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Abstract

The main goal of this paper is to document and analyze the long-term evolution of inequality of opportunity (IOp) in the four largest European economies (France, Germany, Great Britain and Italy). Relative IOp represents an important portion of total income inequality, with values ranging from 30 to 50 percent according to the standard deviation of logs. For all the countries, relative IOp shows a stable or declining time trend. In addition to these descriptive findings, the paper proposes a theoretical framework identifying channels of transmission which may affect IOp. Using this framework, a decomposition focuses on the role of three variables: a) intergenerational persistence in educational attainment, b) return of education, and c) networking activity of parents. While the first two variables exhibit a declining trend in all countries, which as predicted by the model should produce a decline in IOp, the third one appears to be rising in some countries, counteracting the effects of the first two.

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

This paper studies the long-term evolution of inequality of opportunity (IOp) in Western Europe. Following Roemer (1998) and Fleurbaey (2008), inequality of opportunity is defined as the portion of income inequality that can be attributed to inherited individual circumstances such as family background, gender, ethnicity, location of birth[1]. Two main reasons motivate this long-term focus: assessing the dynamics of IOp during the most recent three decades and describing which factors are behind these dynamics. Most of the empirical literature provides a static assessment of inequality of opportunity, a snapshot of its level for a given country at a certain time[2]. This literature has been quite informative as it has highlighted the magnitude of the unfair part of inequality in different areas of the world: among Latin American countries (Ferreira and Guignoux, 2011), in the African context (Brunori et al., 2019), across European countries (Checchi et al. 2016) and, recently, even at the global level (see the results of this research at www.equalchances.org). However, and in contrast with studies on overall inequality, these analyses do not offer insights on whether inequality of opportunity has been on a rising, stable, or decreasing trend; in other words, they do not discuss dynamics of IOp. This paper fills this gap by analyzing the long-term evolution of IOp of the income distribution for the four largest economies in Europe: France, Germany, Italy, and the United Kingdom. By doing so, it moves the empirical literature on IOp closer to the long-term analysis of the evolution of the intergenerational mobility, see Chetty et al. (2017) and Ambar et al. (2018) World Bank (2018).

In addition to documenting that relative inequality of opportunity in incomes has been stable or slightly declining in Western Europe during the last three decades – from around the fall of the Berlin Wall to the most recent available data – this paper uses a decomposition approach to contribute to the analysis of the drivers of this evolution. It shows that the final effect is the result of multiple channels. Three crucial channels through which opportunities shift for the distribution of incomes are discussed in detail: a) changes in inequality of opportunity in education, or intergenerational persistence in education achievements, b) changes of the returns to education, c) additional influence of parental background on the incomes of the offspring. This latter channel labelled “parental networking”, considers the impact of parents on the incomes of the offspring that is not accounted for by the education channel. The decomposition also highlights other possible channels, such as the gender composition of the labor force.

Across all countries the first two channels point towards a downward trend of inequality of opportunity. This is perhaps not surprising given the large democratization of education accomplished in these Western European countries. Enrollment rates for secondary education around 80 percent in the mid-1970s, reached 100 percent around the year 2000; while enrollment in tertiary education increased from around 20 percent to close or above 50 percent during the same period. With such high accomplishments, it is expected that the education of the parents should matter less in explaining dispersion of education levels within the following generation. In addition, the large inflows of educated people pushed down or moderated returns to education so, even when intergenerational

[1] For recent surveys on th literature on inequality of opportunity see Ferreira and Peragine (2015) and Roemer and Trannoy (2015).

[2] An exception is represented by Aaberge et al. (2011) who study the long term evolution of inequality of opportunity in Norway.

persistence of education still matters, a lowered education premium decreases its relevance in explaining inequality in incomes. However, in some countries, the parental networking channel had a counterbalancing effect making IOp decrease by a lesser amount. In any case, identifying this additional 'networking' channel is a useful contribution. It shows an additional way through which parental background can have long term effects on unfair inequality and it can suggest new policies interventions.

Although left for future research, a main finding of this paper, i.e. the changing nature of the unfair inequality – from intergenerational persistence of education to networking – can begin addressing the question of why an increasing proportion of the population has been reporting a worsening of inequality even though measurements of inequality have not recorded a markedly rising trend, at least not for the last decade and a half.[3] This gap between subjective perceptions and objective measurements of inequality has been highlighted in recent papers, see for example Gimpelson and Treisman (2018) and Bussolo et al. (2019). Some argue that individuals simply misperceive inequality and that these mistakes are behind the gap between subjective perceptions and objective measures. But something else may be happening. Individuals may express growing concerns about inequality in a situation where inequality of opportunity, or the unfairness of the process through which inequality is generated, is rising while, at the same time, total inequality, or inequality of an outcome such as incomes, is stable. In such a case, the issue is not one of misperception, but one of increasing relative inequality of opportunity. One clearly needs to estimate changes over time of inequality of opportunity to tackle this puzzle, and this is what is done in this paper.

The paper is organized as follows. The next section introduces the general framework of inequality of opportunity and describes the data used for its empirical estimation. Section 3 discussed the decomposition approach, while section 4 describes the results. Section 5 briefly concludes.

2. The evolution of income inequality and inequality of opportunity in Europe

2.1 The canonical model to measure 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 IOp 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. Here we adopt 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,

[3] A clear example of this mismatch, based on comparing data from the opinion surveys LITs (Life in Transition) and inequality measures estimated from income data, is reported in Bussolo et al. (2018)..

summarized by a variable e, denoting effort,[4] belonging to the set Θ. The outcome of interest is generated by a function $g: \Omega \times \Theta \rightarrow \mathbb{R}$ such that:

$$Y = g(C, e) \quad (1)$$

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. The source of unfairness in this model is given by the effect that circumstance variables have on individual outcomes. In the empirical literature (see Ferreira and Peragine 2015 for a survey), circumstances include gender, age, ethnicity, country and region of birth, parental background (in terms of educational attainment and occupational status).

A parametric implementation of the model above,[5] extensively used in the literature (see Bourguignon et al. 2007), considers estimating by OLS the following equation:

$$Y_i = a + bC_i + \epsilon_i \quad (2)$$

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 $I(\hat{Y})/I(Y)$.

2.2 The Data

Our first exercise consists in tracking the evolution of income inequality and inequality of opportunity in the last decades is Europe. This is not a simple exercise, as it imposes data requirements that are rather demanding:

a) adequate information on circumstances: in addition to gender and age, typically available in survey data, one needs some information on parental background and country of origin;

b) a measure of disposable income that is comparable across time/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.

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[6], which allowed us to process data from three countries (Italy, Germany and France), while a forth country (United Kingdom) was obtained from directly from the original provider[7]. By so doing, we implemented our analysis for the four largest economies in Europe: Italy, Germany, France, U.K.

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

[4] Effort could also be treated as a vector. However, we follow the literature and treat it as a scalar.

[5] 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.

[6] http://www.lisdatacenter.org

[7] https://www.understandingsociety.ac.uk

1993 – 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.

United Kingdom: we started with British Household Panel (BHPS) and replaced it after 2009 using the Understanding Society-Household Longitudinal Survey (UKHLS) – the file includes 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).[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 4.

2.3 The evolution of income and opportunity inequality in European countries: the cross-section analysis

Using these data, total inequality, absolute inequality of opportunity (namely inequality computed over incomes predicted according to circumstances) and relative inequality of opportunity have been estimated for each country and for each survey/year. These measures are reported in tables 5 to 8. Each table includes two indicators of inequality (standard deviation of logs and mean log deviation), which behave in very similar ways, both for income and for opportunity inequality. These tables show the long run view on income and opportunity inequality from repeated cross-sections for the four largest economies in Europe.

In general, the trends of income and opportunity inequality are not dissimilar: the data show light reduction in both opportunity and overall income inequality over time, with the former which represents an important portion (about 40%) of the latter. See section 4.2 for a more detailed analysis.

[8] 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.

[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 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.

A number of possible mechanisms might drive the high correlation between income and opportunity inequality. One that appears plausible is the notion that today's outcomes shape tomorrow's opportunities: large income gaps between today's parents are likely to imply bigger gaps in the quality of education, or access to labor market opportunities, among tomorrow's children. Naturally, the reverse causality probably holds too: if opportunity sets differ a great deal among people, then individual outcomes are also likely to be unequal.

Of course, inequalities in income and opportunities are both endogenously determined: there is a clear quest for causality here, which, however, at this aggregate level is difficult to identify.

Although we do not explicitly address the issue of causality, to move forward in this direction, in the next two sections we propose two alternative decompositions which may help to detect different channels of transmissions of the specific circumstances.

3. The channels of transmission of different circumstances: decomposition methods

3.1 A repeated cross-section approach

This section presents a decomposition of inequality of opportunity into its constituting components in the same vein as the approach used by Solon (2004) for studying intergenerational mobility of incomes. 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.

We assume that parental background affects the income opportunity of the child through two main channels: *educational investment* and *family networking*.[10] The first channel can be simply described by the intergenerational persistence of educational attainment (Black and Devereux, 2011)

$$E_{i\theta} = \delta + \eta E_{i\theta-1} + \epsilon_{i\theta} \tag{3}$$

where $E_{i\theta}$ is the education of the child, $E_{i\theta-1}$ 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).

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 covariates):

[10] 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).

$$\log(Y_{i\theta}) = \alpha + \beta E_{i\theta} + \omega_{i\theta} \quad (4)$$

where $Y_{i\theta}$ 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).[11]

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

$$\log(Y_{i\theta}) = \alpha + \beta E_{i\theta} + \gamma E_{i\theta-1} + \omega_{i\theta} \quad (5)$$

Note that γ, in the equation above, captures the correlation of parental education to the offspring's income beyond that indirectly exerted via the education channel of equation (3). 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.[12] By replacing equation (3) into equation (5) we obtain:

$$\log(Y_{i\theta}) = y_{i\theta} = [\alpha + \delta\beta] + [\gamma + \eta\beta]E_{i\theta-1} + [\omega_{i\theta} + \beta\epsilon_{i\theta}] \quad (6)$$

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

$$I(y_\theta) = I([\alpha + \delta\beta] + [\gamma + \eta\beta]E_{\theta-1} + [\omega_\theta + \beta\epsilon_\theta]) \quad (7)$$

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 consider the *standard deviation of logs* as our inequality indicator.[13] In such a case

$$sd(y_\theta) = \sqrt{var(y_t)} = \sqrt{(\gamma + \eta\beta)^2 var(E_{\theta-1}) + var(\omega_\theta) + \beta^2 var(\epsilon_\theta) + 2\beta cov(\omega_\theta, \epsilon_\theta)} \quad (8)$$

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 (3) and (5). The relative IOp is thus given by the following equation:

[11] This formulation can be derived from the intertemporal maximization of the income stream, when considering the equivalence between immediate entry in the labor market and postponing it in order to spend an additional year in education. See Card 2001.

[12] However, the possible correlation between parental education and children earnings is observationally equivalent to many other explanations. It could reflect the role of competences (literacy and numeracy, as well as non-cognitive skills) that are formed within the family but are valuable in the labor market (see Cappellari et al 2016). Or it could capture role models that are socially determined and helpful in workplace careers (see Bisin and Verdier 2011). Or it could derive from genetic inheritability of unobservable ability, which comes out correlated with educational attainment (for parents) and labor earnings (for children – see Bowles and Gintis 2002)

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

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

$$= \frac{(\hat{\gamma} + \hat{\eta}\hat{\beta})}{\sqrt{(\hat{\gamma} + \hat{\eta}\hat{\beta})^2 + \frac{\hat{\sigma}^2_{\omega_\theta} + \beta^2\hat{\sigma}^2_{\epsilon_\theta} + 2\beta cov(\hat{\omega}_\theta, \hat{\epsilon}_\theta)}{var(E_{\theta-1})}}} \tag{9}$$

Up to this point, equation (9) shows the relationship between relative IOp and the underlying parameters that represent the process generating the distribution of incomes in a given year. However, these parameters may change over time and, given that we have several repeated cross-sections for each country, we can use equation (9) to understand how IOp evolves when these changes actually occur. Equation (9) 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 $\hat{\epsilon}$;[14]
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 additional circumstances. As an example, consider the impact of gender: women are better achievers in schooling, but they are discriminated against in the labor market. Equations (3) and (5) are to be modified accordingly:

$$E_{i\theta} = \delta\phi_i + \eta E_{i\theta-1} + \epsilon_{i\theta} \tag{3$'$}$$

$$\log(Y_{i\theta}) = \alpha\phi_i + \beta E_{i\theta} + \gamma E_{i\theta-1} + \omega_{i\theta} \tag{5$'$}$$

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

$$IOp = \frac{\sqrt{var(\hat{y})}}{\sqrt{var(y)}} = \frac{(\hat{\alpha} + \hat{\delta}\hat{\beta})\sqrt{(\lambda(1-\lambda))} + (\hat{\gamma} + \hat{\eta}\hat{\beta})\sqrt{var(E_{\theta-1})}}{\sqrt{(\hat{\alpha} + \hat{\delta}\hat{\beta})^2(\lambda(1-\lambda)) + (\hat{\gamma} + \hat{\eta}\hat{\beta})^2 var(E_{\theta-1}) + \hat{\sigma}^2_{\omega_\theta} + \beta^2\hat{\sigma}^2_{\epsilon_\theta} + 2\beta cov(\hat{\omega}_\theta, \hat{\epsilon}_\theta)}} \tag{9$'$}$$

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 α, as well as from the gender composition of the labor force.

[14] Recall that these terms capture effort, so it is intuitive that if effort becomes more relevant for explaining overall inequality, than inequality of opportunity should decrease.

3.2. A pseudo-panel approach: age and birth cohort effects in the evolution of inequality of opportunity

A dynamic version of the model presented in the previous section can be obtained by introducing the time dimension in alternative ways. A parsimonious 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 IOp of its citizens, the relevant model considers

$$Y_{it} = a_t + b_t C_{it} + \epsilon_{it} \tag{10}$$

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 assumption is the over-time stability of the population, such that changes in IOp can be attributed to changes in the relevant parameters a and b. Model (10) 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 described by equations (3) and (5). In such a case the relevant model becomes

$$Y_{i\tau t} = a_{t\tau} + b_{t\tau} C_{i\tau t} + \epsilon_{i\tau t} \tag{11}$$

where $Y_{i\tau t}$ is the income of individual i born in year τ and sampled in survey t. In such a case, IOp 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. Our empirical analysis initially adopts the approach described by model (10). 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 (5) is explored in a companion paper. Both these *dynamic* approaches provide interesting and distinct insights on the evolution of IOp.

4 The results of the decomposition analysis

4.1 The empirical implementation

To apply the decomposition of relative inequality of opportunity as shown in equation (9), equations (3) (intergenerational persistence in education) and (5) (augmented 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 9. One can notice that country estimates 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 (5) 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 9 is performed for year survey/year and the results are graphically reported in figures 1, 2, 3 and 4, and discussed in detail in section 4.2 below.

4.2 The results

Our main results are fully summarized by figures 1 to 4**Error! Reference source not found.Error! Reference source not found.**444**Error! Reference source not found.**, and table 10. For each country, these figures show the evolution, roughly across the last three decades, of 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 ($\hat{\eta}$). In addition, to provide some information on the relative magnitude of the different channels, partial elasticities of the relative IOp with respect to each of these three variables has been calculated and reported in table 11.

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 –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 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 educational system and the labor market are working in opposite directions: educational opportunities have widened (in association to a reduced "value" of education), thus contributing to levelling the playing field. Conversely, maybe due to the reduced signaling value of education, the labor market seems to work under imperfect information, and employers put more and more weight on parental background while hiring among potential applicants.

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). The reunification of West and East Germany has not slowed down this process. The reduction of relative IOp seems mostly attributable to the fairly constant decline of intergenerational education persistence, though in recent surveys it is on a rising trend, and a declining return to education. In contrast with Italy, what is impressive is the absence of (statistically significant) effect of parental networking, even if in more recent years this effect becomes positive and significant (see figure 2). Thus, Germans are experiencing a fairer process determining income distribution compared to Italians, though there are indications of possible trend reversals on all dimensions.

France

The availability of a limited number of surveys (six) leads to a less precise identification of trends in this case. The analysis by surveys 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 positive contribution to the level of IOp but a pretty flat time trend, 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 seems mostly driven by the reduction in intergenerational educational persistence (see figure 3).

United Kingdom

The British case is hard to interpret due to the change of survey occurred in 2009. Despite the official announcement of continuity in the survey design, one can notice that all measures do have a significant jump when passing from BHPS to UKHLS in 2009 (indicated by a vertical dashed line).[15] Nevertheless, the analysis by survey (see figure 4) 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, a stable pattern in parental networking is recognizable, associated to a declining trend in both intergenerational education persistence and return to education which are the main drivers of the declining trend of IOp.

Elasticities

Up to this point we have described the trends in IOp and, jointly, those of three key correlates: intergenerational persistence in education, the return of education, and parental networking. Here we attempt to shed some light on the question of what would have been the effect on IOp if only one of these correlates had changed. In other words, we attempt to assess whether the impacts of these variables have similar magnitudes, or not. As in any decomposition exercise, one needs to be careful when interpreting the isolated impact of one factor. Using the decomposition of equation (9), it may be possible to calculate the contribution of, say, parental networking on IOp by varying $\hat{\gamma}$ while

[15] Looking into the details of the distribution of the relevant variables survey by survey, we detect a significant increase in the earnings inequality (the weighed Gini index jumps from 0.42 in 2008 to 0.46 in 2009), which is partly attributable to the oversampling of foreign-born population (their share changes from 0.06 to 0.12 in the relevant year). This may be partly counteracted by top-coding introduced in 2009 at 180000£ per year. The distribution of educational attainment is also sifted upwards, but this difference attenuates when considering the years of education obtained from school leaving age. See also table 4.

keeping the other components of the equation unchanged. However, it is likely that this factor interacts with the others. So, its isolated contribution cannot be thought of as if it was derived by comparing an initial equilibrium value of IOp with a new equilibrium value. This numerical simulation just provides an indication of the direction and strength of the influence of $\hat{\gamma}$ on inequality of opportunity. With this caveat in mind, it is possible to define partial elasticities as follows:

$$Elasticity_{parental\ network} = \frac{\frac{\Delta IOp}{\mathrm{IOp}}}{\frac{\Delta\hat{\gamma}}{\hat{\gamma}}}$$

This expression, or the equivalent ones for intergenerational persistence of education ($\hat{\eta}$), return to education ($\hat{\beta}$), can be evaluated, for each country and for each survey year, using equation (9). Table 11 shows the median value of these partial elasticities across all the years for the four countries. Interestingly, across all the countries, parental networking exhibits the highest elasticity, ranging from 1.4 in Italy to 2.2 in Germany. The other two correlates show much smaller elasticities, close to 1, with the elasticity of return to education slightly larger than that of intergenerational persistence. Note that these elasticities have been calculated by shifting the relevant parameter by 1 percent and this is a change that is relative small when compared with the full period change shown in table 10.

Summing up

In general our proposed decomposition seems useful to account for the observed trends of inequality of opportunity in the income space, being associated to the dynamics of intergenerational persistence in education, to the evolution of the return to education and to the emerging role of parental influence in the labor market beyond education Thus the empirical evidence appear consistent with the conjectures based on equation (9). In addition, it is possible to highlight the following stylized facts:

i) in all countries and surveys considered, inequality of opportunity represents an important portion of total income inequality, ranging from 30% to 50% of the 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.

vi) across countries, IOp shows a much higher elasticity vis-à-vis parental networking then the other correlates, highlighting the relevance of this channel of influence.

5. Conclusions

This paper contributes to the analysis of inequality of opportunity in two 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, the paper proposes a theoretical framework identifying the variables potentially affecting (positively or negatively) inequality of opportunity. A simple model is consequently estimated, and the estimated correlation behave according to the theoretical predictions. The analysis has focused on the role of three variables: the intergenerational persistence in educational attainment, the return of education, and possible networking activity of parents. While the first two variables exhibit a declining trend in all countries, which other things constant should produce a decline in IOp, the third one appears to be rising in some of them countries, thus counteracting the effects of the first twos. 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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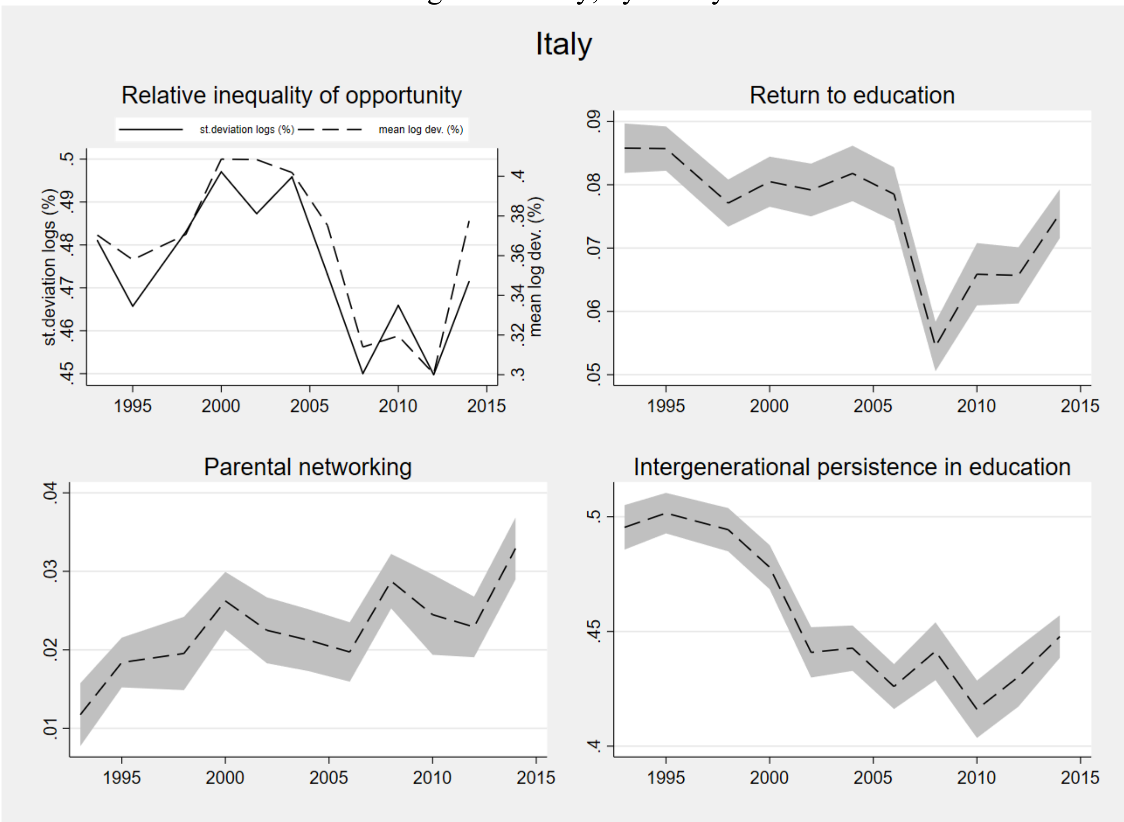
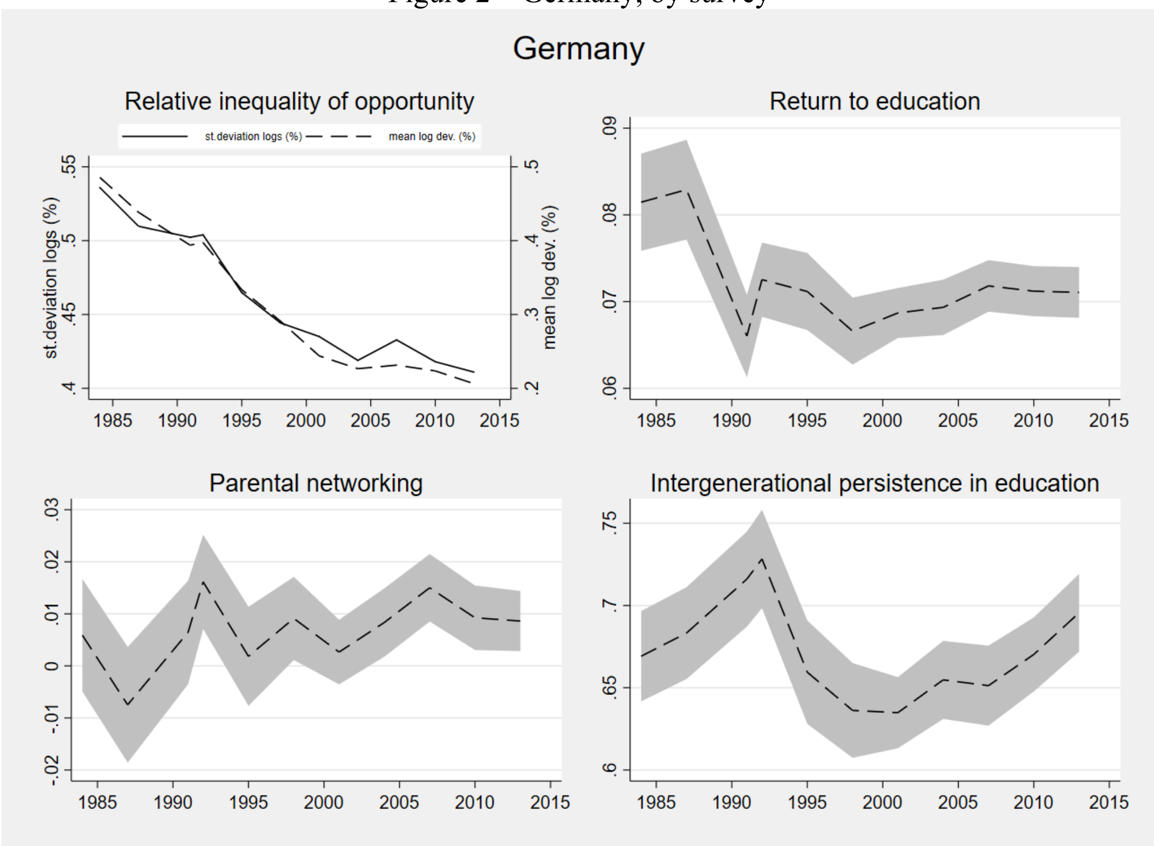
Figure 1 – Italy, by survey



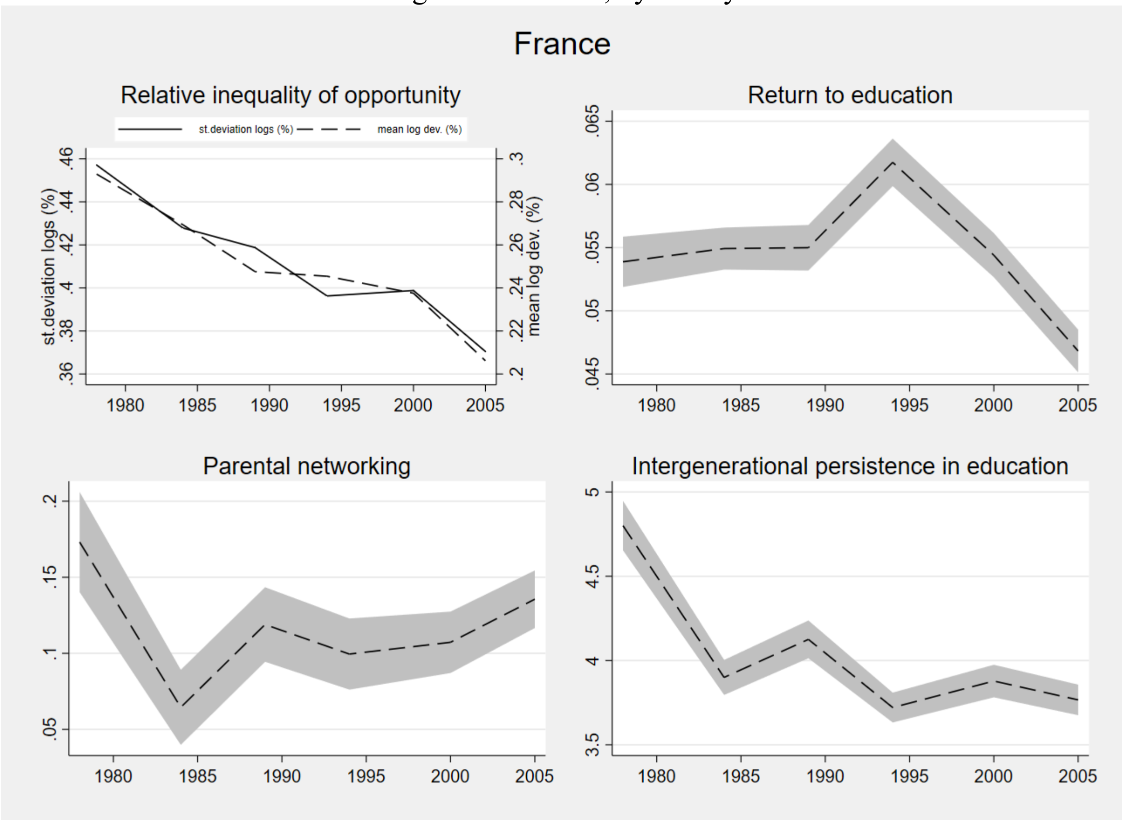
Note: in the estimation of IOp (top left panel), regressors include gender, age, age^2, born in South Italy and foreign citizenship. The grey band represents confidence interval around the point estimates for return to education, networking and persistence as estimated in equations (3), (4) and (5).

Figure 2 – Germany, by survey



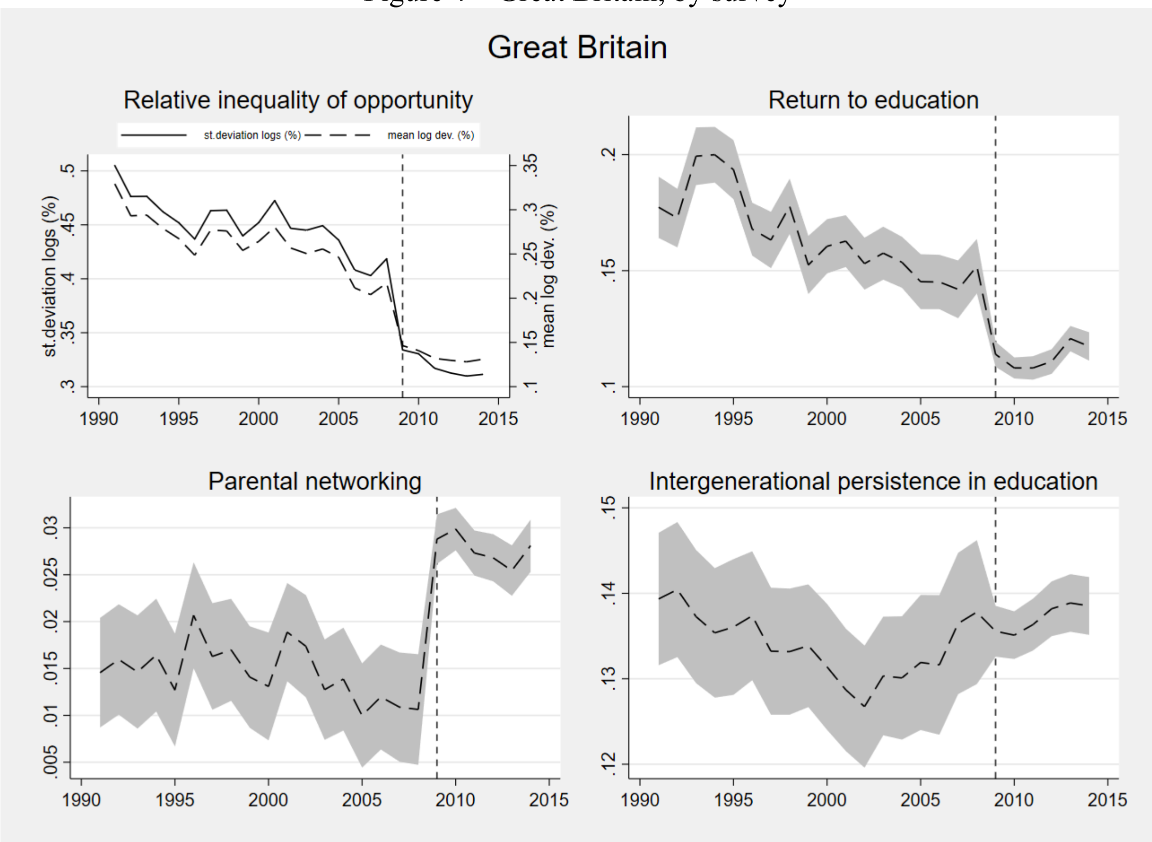
Note: in the estimation of IOp (top left panel), regressors include gender, age, age^2, born in East Germany and foreign citizenship. The grey band represents confidence interval around the point estimates for return to education, networking and persistence as estimated in equations (3), (4) and (5).

Figure 3 – France, by survey



Note: in the estimation of IOp (top left panel), regressors include gender, age, age^2, and foreign citizenship. Parental education is not available and is replaced by a dummy indicating middle-high parental occupations. The grey band represents confidence interval around the point estimates for return to education, networking and persistence as estimated in equations (3), (4) and (5).

Figure 4 – Great Britain, by survey



Note: in the estimation of IOp (top left panel), regressors include gender, age, age^2, born in England and foreign citizenship. Vertical dashed line indicates change of survey. Data trimmed at 99.5th percentile. The grey band represents confidence interval around the point estimates for return to education, networking and persistence as estimated in equations (3), (4) and (5).

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 – 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 6 – 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 7 – 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 8 – 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 9 – Estimation of relevant equations (3)-(4)-(5), by country full sample

	Italy			Germany			France			Great Britain		
	1	2	3	4	5	6	7	8	9	10	11	12
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
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***
	[0.027]	[0.008]	[0.008]	[0.022]	[0.007]	[0.008]	[0.033]	[0.007]	[0.007]	[0.005]	[0.004]	[0.004]
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***
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.000]	[0.001]	[0.001]
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]
years of education		0.078***			0.072***			0.054***			0.132***	
		[0.001]			[0.001]			[0.001]			[0.002]	
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***
	[0.003]	[0.001]	[0.001]	[0.008]	[0.002]	[0.002]	[0.042]	[0.009]	[0.009]	[0.001]	[0.001]	[0.001]
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***
	[0.100]	[0.032]	[0.031]	[0.043]	[0.015]	[0.015]	[0.073]	[0.013]	[0.013]	[0.013]	[0.008]	[0.008]
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***
	[0.075]	[0.067]	[0.068]	[0.092]	[0.055]	[0.056]	[0.070]	[0.039]	[0.040]	[0.023]	[0.033]	[0.029]
Observations	107846	107846	107846	133253	133253	133253	89119	89119	89119	259608	259608	259608
R²	0.439	0.285	0.239	0.162	0.277	0.244	0.241	0.229	0.175	0.209	0.222	0.199

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 highly prestigious occupations

Table 10 – Full period changes of coefficients of: persistence of education ($\hat{\eta}$), return to education ($\hat{\beta}$), parental networking ($\hat{\gamma}$)

	Persistence			Return			Networking		
Country	Start	End	Change	Start	End	Change	Start	End	Change
Italy	0.495	0.448	-10%	0.086	0.075	-12%	0.012	0.033	180%
France	4.801	3.767	-22%	0.054	0.047	-13%	0.173	0.136	-22%
Germany	0.669	0.696	4%	0.081	0.071	-13%	0.006	0.009	46%
United Kingdom	0.139	0.139	-1%	0.177	0.117	-34%	0.015	0.028	93%

Note: For Italy the start and the end of the period are 1993 and 2004 respectively, for France 1978 and 2005, for Germany 1984 and 2013, and for UK 1991 and 2014.

Table 11 – Partial elasticity of inequality of Opportunity with respect to three correlates

	Italy	France	Germany	United Kingdom
Parental networking	1.40	1.43	2.22	1.22
Return to education	0.99	0.99	1.00	0.98
Intergen. persistence of education	0.96	0.97	0.97	0.94