 | 0.438 |
| 1991 | 1.232 | 0.619 | 0.502 | 0.469 | 0.185 | 0.394 |
| 1992 | 1.216 | 0.613 | 0.504 | 0.456 | 0.181 | 0.397 |
| 1995 | 1.177 | 0.547 | 0.465 | 0.435 | 0.145 | 0.334 |
| 1998 | 1.099 | 0.488 | 0.444 | 0.400 | 0.116 | 0.291 |
| 2001 | 1.112 | 0.484 | 0.435 | 0.467 | 0.114 | 0.244 |
| 2004 | 1.090 | 0.457 | 0.419 | 0.449 | 0.102 | 0.227 |
| 2007 | 1.048 | 0.454 | 0.433 | 0.433 | 0.100 | 0.231 |
| 2010 | 1.032 | 0.431 | 0.418 | 0.407 | 0.091 | 0.224 |
| 2013 | 0.980 | 0.403 | 0.411 | 0.387 | 0.080 | 0.206 |
| Total | 1.136 | 0.515 | 0.449 | 0.453 | 0.134 | 0.286 |

Table 8 – Inequality and inequality of opportunity – France

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| survey | st.dev.log incomes | st.dev.log predicted incomes (absolute IOp) | relative inequality of opportunity (2/1) | mean log deviation incomes | mean log deviation predicted incomes (absolute IOp) | relative inequality of opportunity (5/4) |
| France | | | | | | |
| 1978 | 1.22 | 0.558 | 0.457 | 0.505 | 0.148 | 0.293 |
| 1984 | 1.099 | 0.471 | 0.429 | 0.399 | 0.107 | 0.269 |
| 1989 | 1.02 | 0.428 | 0.419 | 0.363 | 0.09 | 0.247 |
| 1994 | 1.121 | 0.444 | 0.396 | 0.398 | 0.098 | 0.245 |
| 2000 | 1.019 | 0.406 | 0.399 | 0.347 | 0.082 | 0.238 |
| 2005 | 0.981 | 0.363 | 0.37 | 0.32 | 0.066 | 0.206 |
| Total | 1.076 | 0.444 | 0.411 | 0.387 | 0.098 | 0.249 |

Table 9 – Inequality and inequality of opportunity – Great Britain

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| survey | st.dev.log incomes | st.dev.log predicted incomes (absolute IOp) | relative inequality of opportunity (2/1) | mean log deviation incomes | mean log deviation predicted incomes (absolute IOp) | relative inequality of opportunity (5/4) |
| Great Britain | | | | | | |
| 1991 | 1.011 | 0.510 | 0.505 | 0.391 | 0.129 | 0.329 |
| 1992 | 0.994 | 0.473 | 0.476 | 0.378 | 0.111 | 0.294 |
| 1993 | 0.983 | 0.467 | 0.475 | 0.369 | 0.108 | 0.293 |
| 1994 | 0.989 | 0.456 | 0.461 | 0.369 | 0.103 | 0.278 |
| 1995 | 0.985 | 0.445 | 0.451 | 0.368 | 0.098 | 0.267 |
| 1996 | 0.966 | 0.418 | 0.433 | 0.353 | 0.087 | 0.246 |
| 1997 | 0.954 | 0.441 | 0.462 | 0.346 | 0.096 | 0.277 |
| 1998 | 0.947 | 0.437 | 0.462 | 0.343 | 0.094 | 0.275 |
| 1999 | 0.947 | 0.416 | 0.440 | 0.337 | 0.086 | 0.254 |
| 2000 | 0.925 | 0.415 | 0.448 | 0.325 | 0.085 | 0.260 |
| 2001 | 0.904 | 0.425 | 0.470 | 0.318 | 0.089 | 0.279 |
| 2002 | 0.936 | 0.416 | 0.444 | 0.332 | 0.084 | 0.254 |
| 2003 | 0.911 | 0.406 | 0.446 | 0.322 | 0.080 | 0.250 |
| 2004 | 0.886 | 0.394 | 0.445 | 0.303 | 0.076 | 0.251 |
| 2005 | 0.899 | 0.390 | 0.434 | 0.306 | 0.075 | 0.244 |
| 2006 | 0.874 | 0.353 | 0.404 | 0.295 | 0.062 | 0.208 |
| 2007 | 0.878 | 0.354 | 0.403 | 0.304 | 0.062 | 0.203 |
| 2008 | 0.857 | 0.358 | 0.417 | 0.291 | 0.063 | 0.216 |
| 2009 | 0.991 | 0.329 | 0.332 | 0.360 | 0.053 | 0.146 |
| 2010 | 0.926 | 0.301 | 0.325 | 0.324 | 0.045 | 0.138 |
| 2011 | 0.924 | 0.290 | 0.314 | 0.317 | 0.042 | 0.132 |
| 2012 | 0.925 | 0.288 | 0.311 | 0.315 | 0.041 | 0.130 |
| 2013 | 0.920 | 0.282 | 0.307 | 0.311 | 0.040 | 0.127 |
| 2014 | 0.933 | 0.290 | 0.311 | 0.317 | 0.042 | 0.133 |
| Total | 0.933 | 0.350 | 0.375 | 0.327 | 0.063 | 0.190 |

Table 10 – Inequality and inequality of opportunity – Switzerland

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| survey | st.dev.log incomes | st.dev.log predicted incomes (absolute IOp) | relative inequality of opportunity (2/1) | mean log deviation incomes | mean log deviation predicted incomes (absolute IOp) | relative inequality of opportunity (5/4) |
| Switzerland | | | | | | |
| 1999 | 1.194 | 0.456 | 0.382 | 0.428 | 0.102 | 0.237 |
| 2002 | 1.223 | 0.448 | 0.366 | 0.449 | 0.100 | 0.222 |
| 2005 | 1.225 | 0.386 | 0.315 | 0.496 | 0.075 | 0.150 |
| 2008 | 1.240 | 0.370 | 0.298 | 0.491 | 0.069 | 0.140 |
| 2011 | 1.132 | 0.381 | 0.337 | 0.454 | 0.073 | 0.160 |
| 2014 | 1.149 | 0.369 | 0.322 | 0.447 | 0.068 | 0.151 |
| Total | 1.189 | 0.396 | 0.333 | 0.461 | 0.078 | 0.171 |

Table 11 – Estimation of relevant equations (7)-(9)-(10), by country full sample

| | Italy | | | Germany | | | France | | | Great Britain | | | Switzerland | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| dep.variable | years of education | log personal disposable income | log personal disposable income | years of education | log personal disposable income | log personal disposable income | years of education | log personal disposable income | log personal disposable income | years of education | log personal disposable income | log personal disposable income | years of education | log personal disposable income | log personal disposable income |
| female | -0.664*** | -0.785*** | -0.834*** | -0.860*** | -0.928*** | -0.989*** | -0.509*** | -0.779*** | -0.807*** | -0.042*** | -0.537*** | -0.542*** | -0.930*** | -0.650*** | -0.738*** |
| | [0.027] | [0.008] | [0.008] | [0.022] | [0.007] | [0.008] | [0.033] | [0.007] | [0.007] | [0.005] | [0.004] | [0.004] | [0.028] | [0.015] | [0.015] |
| age | -0.089*** | 0.029*** | 0.034*** | -0.019*** | 0.012*** | 0.015*** | -0.103*** | 0.023*** | 0.020*** | -0.022*** | 0.021*** | 0.027*** | -0.020*** | 0.024*** | 0.026*** |
| | [0.001] | [0.002] | [0.002] | [0.001] | [0.002] | [0.002] | [0.001] | [0.002] | [0.002] | [0.000] | [0.001] | [0.001] | [0.001] | [0.004] | [0.004] |
| age² | | -0.000*** | -0.000*** | | -0.000*** | -0.000*** | | -0.000*** | -0.000*** | | -0.000*** | -0.000*** | | -0.000*** | -0.000*** |
| | | [0.000] | [0.000] | | [0.000] | [0.000] | | [0.000] | [0.000] | | [0.000] | [0.000] | | [0.000] | [0.000] |
| years of education | | 0.078*** | | | 0.072*** | | | 0.054*** | | | 0.132*** | | | 0.095*** | |
| | | [0.001] | | | [0.001] | | | [0.001] | | | [0.002] | | | [0.004] | |
| parental education (yrs) | 0.460*** | 0.022*** | 0.058*** | 0.667*** | 0.005** | 0.054*** | 3.953*** | 0.113*** | 0.328*** | 0.114*** | 0.018*** | 0.033*** | 0.325*** | 0.023*** | 0.054*** |
| | [0.003] | [0.001] | [0.001] | [0.008] | [0.002] | [0.002] | [0.042] | [0.009] | [0.009] | [0.001] | [0.001] | [0.001] | [0.007] | [0.004] | [0.004] |
| born in a specific regions | -0.602*** | -0.378*** | -0.426*** | 0.666*** | -0.184*** | -0.136*** | | | | -0.026*** | 0.005 | 0.001 | | | |
| | [0.028] | [0.009] | [0.009] | [0.029] | [0.007] | [0.008] | | | | [0.006] | [0.004] | [0.005] | | | |
| born abroad | -0.685*** | -0.475*** | -0.524*** | 0.375*** | -0.253*** | -0.227*** | -2.199*** | -0.105*** | -0.225*** | 0.376*** | -0.130*** | -0.080*** | -0.013 | -0.147*** | -0.149*** |
| | [0.100] | [0.032] | [0.031] | [0.043] | [0.015] | [0.015] | [0.073] | [0.013] | [0.013] | [0.013] | [0.008] | [0.008] | [0.051] | [0.026] | [0.027] |
| constant | 10.901*** | 8.052*** | 8.591*** | 6.063*** | 8.574*** | 8.897*** | 11.077*** | 8.922*** | 9.458*** | 10.678*** | 7.157*** | 8.352*** | 10.380*** | 8.874*** | 9.759*** |
| | [0.075] | [0.067] | [0.068] | [0.092] | [0.055] | [0.056] | [0.070] | [0.039] | [0.040] | [0.023] | [0.033] | [0.029] | [0.103] | [0.110] | [0.103] |
| Observations | 107846 | 107846 | 107846 | 133253 | 133253 | 133253 | 89119 | 89119 | 89119 | 259608 | 259608 | 259608 | 30984 | 30984 | 30984 |
| $R^2$ | 0.439 | 0.285 | 0.239 | 0.162 | 0.277 | 0.244 | 0.241 | 0.229 | 0.175 | 0.209 | 0.222 | 0.199 | 0.211 | 0.144 | 0.119 |

Robust standard errors in brackets - sample weights - survey dummies included - statistical significance *** p<0.01, ** p<0.05, * p<0.1

Specific regions include South for Italy, East for Germany, England for Great Britain.- parental education for France correspond to high occupations

Table 12 – Estimation by age-cohort subgroups – Italy

*number of observations*

| | age groups | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| birth cohorts | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 | 50-54 | 55-59 | 60-64 | 65-69 | 70-74 | 75-80 | Total |
| (1910-1914) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 199 | 199 |
| (1915-1919) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 126 | 772 | 898 |
| (1920-1924) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 205 | 1638 | 1433 | 3276 |
| (1925-1929) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 240 | 2076 | 1708 | 1724 | 5748 |
| (1930-1934) | 0 | 0 | 0 | 0 | 0 | 0 | 266 | 2267 | 2165 | 2026 | 1607 | 8331 |
| (1935-1939) | 0 | 0 | 0 | 0 | 0 | 322 | 2512 | 2535 | 2656 | 1676 | 1568 | 11269 |
| (1940-1944) | 0 | 0 | 0 | 0 | 285 | 2616 | 2677 | 2643 | 1643 | 1705 | 0 | 11569 |
| (1945-1949) | 0 | 0 | 0 | 286 | 2896 | 3047 | 3017 | 1947 | 1956 | 0 | 0 | 13149 |
| (1950-1954) | 0 | 0 | 270 | 2482 | 3052 | 3112 | 1866 | 2018 | 0 | 0 | 0 | 12800 |
| (1955-1959) | 0 | 259 | 2395 | 2830 | 2914 | 1855 | 1847 | 0 | 0 | 0 | 0 | 12100 |
| (1960-1964) | 194 | 2068 | 2663 | 2921 | 1895 | 2028 | 0 | 0 | 0 | 0 | 0 | 11769 |
| (1965-1969) | 1047 | 1868 | 2386 | 1732 | 1730 | 0 | 0 | 0 | 0 | 0 | 0 | 8763 |
| (1970-1974) | 787 | 1479 | 1157 | 1351 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4774 |
| (1975-1979) | 593 | 681 | 872 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2146 |
| (1980-1984) | 343 | 508 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 851 |
| (1985-1989) | 204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 204 |
| Total | 3168 | 6863 | 9743 | 11602 | 12772 | 12980 | 12185 | 11650 | 10701 | 8879 | 7303 | 107846 |

*(relative) inequality of opportunity*

| | age groups | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| birth cohorts | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 | 50-54 | 55-59 | 60-64 | 65-69 | 70-74 | 75-80 |
| (1915-1919) | | | | | | | | | | | 0.401 |
| (1920-1924) | | | | | | | | | | 0.381 | 0.402 |
| (1925-1929) | | | | | | | | | 0.43 | 0.483 | 0.442 |
| (1930-1934) | | | | | | | | 0.489 | 0.482 | 0.450 | 0.371 |
| (1935-1939) | | | | | | | 0.500 | 0.495 | 0.456 | 0.470 | 0.402 |
| (1940-1944) | | | | | | 0.524 | 0.501 | 0.530 | 0.526 | 0.508 | |
| (1945-1949) | | | | | 0.466 | 0.542 | 0.526 | 0.440 | 0.475 | | |
| (1950-1954) | | | | 0.476 | 0.506 | 0.489 | 0.472 | 0.449 | | | |
| (1955-1959) | | | 0.505 | 0.509 | 0.530 | 0.505 | 0.455 | | | | |
| (1960-1964) | | 0.503 | 0.508 | 0.483 | 0.463 | 0.505 | | | | | |
| (1965-1969) | 0.465 | 0.502 | 0.462 | 0.477 | 0.494 | | | | | | |
| (1970-1974) | 0.454 | 0.476 | 0.404 | 0.481 | | | | | | | |
| (1975-1979) | 0.431 | 0.406 | 0.438 | | | | | | | | |
| (1980-1984) | | 0.417 | | | | | | | | | |

Table 13 – Deaton's decomposition by age-cohort subgroups – Italy - OLS

| | 1 | 2 |
|---|---|---|
| | unconstrained | constrained |
| dep.variable | IOp st.dev.log | IOp st.dev.log |
| age=27 | 0.007 | 0.089** |
| | [0.034] | [0.033] |
| age=32 | 0.032 | 0.101*** |
| | [0.026] | [0.031] |
| age=37 | 0.022 | 0.084*** |
| | [0.028] | [0.029] |
| age=42 | 0.04 | 0.094*** |
| | [0.026] | [0.028] |
| age=47 | 0.043* | 0.090*** |
| | [0.024] | [0.026] |
| age=52 | 0.060** | 0.099*** |
| | [0.022] | [0.025] |
| age=57 | 0.042* | 0.072*** |
| | [0.021] | [0.023] |
| age=62 | 0.040** | 0.063*** |
| | [0.019] | [0.021] |
| age=67 | 0.037** | 0.052** |
| | [0.018] | [0.020] |
| age=72 | 0.039** | 0.046** |
| | [0.017] | [0.019] |
| birth=1917 | | 0.093* |
| | | [0.050] |
| birth=1922 | -0.039 | 0.05 |
| | [0.031] | [0.044] |
| birth=1927 | 0.017 | 0.104** |
| | [0.029] | [0.042] |
| birth=1932 | 0.018 | 0.092** |
| | [0.027] | [0.040] |
| birth=1937 | 0.035 | 0.102** |
| | [0.025] | [0.039] |
| birth=1942 | 0.076*** | 0.136*** |
| | [0.025] | [0.038] |
| birth=1947 | 0.048* | 0.099** |
| | [0.025] | [0.037] |
| birth=1952 | 0.036 | 0.079** |
| | [0.025] | [0.036] |
| birth=1957 | 0.062** | 0.098*** |
| | [0.025] | [0.035] |
| birth=1962 | 0.056** | 0.083** |
| | [0.025] | [0.033] |
| birth=1967 | 0.054** | 0.073** |
| | [0.026] | [0.033] |
| birth=1972 | 0.032 | 0.044 |
| | [0.028] | [0.033] |
| birth=1977 | 0.017 | 0.02 |
| | [0.030] | [0.034] |
| survey=1994 | 0.016 | -0.007* |
| | [0.014] | [0.004] |
| survey=1999 | 0.035** | 0.012* |
| | [0.014] | [0.007] |
| survey=2004 | 0.02 | -0.005* |
| | [0.012] | [0.003] |
| survey=2009 | -0.011 | |
| | [0.012] | |
| Constant | 0.385*** | 0.315*** |
| | [0.021] | [0.041] |
| Observations | 53 | 53 |
| R-squared | 0.81 | |

Standard errors in brackets - statistical significance *** p<0.01, ** p<0.05, * p<0.1
Constraints: ( 1) - survey1 - survey2 - survey3 - omitted.survey4 - omitted.survey5 = 0
( 2) - survey1 - 5*survey2 - 10*survey3 - 15*omitted.survey4 - 20*oomitted.survey5 = 0

Figure 11 – Age profiles for inequality of opportunity, by birth cohorts - Italy

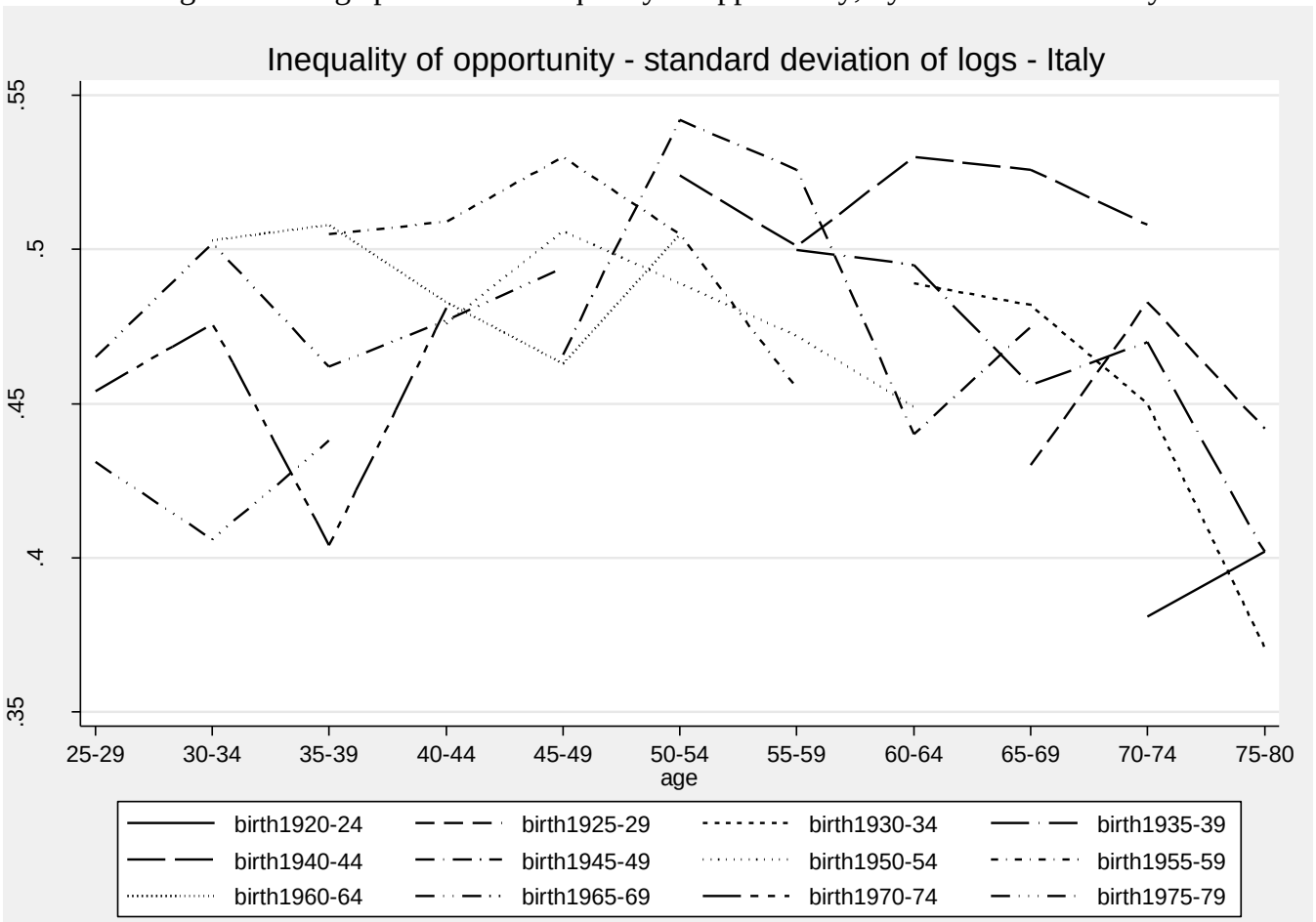



Figure 12 – Profiles for inequality of opportunity, by birth and cohorts – Italy