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The long term evolution of inequality of opportunity

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The long term evolution of inequality of opportunity[♣]

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Abstract

This paper uses a parametric approach to measure inequality of opportunities. It builds a simple theoretical model offering predictions on the changes of inequality of opportunity. It is expected to decline with the decline in intergenerational persistence in education, in the labour market return to education and in the networking activity associated to parental background; these predictions are then taken to the data.
The empirical analysis studies the evolving distribution in personal disposable incomes in five European countries (Italy, Germany, France, Great Britain and Switzerland) over a long time span. Thanks to extended samples, time trends show 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 countries considered. Depending on the inequality index, the inequality of opportunity (IOp) account between one third (MLD) and half (standard deviation of logs) of total inequality in personal disposable incomes. Inequality trends are then decomposed into age profiles and birth cohort changes. 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.
When interpreting thee observed dynamics, two parameters (intergenerational persistence in educational attainment and return of education) exhibit a declining trend, whereas the third one (networking activity of parents) is rising in most countries. The combined effect of the three movements yields a declining trend whenever the former twos dominate the latter.

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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: most of the empirical analyses use snapshot income distribution as the relevant distribution of individual advantages, and are limited to computation of inequality of opportunity in a given point in time for a given country or set of countries[1].

This paper instead is concerned with the evolution of inequality of opportunity. In addition, we exploit the time variation of EOp in order to study its main determinants. By so doing, we move the research on EOp a step forward by proposing and testing a (simple) empirical model that can explain the generation of inequality of opportunity in a given economy.

There are three different ways one can analyse 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 dataset 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 demanding. 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 outcome 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 Ω, 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 Θ. The outcome of interest is generated by a function $g: \Omega \times \Theta \rightarrow \mathbb{R}$ 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 on 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:

$$Y_{it} = a_t + b_tC_i + c_tC_{it} + \epsilon_{it} \tag{4}$$

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 set 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

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

where Y_{it} is the income of individual i sampled in survey t. The data generating process is allowed to change overtime among random draws from the (same country) population. The implicit assumption is the overtime stability of the population, such that changes in EOp can be attributed to

[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.

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 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 τ 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 τ's; for a specific birth cohort τ, repeated observations refer to different dates of survey t's; for a specific age cohort $(t - \tau)$, repeated observations refer to different life cycles. In the sequel we will exploit both the approaches described by models (5) and (6), showing that they provide different views on the evolution of EOp.

2.2 Our empirical model

In the sequel we aim to decompose measured inequality of opportunities into its constituting components, in the same vein of 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 θ denote generations.[4]

We assume that parental background affect 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_{it} is the education of the child, E_{it-1} is the education of the parents, η is a measure of intergenerational persistence and ϵ 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).

Obtaining education is valued in the labour 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 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 usual demographic information

[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, neighbourhood), our model is observationally equivalent to many other models of intertemporal transmission of social status. See for example DeFraja (2002)

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

where Y_{it} is the income of the child, β is the standard return to education and ω is a random error (capturing unobservable components – ability, effort – but also unpredictable components – luck). If we consider that parents may possess other channels of influencing children outcomes, we may consider an *extended mincerian equation* like the following

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

The inclusion of parental education can be justified as proxy for family networking in non-competitive labour markets, where connections referral 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 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 anticipated, a relative measure of inequality of opportunity 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 equation (9). As a consequence the relative IOp is 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.

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

Equation (13) indicates that other things constant IOp declines when:
① there is a reduction in the intergenerational persistence of education $\hat{\eta}$
② there is a reduction in the (private) return to education $\hat{\beta}$
③ there is a reduction in the effect of family network in the labour market $\hat{\gamma}$
④ there is an increase in the variance and covariance of the non-observable components $\hat{\omega}$ e $\hat{\epsilon}$
⑤ there is a reduction in the variance of the educational attainment of the previous generation.

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

The same approach can be used to study other attributes that may be responsible for inequality of opportunities. As a final example, consider the impact of gender: women are better achievers in schooling, but they are discriminated against in the labour 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 ϕ_i is a dummy variable for women, δ is the mean school gap achieved by women and α is the gender wage gap. Since $var(\phi) = \lambda(1-\lambda)$, where λ is the fraction of women in the working population, then we get that relative inequality of opportunity now reads

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

Now inequality of opportunity will also depends on whether the schooling advantage $\delta\beta$ for women exceeds (or falls short of) the labour market disadvantage α, as well as from the gender composition of the labour force.

3. The data

In order to provide consistent estimates of the IOp described by equation (13) we have to 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 is 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)[7], 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 112690 individuals, which reduces to 107846 when considering non-missing information.

Germany: German Socio-economic Panel (SOEP) – 11 surveys, covering the period 1984-2013 – originally including 156338 individuals, then reduced to 133467 in case of non-missing one.

France: Household Budget Survey (HBS), conducted by the Banque de France) – 6 surveys, covering the period 1978-2005 – originally consisting of 97306 individuals, declining to 89119 when missing information is excluded

Switzerland: Swiss Household Panel (SHP) – 6 surveys, covering the period 1999-2014 – originally consisting of 43102 individuals, which then decline to 31273 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 434253 individuals, which then decline to 308625 valid observations.

Our selection rules include individuals aged 25-80 with a positive disposable income, harmonized according to the LIS procedure (variable DPI).[8] 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.[9] Descriptive statistics at survey/country disaggregation are reported in tables 1 to 5 in the Appendix.

Using these data, we have estimated total inequality, absolute inequality of opportunity (namely inequality computed over incomes predicted according to circumstances) and relative inequality of

[7] Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (Italy 1993-2014, Germany 1984-2013, France 1978-2005, Switzerland 1999-2014). Luxembourg: LIS.

[8] In order to avoid negative values associated to logs, we have actually excluded all individuals with yearly incomes below 10. Data for UK 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.

[9] 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,...) or [6]executive, liberal profession. We interpret this variable as the (likely) completion of secondary or tertiary education.

opportunity (see equation (13)). These measures are 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 order to compute the predicted income according to circumstances we have resorted to the estimation of the reduced form described by equation (10). However, in order to study the decomposition proposed in the previous paragraph, we have also estimated equations (7) (intergenerational persistence in education) and (9) (*mincerian* wage equation). These estimates were conducted at country/survey level; for illustrative purposes, they have been repeated at country level and 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 favouring educational attainment of the next negation, 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 exhibit 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).

As we have already mentioned, the estimation of the models reported in table 11 can be replicated at survey level (as reported in figures 1-3-5-7-9 discussed in the next paragraph). However the sample sizes are large enough to allow the estimation at a more disaggregated level. 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 opportunities 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 satisfies a sufficient numerousness and are therefore retained for estimation of (relative) inequality of opportunities (bottom part of table 12). Once we have obtained these measures, if we ask ourselves what is the time pattern of IOp, 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 neighbouring birth cohorts. Thus we need more rigorous methods to summarise 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 the 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 observation 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 summarised by figures 1 to 10. For each country we report two sets of estimates:

a) the first set contains the analysis by survey and reports the values of four different estimates: relative inequality of opportunity, return to education, parental network and the intergenerational persistence in education (figures 1-3-5-7-9);
b) the second set contains the same estimates calculated at different ages and for different birth cohorts. Hence reports respectively the age and the cohort profiles of each of the four estimates mentioned above (figures 2-4-6-8-10).

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 2000's and then a reverse jump at the beginning of the 2010. 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).

Surprisingly, the intergenerational persistence of education shows a clear declining trend. While this latter 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 60's, with some signals of trend reversal in recent years, apparently in contradiction with a stationary inequality of opportunity in income. However, such apparent contradiction may be explained by the declining trend of the return to education and by the increasing trend of parental networking. Our suggested interpretation is that the increased equality of educational opportunities (associated to the decrease in intergenerational education persistence) has failed to translate into a decrease of opportunity inequality in income because of the increasing role of parental networking and the reduced "value" of education in the labour market.

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 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 80's and then a fairly stable pattern (see figure 3).

As for the age profiles, results shows 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 case of standard deviation of logs (between 20% and 30% in case of MLD). This is complemented by a decreasing trend in the intergenerational education persistence. On the other hand, the 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 2000's). 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 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 shows 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 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 shows 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 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 opportunities (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 labour market. This mechanism seems to be at work notably 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 seem to weaken over the life cycle. This pattern marks a difference of inequality of opportunity with respect to what is generally found for income or consumption inequalities, which generally follow an increasing path;
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 the intergenerational education persistence, while Germany is characterized by a stable trend of intergenerational education persistence;
viii) the cohort analysis, 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 younger generation experiencing a 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 of all, 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 countries considered in the present analysis. Depending on the inequality index we choose, the inequality of opportunity account 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, we have proposed a theoretical framework offering predictions on the changes of inequality of opportunity. Our analysis has focused on the role of three parameters: the intergenerational persistence in educational attainment, the return of education and the networking activity of parents. While the first two parameters exhibit a declining trend, which other things constant should produce a decline in IOp, the latter appears rising in many countries, thus counteracting the same decline. As a consequence, the fair optimism that descriptive statistics do suggest with respect to income inequality should be mitigated by paying attention to educational persistence and labour market segmentation.

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Figure 1 – Italy, by survey

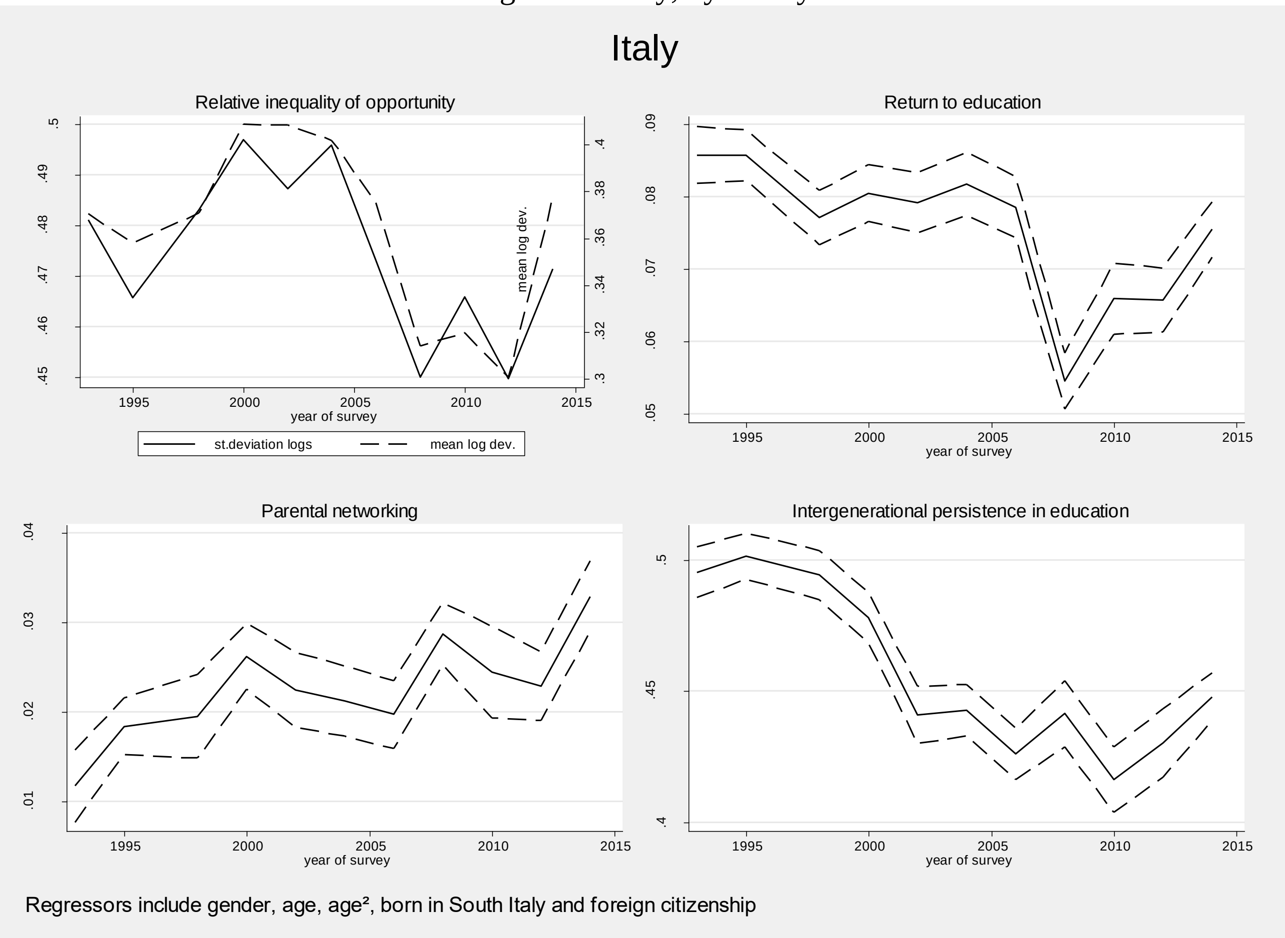


Figure 2 – Italy, age-cohort decomposition

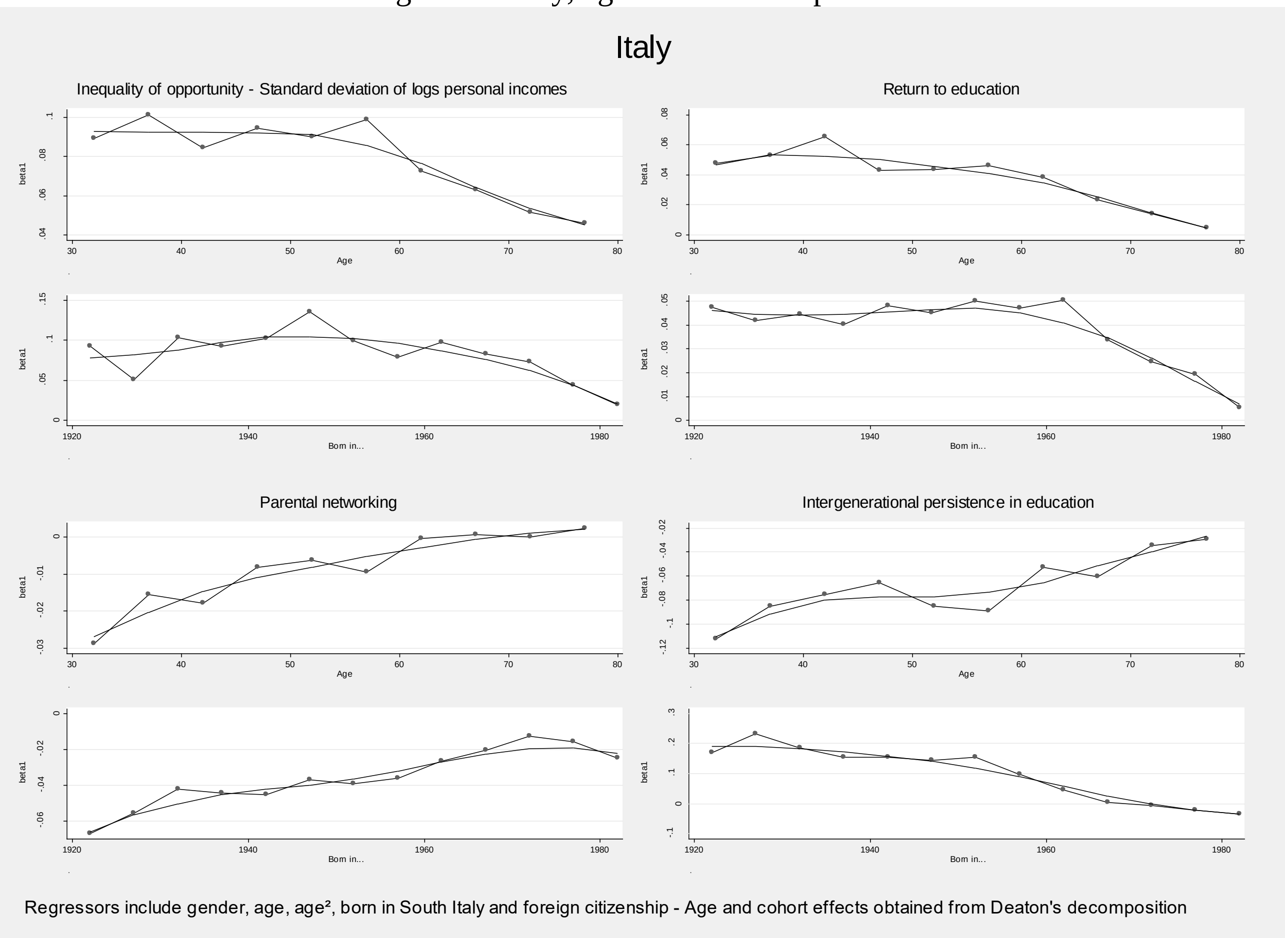


Figure 3 – Germany, by survey

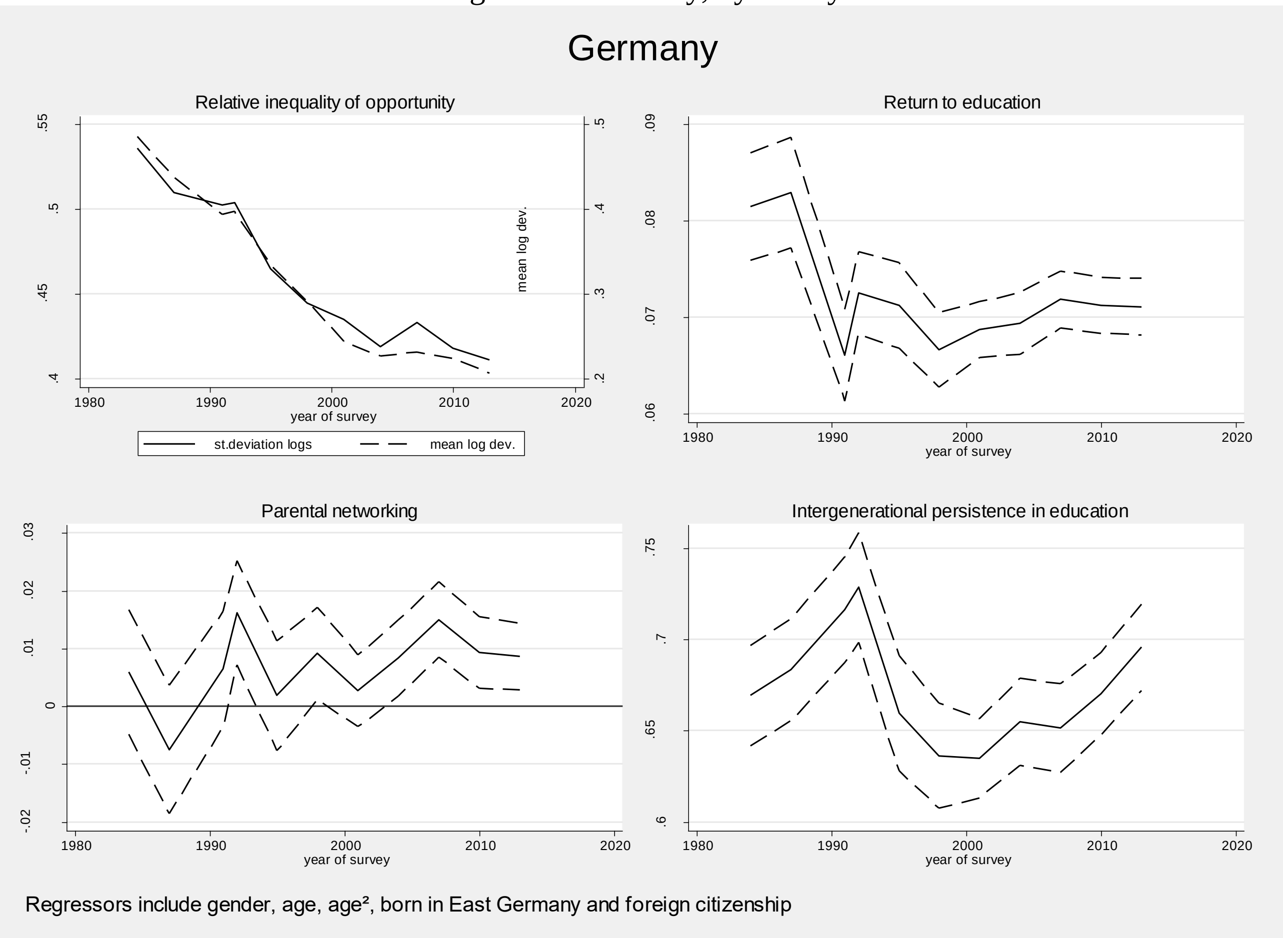


Figure 4 – Germany, age-cohort decomposition

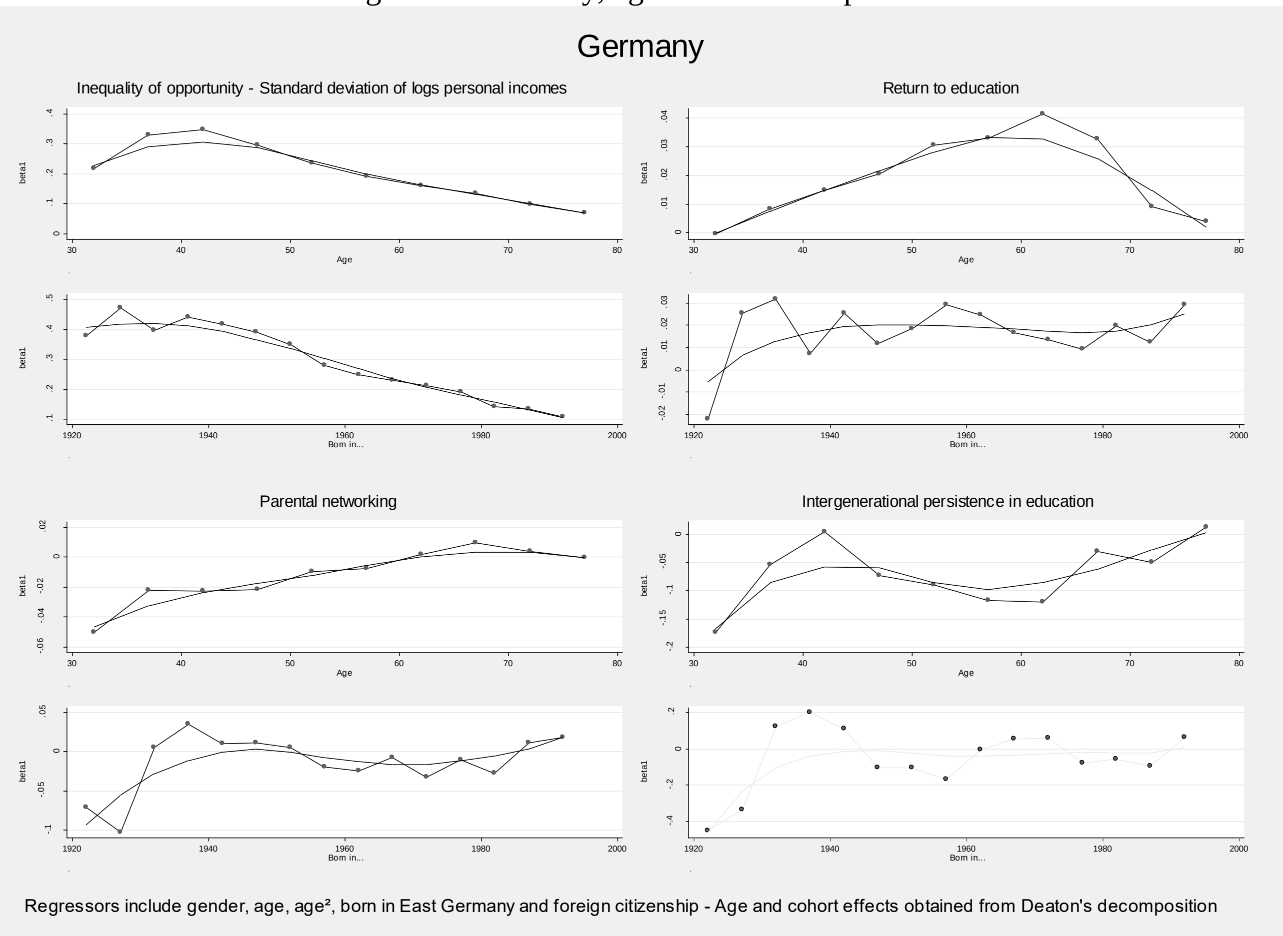


Figure 5 – France, by survey

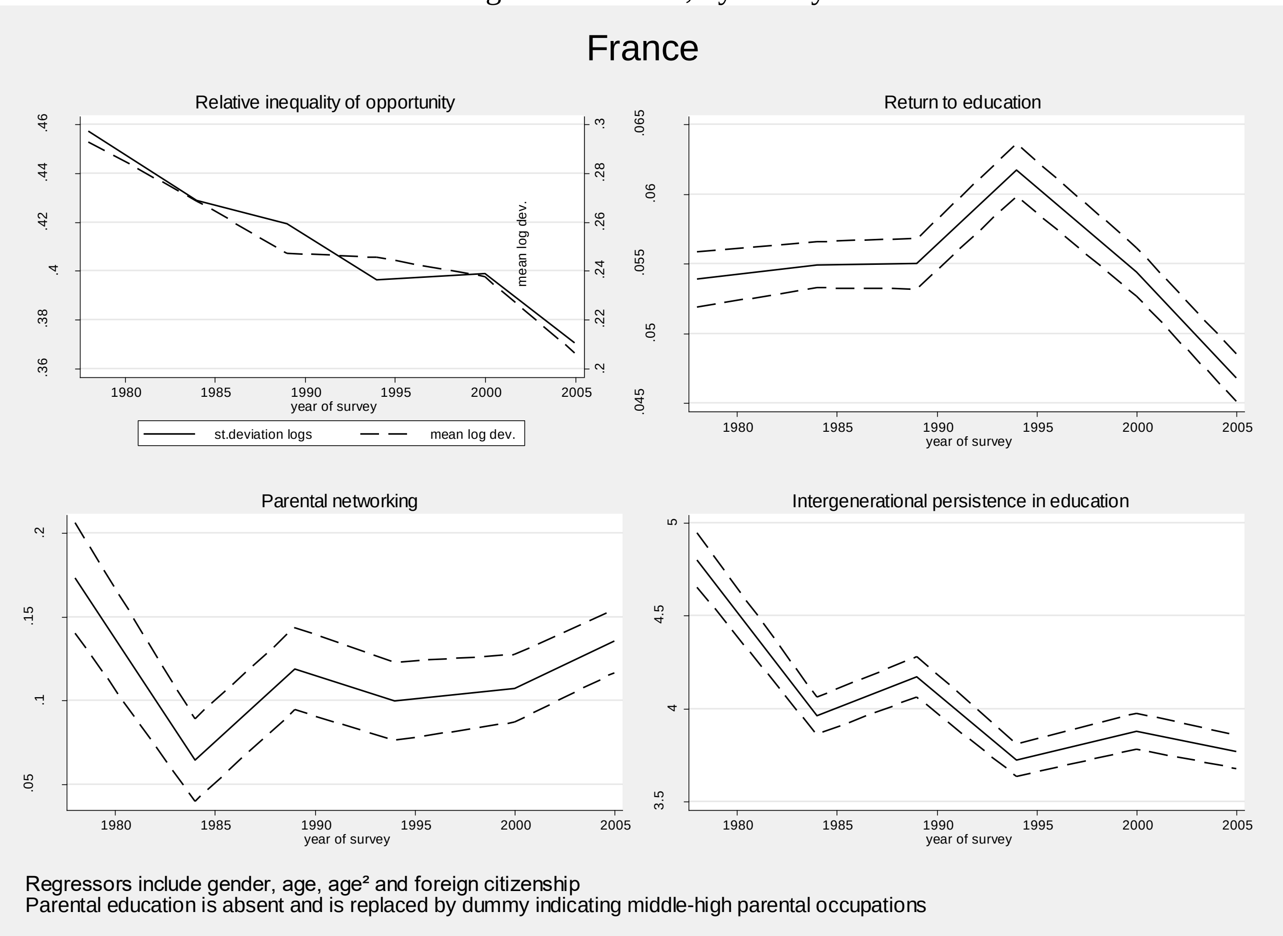


Figure 6 – France, age-cohort decomposition

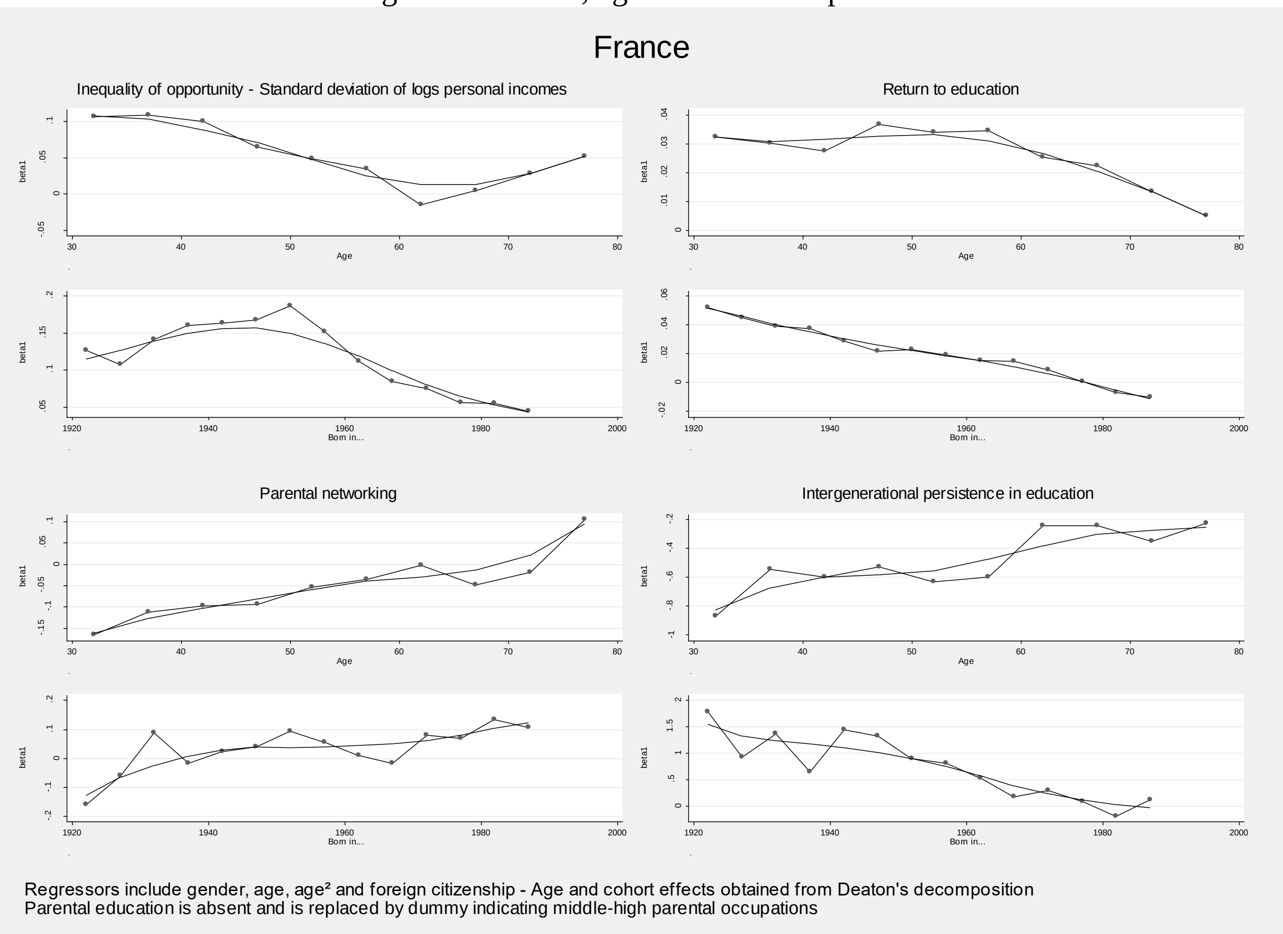


Figure 7 – Great Britain, by survey

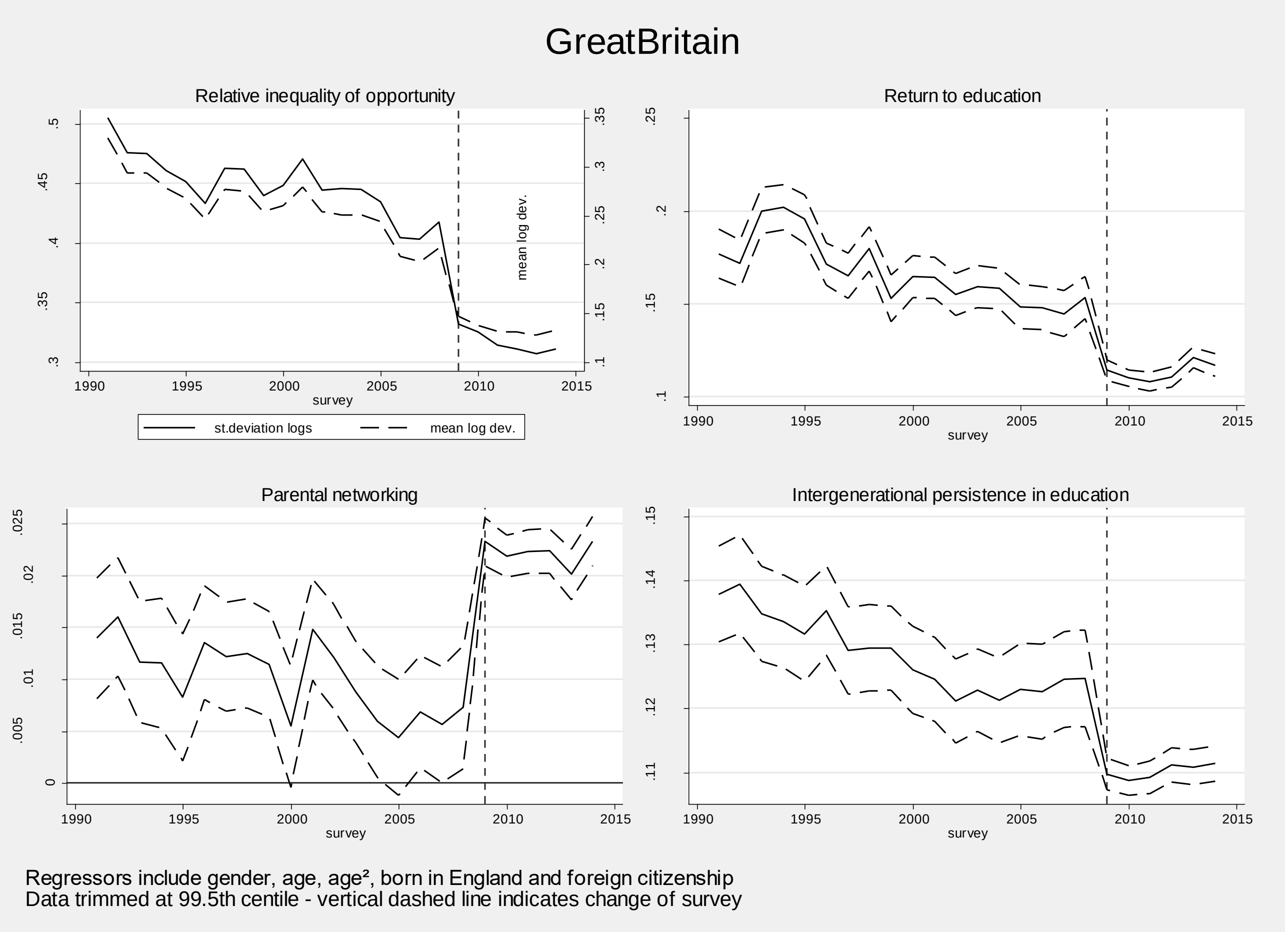


Figure 8 – Great Britain, age-cohort decomposition

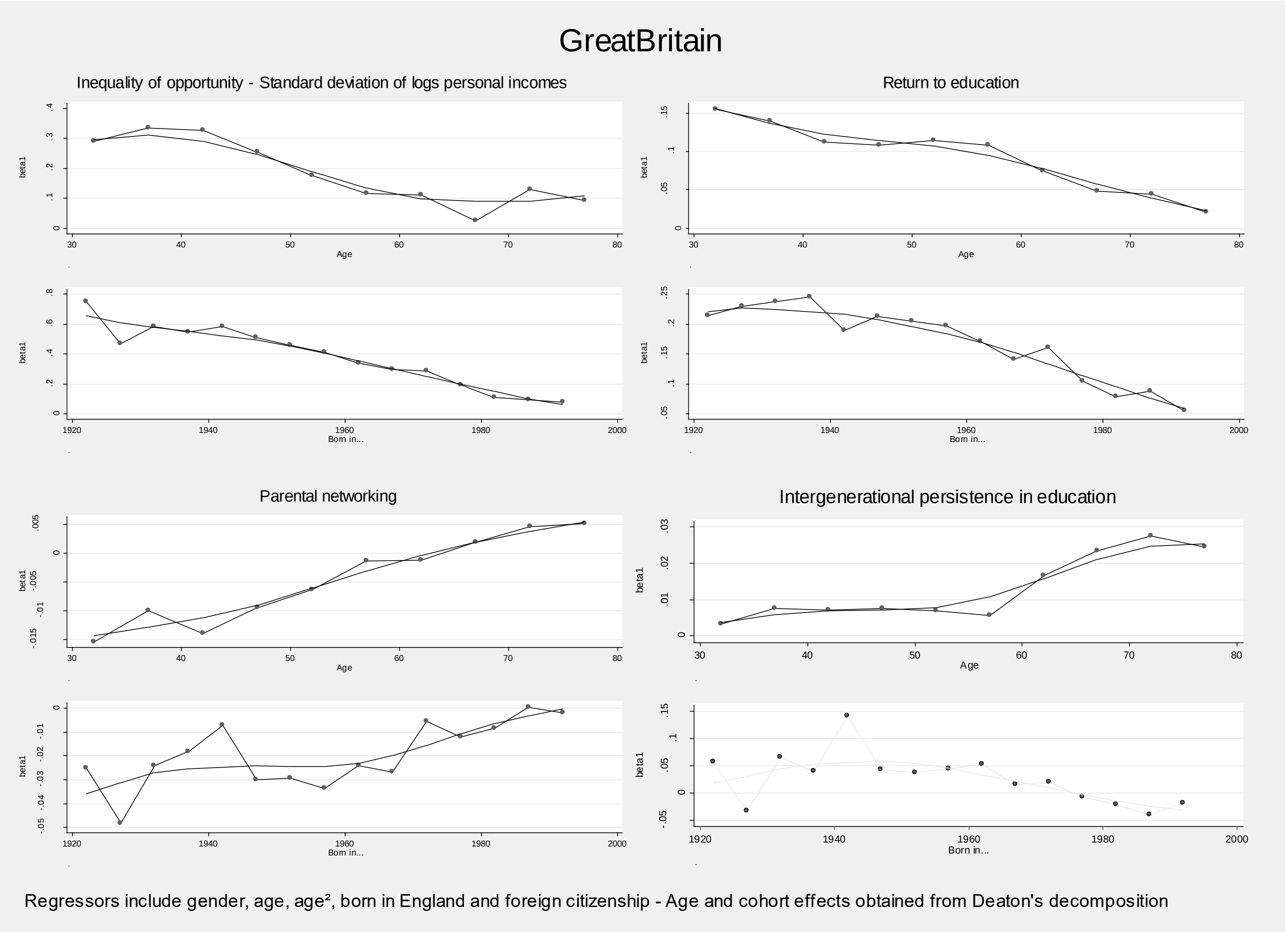


Figure 9 – Switzerland, by survey

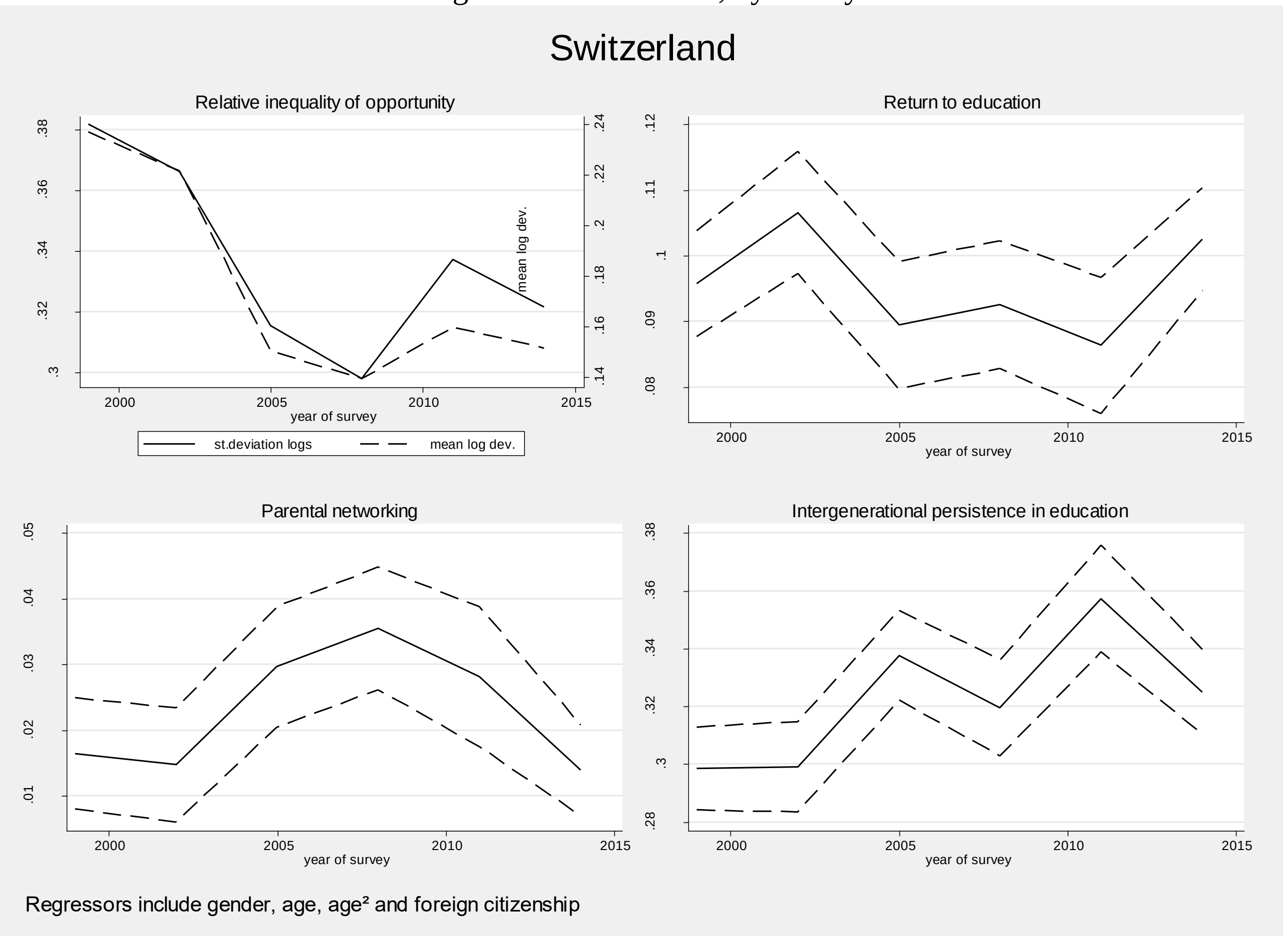
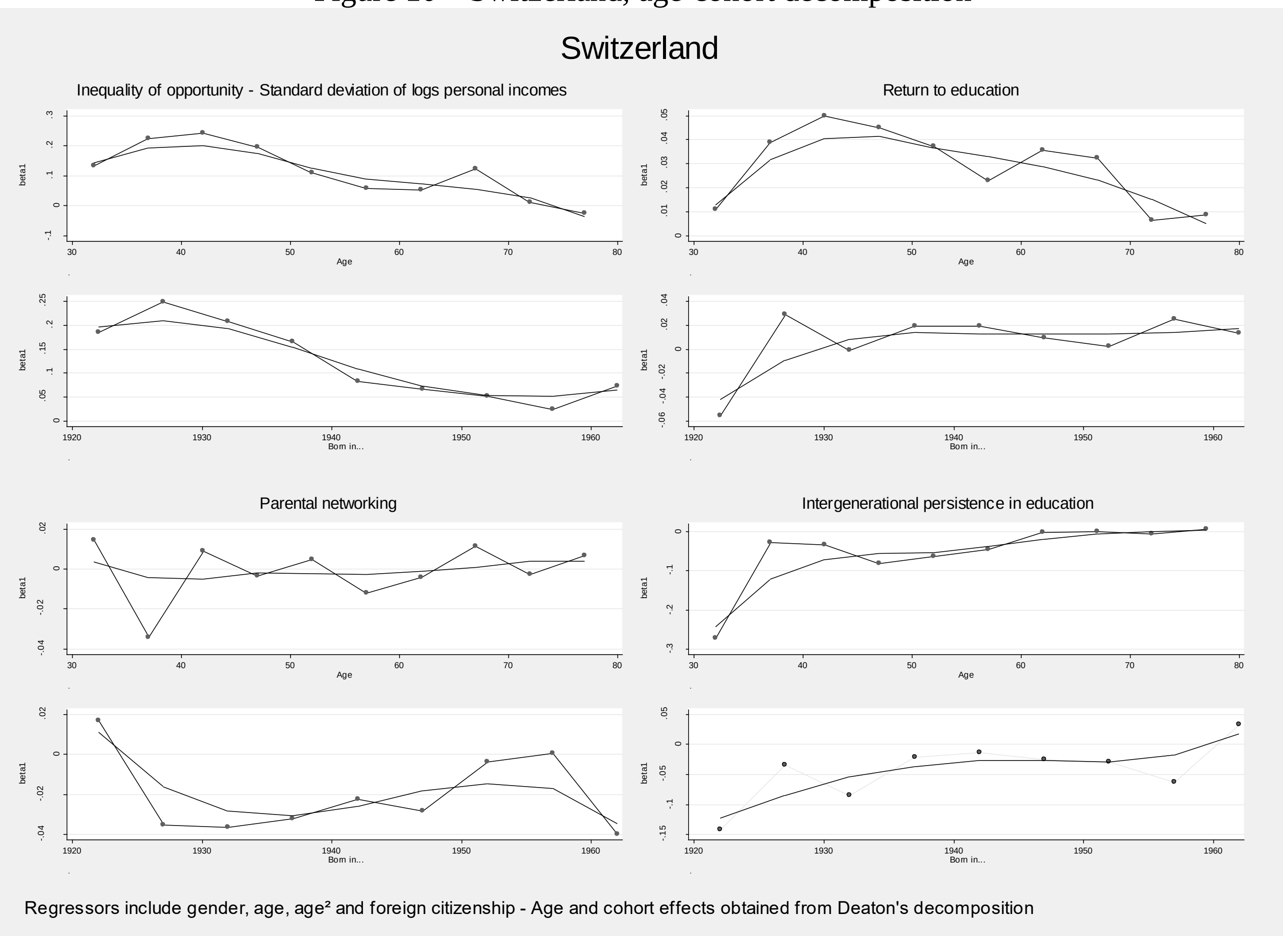


Figure 10 – Switzerland, age-cohort decomposition



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

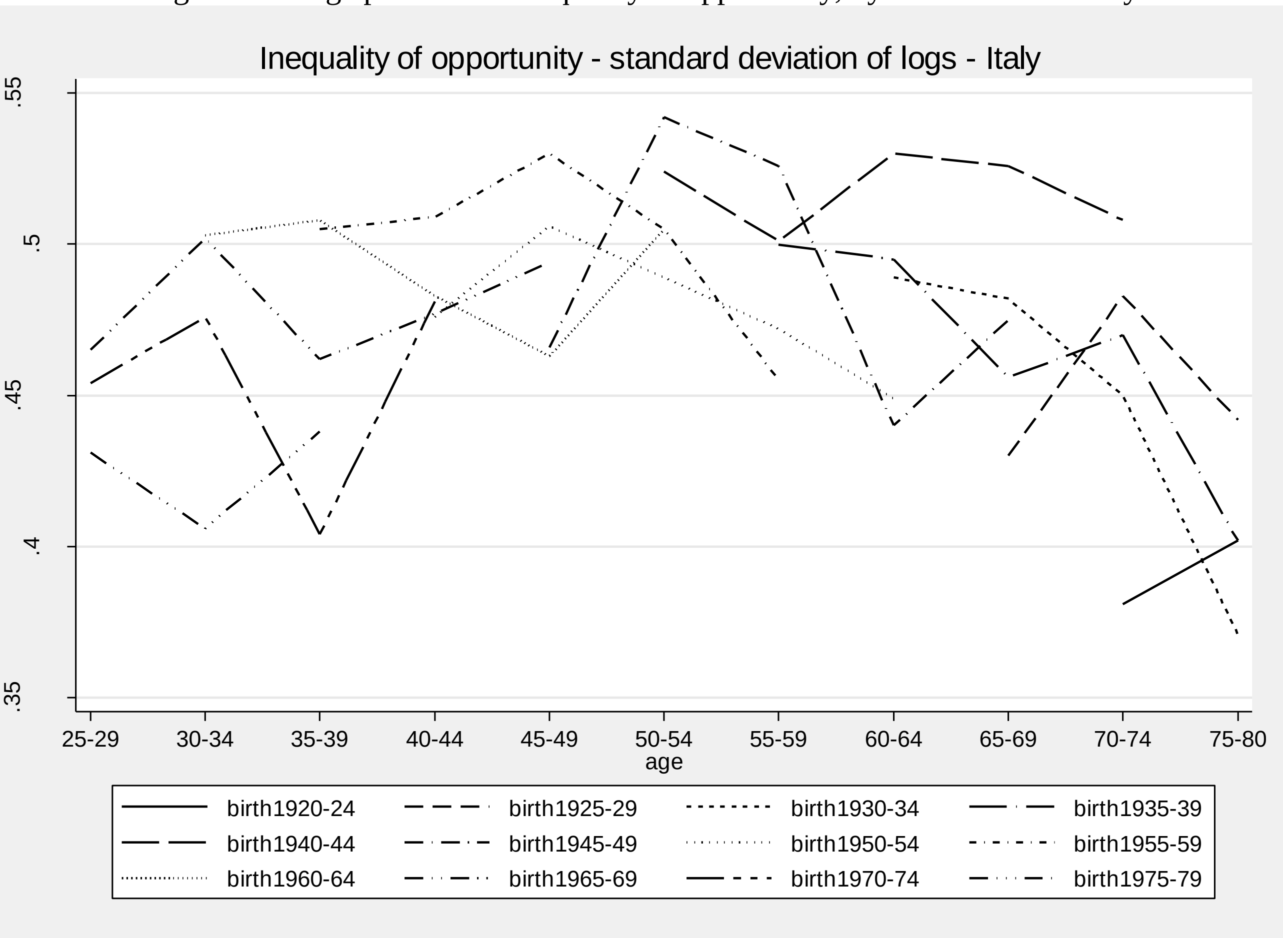


Figure 12 – Profiles for inequality of opportunity, by birth and cohorts – Italy