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Does the Expansion of Higher Education Reduce Educational Inequality?: Evidence from 12 European Countries

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Abstract

Expansion of higher education leads in principle to attainments' equalization. Using EU-SILC dataset, this hypothesis is tested for 12 European countries. The paper novelty is to convert multi-dimensional information on parental background in a continuous scale to express origins in relative terms, eliminating the influence of compositional changes. It is shown that the higher education expansion brought about an increase in background-related inequality, which mainly occurred in last decade and has been concentrated in the bottom-half of the background distribution. In the top half, a timid inversely U-shaped relationship emerged especially when considering the transition from upper-secondary to tertiary education.

Keywords: Higher Education Expansion, Educational Inequality, Family Background, Measuring Family Background.

JEL classification: I21, I23, J62.

1. Introduction

In principle educational inequality associated to differences in parental background should decline together with the average educational attainment in the population. On one hand, better educational levels foster economic growth relaxing constraints to human capital accumulation of worse-off offspring. On the other hand, the benefits of an expansion should gradually trickle down to less-advantaged social classes as maximal levels of formal education are saturated by the rich; an argument known by sociologists as the 'modernization hypothesis' (e.g. Treiman 1970)[1]. As a corollary, the extent to which opportunities are equalized in correspondence to a certain educational level is connected to the country stage of development. According to this view, tertiary education represents the relevant level in order to empirically scrutinize the modernization hypothesis for developed economies such as European ones.

In this paper, the hypothesis that the expansion of higher education reduced the effect of background on attainments is empirically tested comparing the evolution of educational inequality in main European countries. Two requirements should be satisfied in order to rigorously establish comparisons over time and across countries: 1. a dataset with a unique survey design; 2. a measure of parental background that consents to depurate from compositional effects associated to changes in the distribution of parental characteristics.

The retrospective module of the EU-SILC dataset on intergenerational mobility meets the first requirement as it contains several information on the parental socio-economic status. Moreover, only few studies have analysed the relation between education expansion and inequality using this dataset, but mainly focussing on estimates of parent-child correlations (Di Paolo et al. 2010).

Concerning the second requirement, I build a quasi-continuous measure of parental background in order to account for changes over time in the distribution of parental characteristics (Blanden and Machin 2004). Building such a measure is important to overcome the main limit of the EU-SILC dataset, which includes information on multi-dimensional aspects of parental background (educational attainments, occupational levels…) without providing an immediate ranking of parental socio-economic backgrounds on a single scale. Note that only quantitative measures of socio-economic background, essentially income, convey sufficient information on the parental capacity to successfully support child educational development and, at the same time, consent to express parental positions in relative terms.

In particular, the measure of parental background here developed exploits information on the several background variables available in the EU-SILC dataset in a hierarchical order to obtain a one-dimensional ranking of parental positions. A first step in this direction consists in quantifying either parental education or occupations. Whereas the former variable is concentrated in few mass points making the quantification problematic, the latter is available at a finer level of details in the EU-SILC dataset and can be converted in a

1. As a variant of this hypothesis, recent works suggest the possibility that the increased diversification in the University offer (by type of college, field and duration of the course) might have translated the background advantage from a quantitative to a qualitative dimension (e.g. Clancy and Goastellec 2007, Shavit et al. 2007, Oecd 2008). This case fits well with the European situation where higher education expansion has been achieved throughout the creation of new university sites, often offering short technically oriented programs (Oecd 2008). On the other hand, the emergence of further high qualifications (i.e. master degrees) can continue to guarantee the persistence of background advantages, notwithstanding the greater equalization at lower levels.

continuous index of occupational status or prestige used by sociologists. The choice of using occupation as the basic background variable is also justified by preliminary between-within decompositions showing that, for each country, quintiles of a distribution of occupational status explain a greater fraction of the variance in child tertiary attainments than parental education[2]. The particular index I choose for re-expressing parental occupations on a continuous scale is the ISEI as it is widely used and empirically validated on a large dataset (Gazeboom et al. 1992).

As a second step, I refine the distribution of the parental ISEI making use of other background information. This allows me to smoothen the crude distribution of parental ISEI and better identify the true parent's position in the social scale. Specifically, this refinement consents to well establish measures of educational inequality at various points of the distribution, i.e. inter-quintile differences; therefore assessing the effect of the higher education expansion on inequality in the bottom and in the top half of the distribution. What emerges is that, apart in countries with equalizing higher educational policies, i.e. Netherlands and Finland, the expansion of higher education increases the gap at the bottom of the distribution of parental backgrounds. In turn, the gap between the fifth and the third quintile displays a timid inversely U-shaped pattern that points to an equalization effect in favour of the middle class. However, the modernization hypothesis appears as strongly disconfirmed by the present analysis.

The remaining of the paper is organized as follows. Next section briefly summarizes the existing literature on the expansion of higher education. Section 3 describes the dataset and provides more details on the empirical strategy. Section 4 presents the main results whereas section 5 discusses these results.

2. Related Literature

In the field of the economics of education, there is a broad consensus on the fact that parental characteristics are the single most important determinant of child educational achievements (Becker and Tomes 1986, Haveman and Wolfe 1995, Hanusheck and Woessmann 2008). In particular, parental background affects child attainments at each single stage of the educational sequence and, since the process of skill formation is self-reinforcing, equalization of opportunities is more difficult to obtain the latter policy interventions are implemented (e.g. Carneiro and Heckman 2003). For instance, both later schooling tracking and pre-schooling education have a positive effect on equalization of achievements (Brunello and Checchi 2007, Schuetz et al. 2008)[3].

The influence of the family background continue also at later stage of the child carrier and is particularly strong on the choice of entering university education. Three main channels render this choice dependent on background: financial constraint, pre-existing ability (genetic or acquired in previous steps) and preferences, i.e. differences in risk aversions and self-confidence. Especially for the US, empirical analyses and related policy evaluations keep debating the causal impact of these factors, but reach no uniform conclusions (e.g.

2. Detailed results are available upon request.
3. The latter policy offsets a bad home environment in the crucial stage where offspring develop cognitive abilities. The former allows postponing the choice of the type of school at an age when parental influence is supposedly weaker. Also, greater school heterogeneity in terms of background appears to reduce the influence of parents on PISA test scores (Raitano and Vona 2010).

Ellwood and Kane 2000, Cameron and Heckman 2001, Carneiro and Heckman 2002). Conversely, there is a more general consensus on the fact that well-off offspring are more willing to accept the risks associated to higher education investments (e.g. Belzil and Leonardi 2007). Hence, these considerations have been incorporated in new policies aimed at reducing this risk misperception[4].

Rather than focusing on policy evaluations and estimations of the causal impact of background on educational choices, another strand of literature looks at changes over time in educational inequality attempting to validate the modernization hypothesis. From a methodological point of view, studies in this vein use birth-cohort variations to mimic changes over time and mainly differ in the measure of background adopted.

Among studies that use quantitative measures of background, a bunch of works considers the evolution of educational inequality in cross-country comparisons. A seminal paper by Ram (1989) models the relationship between the standard deviation and the mean of years of schooling. His estimates show that this relationship is inversely U-shaped both in cross-country and in time-series regressions for the US. More recently, Vinod et al. (2002) counter-argues that this finding is sensible to the particular measure of inequality chosen, i.e. the standard deviation. In a study covering a wide range of countries, Hertz et al. (2007) provide evidence in favour of a generalised decline in intergenerational correlations between parental and child years of education. Similar findings are obtained by Di Paolo et al. (2010) for European countries, using the EU-SILC dataset as in my work, and by Chevalier et al. (2003), using the OECD adult literacy survey. The latter work, however, casts doubts on the equalising effect of the higher education expansion.

Lack of well-distributed and continuous measures of parental background, essentially income, makes it difficult to analyse changes in intergenerational inequality over time expressing offspring origins in relative terms, e.g. quintiles. Distinct exceptions are the papers of Acemoglu and Pischke (2001) and of Blanden and Machin (2004) that analyse inequality changes brought about by the expansion of college attainments in the US and the UK[5], respectively. In the former paper, Acemoglu and Pischke (2001) estimate the elasticity of enrolment to income and show that the expansion of higher education during the 80s especially benefited children from the two top income quartiles. In the latter, Blanden and Machin (2004) estimate various functional form of the relationship between parental income and college attainment for three cohorts going to university in the 1970, 1980 and 1990. They found that the difference in the probability of having a degree between the top and the bottom quintile of parental income increases over time, even when controlling for individual abilities, i.e. test scores. Both studies conclude that the expansion of higher education has mainly benefited children from relatively rich families[6].

Given the scarcity of data on parental incomes, most studies adopt categorical background variables. For Italy, Checchi et al. (2008) show a declining trend in the correlation between parent and child education. For

4. A well-known example is income contingent loans, i.e. repayments of loans depending on future revenues. For a broader discussion of higher educational policies see Garcia Penalosa and Walde (2000) and Johnstone (2004).

5. Actually there are several papers on relationships between parental background and higher education attainments in the UK reaching similar results as the ones of Blanden and Machin (2004). For instance: Galindo-Rueda and Vignoles (2005), Machin and Vignoles (2004), Blanden (2004).

6. For Sweden, Holzer (2006) shows that opening new colleges does not allow to reduce the association between parental income and child attainments. A similar result is obtained for Italy by Checchi et al. (2008).

higher education, however, the gap in the probabilities of attaining college education between children of, respectively, college and lower secondary graduates displays an increasing trend. Educational mobility is also assessed in two other comparative studies regarding Italy: both the US (Checchi et al. 1999) and Spain (Di Paolo 2010) appear characterized by a higher educational mobility[7]. In an analysis covering German children born between the 1929 and the 1978, Heineck and Riphahn (2009) observe persistency in background-related inequality for high degrees. The French literature emphasizes the persistent advantage of well-off pupils in entering elite universities, i.e. grande écoles, that ensure substantial wage gains (Albouy and Wanecq 2003, Gurgand and Maurin 2007). However, also access to general university has been characterized by a non-decreasing inequality (e.g. Duru-Bellat et al. 2008).

In the sociological literature, the adoption of categorical variables emphasizes the importance of discontinuities in the effect of social classes—mainly defined on occupational categories—on achievements. A comprehensive study of Breen et al. (2009) assesses the evolution of educational inequality across cohorts borne between the 1908 and the 1964 using high quality data for 8 European countries. Their findings partially contradict previous ones of Shavit and Blossfeld (1993) and show a generalized decline in educational inequality. However, educational inequality seems to persist when the transition to tertiary education is considered. For Ireland, Whelan and Hannah (1999) provide evidence of a decline of the class effect for cohorts born between 1930 and 1969, but again not for the likelihood of completing a tertiary degree. In the Finnish case, Kivinen et al. (1995) find that there have been no changes in the probability of entering university education for 20-24 years old children in 1985 and 1990. Higher education inequality appears mainly stable also in the studies collected by Shavit et al. (2007)[8]. Finally, Koucky et al. (2009) combine data of four waves of the European Social Survey covering a time span of six decades (1950-2007) and 22 European countries to analyse the long-term evolution of higher education inequality. Unlike other studies, they express both education and occupation in quartiles to depurate from compositional changes in the distribution of parental characteristics. In doing so, they obtain different results showing a declining pattern, especially for Ireland, Finland and Spain[9].

The next section offers more details on the way of measuring backgrounds and on the dataset.

3. Measuring Parental Background

The key point of this paper is to build a continuous background variable that enables to express origins in relative terms and hence replicate analyses made using parental income (e.g. Blanden and Machin 2004). Similar to us, Koucky et al. (2009) express origins in relative terms by transforming both education and

7. Di Paolo (2010) focuses on higher education attainments also using the EU-SILC dataset and shows that the gap in predicted probability of attaining college education conditioned to parental education slightly decreases in Spain, whereas it increases in Italy.
8. This study offers an unusual interpretation of the effect of higher education expansion on inequality. In particular, since the expansion of education increases the heterogeneity in the population eligible to the next level, maintaining background-related inequality unchanged at a higher rate of participation should be interpreted as a relative reduction in higher education inequality.
9. Note that this disagreement with other studies can be due to the longer time span covered: in most countries higher education inequality declines until the 1980s and then grows again reaching the levels of the 1970s.

occupation into a continuous scale. However, it is not clear how they obtain the required data variation to build balanced quartiles for the four background variables they considered, i.e. education and occupation for both parents. Also, they use all four background variables to explain tertiary education attainment, not providing a synthetic measure of change.

In this paper, I adopt a different strategy and construct a unique distribution of background from which I derive quintiles of origins[10]. This distribution is built in two steps. First, conversion of ISCO occupation into the ISEI index of occupational status is made following the scale provided by Gazeboom and Treiman (1996). The ISEI index relies on the idea that "occupation is the intervening activity linking education and income" (Ducan 1961, p. 116-7). Practically, it is obtained as to maximize the indirect impact of education on earnings and validated on a large dataset covering 16 countries for various years (for further details see Gazeboom et al. 1992). However, since ISCO codes are available only at two-digit level in the EU-SILC dataset, the distribution of parental ISEI is itself non smooth and, especially for older cohorts and less-developed countries, is clustered in few mass points making the construction of balanced quintiles difficult.

As a second step, I span the derived distribution of ISEI using other background information in a hierarchical order. The criteria used to refine the parental ISEI distribution are in order of importance: immigrant status, ISEI of the parent with the lowest level, parental education, the occurrence of financial problems, the number of siblings and the presence of both parents. It is worth noticing that robust checks available upon request show that inverting the hierarchical order of these additional criteria does not substantially affect the results. Finally, I use this distribution to derive quintiles of origin from which to measure educational inequality.

The remaining of this section presents in brief the EU-SILC dataset and issues related to the choice of key variables. In 2005 EU-SILC dataset, information on the home parental background are collected in retrospective fashion reconstructing the home background at the age of 14. To be sure, for each parent the dataset provides three key proxies of the home environment: the highest ISCED level of education attained, the main occupation and the presence of financial problems through adolescent period, which also captures eventual temporary shocks in the phase of key educational choices. Taken together, these variables account for the cultural, mainly parental education, and socio-economic, mainly parental occupation, channels that affect the probability of success in education. Additionally, variables on family composition (number of siblings and presence of both parents) and immigrant status describe complementary aspects of the home environment.

Concerning the choice of the countries to compare, I excluded Sweden for the small response rate to the intergenerational section of the questionnaire. Also Germany is not included for the well-known problem of educational attainments that are unrepresentative of the population ones in EU-SILC (see Causa et al. 2010). Overall, I kept 12 countries representative of different welfare regimes: Nordic (Denmark, Finland), Southern European (Italy, Spain, Portugal, Greece), Anglo-Saxon (Ireland, UK) and Central-Northern European (France, Belgium, Netherlands, Austria).

10. The idea of spanning the distribution of background using ISEI has been first developed in a paper with Michele Raitano to examine the correlation between a continuous measure of occupational mobility and individual earnings (Raitano and Vona 2011).

As usual in the literature, I approximated changes over time with birth cohort variations and choose to group offspring in relatively large birth cohorts of ten years within the range 1940-1980. The choice of considering large cohorts is motivated by the small sample size for most countries (see tab. 1). Moreover, since typical graduation times vary in the countries considered (see Oecd 2008), I slightly adjusted the lower bound of the youngest cohort to take this fact into account[11]. Finally, with the purpose of reducing the drop of information due to missing variables of background[12], I decided to only keep the information on the maximum level of parental occupation and education[13].

4. Results

4.1 Descriptive Analysis

For each country and cohort, table 2 provides a descriptive summary of the evolution of main background variables (educational attainments and ISEI index of occupational status) and of the dependent variable, namely: tertiary education attainments. This table shows that the usual country ranking in terms of attainments is respected in the dataset used (e.g. Oecd 2005). Therefore, countries considered substantially differ both in their initial distribution of parental characteristics in terms of occupational and educational levels, and in the patterns of accumulation of university graduates.

The pronounced change in the distribution of parental occupations, as measured by the ISEI index, and educational levels supports the methodological emphasis posed on building a measure of parental background which consents to neutralize these changes. Again cross-country differences emerge starkly with improvements in parental education and occupations occurred especially in Nordic countries and to a less extent in Anglo-Saxon and central European ones.

Looking at the fraction of tertiary educated, the United Kingdom represents the only country characterized by both a high initial level and a fast growth of college graduates. As would be expected, the fraction of college graduates expands faster in countries starting from a lower initial level, i.e. below 15%, but the increase has been significantly larger in France and Spain with respect to Italy, Portugal and Greece. Among the country with an average initial endowment of college graduates, Ireland exhibits the most impressive expansion while the increase has been very limited in Austria.

4.2 Basic Econometric Analysis

In the baseline econometric specification, I use a probit model where child tertiary education attainment is a function of the parental occupation and other background variables plus basic individual controls, i.e. the

11. In particular, for all countries I take 25 as the minimum age for graduation. Exceptions are Finland (27 years old), Denmark (27), Italy (26), Austria (27) and Portugal (26). Data on graduation times are taken from Koucky et al. (2009).
12. It is worth noticing that the distribution of missing is not dependent upon family background. For instance, regressing a dummy of parental missing for occupation on parental education and occupation, the R^2 is around 1%.
13. This short-cut implies taking, in most cases, the father characteristics, especially in countries where the rate of female participation to the labour force was particularly small.

vector $\mathbf{Z}$[14]. The probability of having a tertiary degree *T* for an individual *i* is regressed separately for each cohort *c*:

$$\mathrm{T}_{i,c} = \alpha_{i,c} + \gamma_c \mathbf{Z}_{i,c} + \beta_c \cdot f_{i,c}(\mathrm{isei}) + \varepsilon_{i,c} \qquad (eq.1),$$

where $\varepsilon_{i,c}$ is an error term. Following Blanden and Machin (2004), the variable of interest, the parental ISEI, enters this relationship either in a linear form or as dummies for each quantile of the smoothened distribution of parental ISEI; that is: $f_{ic}(\mathrm{isei})=\Sigma_j Q_{icj}$ where Q_{icj} is a dummy assuming value 1 if the parent of individual *i* is in *j*-th quintile of cohort *c*. In the latter case, I measure inequality as the difference in the estimated marginal effect of two quintiles of the ISEI distribution. Likewise, changes over time in inequality are captured by changes over time in these marginal effects.

In view of the multi-dimensionality of the background information included in the EU-SILC dataset, tables 3a-3l display for each country the estimated marginal effects of main background variables for the two specifications of *f*(isei).

A first important result is that the estimated effect of different background variables follows different patterns. The marginal effect of parental education declines or remains stable almost everywhere. In more equal countries, like Netherlands and Finland, only the coefficient associated to parents with tertiary education is significant for the youngest cohort. In spite of this declining trend, each improvement in parental education still remains associated to a significantly higher probability of finishing college in France, Southern European and Anglo-Saxon countries. Notice that the latter two groups of countries are also the ones displaying less intergenerational mobility (e.g. d'Addio 2007).

An opposite trend is followed by the background variables related to parental occupations, based on the ISEI index and on the smoothened ISEI distribution. With the distinct exception of Finland and Netherlands, both estimated coefficients for the linear ISEI and for the ISEI quintiles display a non decreasing pattern, pointing to an increasing importance of background, at least along this 'socio-economic' dimension. A clear increasing pattern is observed especially in the ISEI-quintile specification. Measuring inequality with the estimated marginal effect of the fifth ISEI quintile as in Blanden and Machin (2004), one can observe a widespread increase of inequality. This increase is particularly pronounced in France, Belgium, Portugal, Italy and the UK (but following an U-shaped pattern). Besides, inequality at the bottom of the distribution can be approximated by the estimated marginal effect of being in the third quintile of the ISEI distribution. This effect appears to increase and to be significantly different from zero in Belgium, Spain, France, Denmark (but all concentrated in the last cohort), the UK (but with a U-shaped pattern) and to a less extent in Portugal and Greece.

Finally, the dummy variable for 'financial problem when young' is persistently significant only in Italy and Spain, while it turns out significant for the last cohort also in Ireland and Belgium[15]. In turn, the sign of the dummy for immigrant does not appear coherent over time and across countries.

14. **Z** includes parental education, dummy for financial problem when young, immigrant status, presence of both parents when young, number of siblings, age, chronic illness.

4.3. The Evolution of Inter-Quintile Differences

The contrasting evolution of the association between different parental variables and child tertiary attainments makes it difficult to believe that the surrogate parental distribution alone can provide sufficient statistics of parental background as it would income. In particular, the estimated marginal effects of ISEI quintiles only capture a direct effect of parental occupation on the probability of attaining a college degree, but do not account for the indirect effect due to the fact that other background variables are strongly correlated with parental occupation (e.g. parental education, immigrant status, etc.). Since this indirect compositional effect is likely to be a key determinant of educational inequality, inter-quintile gaps in estimated marginal effects should represent a lower bound of the real association between parental background and child educational attainments.

In principle, the sum of the direct and the indirect effect can be simply computed by estimating eq. 1 separately for each quintile of the ISEI distribution and then predict the correspondent probability of getting a degree. Unfortunately, small sample sizes in certain countries render these separate regressions not reliable. A practical way of overcoming this problem consists in approximating the inter-quintile differences in the predicted probabilities obtained in separate regressions with inter-quintile differences explained only by differences in parental characteristics in each quintile. More precisely:

$$P_{c,j}\left[T;\ Q_j\right]-P_{c,j-1}\left[T;\ Q_{j-i}\right]\cong\Phi_{\mathrm{c}}\left(\alpha_{\mathrm{c,j}}+\hat{\beta}_{\mathrm{c}}\cdot\mathrm{isei}_{\mathrm{c,j}}+\hat{\gamma}_{\mathrm{c}}\mathbf{Z}_{\mathrm{c,j}}\right)-\Phi_{\mathrm{c}}\left(\alpha_{\mathrm{c,j-1}}+\hat{\beta}_{\mathrm{c}}\cdot\mathrm{isei}_{\mathrm{c,j-1}}+\hat{\gamma}_{\mathrm{c}}\mathbf{Z}_{\mathrm{c,j-1}}\right)\quad (eq.2),$$

where $P_{c,j}$ is the average predicted probability of attaining a tertiary degree for quintile *j* and cohort *c,* Φ_c is the normal distribution and the vector $(\hat{\beta}_c,\hat{\gamma}_c)$ is the one estimated in eq.1 under *f*(isei)=isei. This approximation is equivalent to assume that all offspring have access to the same schooling production function, i.e. the estimated coefficients in eq. 1 are independent to the measure of background used here[16].

In figures 1a-1l, I plot for each country the inter-quintile gaps in the predicted probabilities and the real frequencies of tertiary educated by quintiles of the surrogate distribution of origins. The overall level of

15. Note that this variable is missing for many countries.

16. A fully-fledged decomposition would entail to account also for differences in the schooling production function across quintiles, i.e. in the βs. In particular, this enables to derive a price-endowment-price in an Oaxaca-Blinder fashion. In formula:

$$P_c\left[E=T;\ \mathrm{P}=Q_j\right]-P_c\left[E=T;\ \mathrm{P}=Q_{j-i}\right]=\underbrace{\Phi\left(\alpha_j+\beta_j isei+\gamma_j Z_{\mathrm{j}}\right)-\Phi\left(\alpha_j+\bar{\beta}isei_j+\bar{\gamma}Z_j\right)}_{\text{price effect higher quintile}}-$$

$$\underbrace{\Phi\left(\alpha_{j-1}+\beta_{j-1}isei+\gamma_{j-1}Z_{\mathrm{j-1}}\right)-\Phi\left(\alpha_{j-1}+\bar{\beta}isei_{j-1}+\bar{\gamma}Z_{j-1}\right)}_{\text{price effect lower quintile}}+\underbrace{\left\{\Phi\left(\alpha_j+\bar{\beta}isei_j+\bar{\gamma}Z_j\right)-\Phi\left(\alpha_{j-1}+\bar{\beta}isei_{j-1}+\bar{\gamma}Z_{j-1}\right)\right\}}_{\text{endowment effect}}$$

The inter-quintile gap in predicted probability is decomposed in three terms: the first and the second are the gap in predicted probabilities that would emerge if coefficients are allowed to vary across quintiles, the third term is the fraction of the gap that can be ascribed to overall differences in individual characteristics across quintiles. I consider in what follow only the endowment effect due to the small number of observations to estimate separately for each cohort-quintile coefficients βs and γs. However, the approximation does a good job in predicting both real inter-quintile differences, see fig 1a-1l, and predicted differences computed in separated regressions for the three countries with quite large samples (Italy, France and Spain). Results are available upon request.

inequality is measured by the difference between the predicted probability calculated in the 5th and in the first quintile. In turn, inequality at the bottom (resp. top) of the background distribution is equal to the difference in predicted probabilities between the 3th (resp. the 5th) and the first (resp. the 3th) quintile.

Figures 1a-1l and tables 4a-4l show that approximating real inter-quintile differences with predicted ones estimated through eq. 2 leads to quite accurate results. In general, inter-quintile gaps in predicted probabilities catch particularly well the size and the trends of real inter-quintile differences. Only in Denmark, the dramatic increase of bottom inequality in the youngest generation, also observed in the baseline model of eq.1, is not predicted using this approximation[17]. Finally, in Anglo-Saxon countries and in Greece, one can observe imprecise estimations of the size of inter-quintile differences with respect to real data, especially at the bottom and at the top of the distribution of backgrounds.

Looking at the main results, inequality at the bottom of the background distribution tends to increase everywhere but in Finland and to a less extent in Netherlands, two countries characterized by decreasing educational inequality also in other studies (Shavit and Blossfeld 1993, Koucky et al. 2009). The acceleration of the Q3-Q1 difference in both predicted probabilities and real frequencies has been particularly pronounced especially in Anglo-Saxon countries, France, Belgium, Greece, Spain and Denmark. This increase occurred mainly in the last period, confirming findings in sociological works (e.g. Koucky et al. 2009).

On the contrary, inequality at the top of the background distribution displays a more heterogeneous pattern across countries. In particular, it appears to increase in Italy, France and to a less extent Portugal and Austria, stays constant in Spain, Netherlands, the UK, Greece, and declines in remaining countries. Moreover, for above-the-median inequality, no common breaks or pattern reversions are observed for the last cohort.

Combining these two effects, the increasing trend at the bottom prevails and pushes overall inequality up almost everywhere, except in Finland and the Netherlands. Even if the acceleration in overall inequality mainly occurs in the last decades, this finding disconfirms, or at least casts serious doubts, on the original version of the modernization hypothesis. On top of that, country characteristics in terms of intergenerational inequality or welfare state regimes do not seem sufficient to explain observed patterns.

5. Testing the Modernization Hypothesis

In this section, I directly test the modernization hypothesis by estimating the relationship between tertiary education attainment and background-related educational inequality. The previous analysis consents to look at the effect of the higher education expansion in different parts of the surrogate background distribution, hence assessing whether this expansion trickles-down in all segments of the population or just benefited middle class offspring.

17. However, these results for Denmark can be driven by the small sample size and the choice of the age cohort. Using a larger cohort, i.e. [25-35], table 4h displays a significantly less pronounced increase of bottom end inequality, probably associated to the fact that well-off offspring are more likely to attend post-graduate programs than their less advantaged peers. For the other countries for which we assumed a larger young cohort (Italy, Finland, Portugal, Greece), robust checks varying the age of the youngest cohort do not affect previous results.

The simple empirical strategy I pursue to answer this question is to estimate 'kind of' Kuznets-curve relationships between the fraction of tertiary educated and three measures of educational inequality, i.e. Q5-Q3, Q3-Q1 and Q5-Q1. To depurate from factors disturbing this relationship, I add a full set of cohort-country area[18] dummies D_{ic} and control for the age when the choice among different school tracks is made. As well-known in the literature (e.g. Dustmann 2004, Brunello and Checchi 2007), earlier school tracking is likely to increase the probability that children from worse-off families end up in vocational schools that do not provide the adequate preparation for university education[19]. More precisely, I estimate the following relationship:

$$\mathrm{ineq}(h_{i,c}) = \beta \cdot g(\mathrm{h}_{i,c}) + \gamma \cdot \mathrm{age\_track}_i + \varphi \cdot \mathrm{D}_{i,c} + \varepsilon_{i,c} \qquad (eq.3),$$

where h_{ic} is the fraction of graduate in country i and cohort c. The functional form g(h) is chosen looking at bivariate correlations between h and $ineq$(h). These correlations suggest a linear specification for Q5-Q1 and Q3-Q1 inter-quintile differences, whereas a quadratic one is the best one when Q5-Q3 top inequality is involved. Moreover, as inequality measures, we consider either predicted or real inter-quintile differences or the marginal effect of the fifth quintile of the background distribution.

Note again that considering both bottom and top indexes of inequality makes it possible to assess up to which point the higher education expansion trickles down to lower segments of the population.

For predicted values, table 5 shows that the estimated association between educational inequality and the fraction of college graduates is always significant for all measures of inequality. This first important result disconfirms the modernization hypothesis: aggregate inequality tends to be positively correlated with higher educational attainments. As expected, a smaller but still significant association between higher education achievement and inequality is observed by using the estimated marginal effect for the fifth quintile as a measure of inequality (tab. 5 col. 9). This finding is consistent with the fact that the marginal effect of Q5 does not incorporate the indirect effect of other background variables positively correlated with ISEI quintiles. Finally, the size of the association between higher education attainment and various inequality measures is rather similar for both real and predicted Q5-Q1 differences.

Later school tracking appears to negatively affect inequality in the upper tail, but this result should be interpreted with great care. In fact, age track is time-invariant measure and does not captures possible changes in tracking policy over time because information on these changes are difficult to collect for each country and especially for older cohorts.

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18. These dummies reflect the four welfare regimes considered: Nordic (Denmark, Finland), Southern European (Italy, Spain, Portugal, Greece), Anglo-Saxon (Ireland, UK) and Central-Northern European (France, Belgium, Netherlands, Austria). Cohort per group of country interactions are included to account for country-specific time trends.

19. For sake of space, I do not report the data on age of tracking that are available from the paper of brunello and Checchi (2007). Note that educational policies affecting intergenerational educational inequality are many: such as pre-school enrollment, expenditures in public education, years of compulsory education, peer composition, student-teacher ratios, etc (Schuetz et al. 2008). For most of these variables long time series are not available. However, the scarce number of observations (48=4 cohort* 12 countries) would make it difficult to have enough degrees of freedom to correctly estimates more policy variables. In the extension § 5.1, I add also years of compulsory schooling in the explanatory variables.

An inversely U-shaped relationship is observed for inequality in the top half of the distribution, see tab. 5 col. 3. To be sure, inequality begins to decrease once the fraction of college graduates goes above 0.4. Since most countries have a number of graduates below 0.4, it is not surprisingly that a linear specification of the *g(.)* brings the positive association between expansion and inequality to prevail. With real data for the Q5-Q3 difference, the inversely U-shaped relationship completely disappears whilst, in the linear specification, the coefficient for college graduates is positive and significant at cut-off level of 85%.

Inequality in the bottom half of the distribution is uniformly increasing using either real or predicted data. Again, the size of the coefficient is rather similar in both cases. However, in the case of predicted inter-quintile differences, bottom half inequality explains only 0.58 of total inequality, while this fraction amounts to 2/3 with real data.

5.1 Robust Checks and Extensions

Looking at figures 1a-1l, the raise of educational inequality occurred mainly in the last cohort. Moreover, observed patterns can be driven by outliers and other policies might constitute significant confounding factors. Therefore, robust checks to test for these possible sources of bias are in order.

Results available upon request are surprisingly unchanged to the exclusion of any country. Nothing changes also if I carry out estimates only for the last three birth cohorts. Rather, considering only the first three cohorts brings a larger change in the results. In particular, for measures of inequality based on real data, both relationships between top/bottom inequality and higher education attainments remain significant around the cut-off level of 85-90% (tab. 6 col. 6-7)[20]. Moreover, only little increases in R^2 but no substantial changes in the results are observed by including country-cohort years of compulsory schooling in the explanatory variables[21]. As a final check, it is interesting to see if the gap in predicted probabilities of getting a degree declines at least between the two highest quintiles. Whereas the coefficient associated to higher education attainment turns out insignificant for both predicted and real inter-quintile gaps, it becomes negative, very large and significant at 80% only for real values (tab. 6 col. 1-2).

Among the alternative explanations that can be explored with the EU-SILC dataset, the change in the immigrant composition might have played an important role. The proportion of offspring with relatively worse linguistic and socio-economic characteristics should increase with the number of immigrants, hence modifying the composition of potential entrants in college education. To neutralize this compositional change, I calculate real inter-quintile differences only for non immigrants and for countries experiencing a significant inflow of immigrants in the dataset used[22]. Table 7 points to a generalized but small decrease of inequality in the bottom tail of the distribution. However, overall inequality is left substantially unaffected as the increase over time in the share of immigrants was in most counties not so large to generate a substantial

20. For predicted inter-quintile differences, only the relationship between bottom tail inequality and higher education attainments becomes less significant.
21. Results are available upon request. Information on country-cohort years of compulsory schooling are available in the background paper of Fort (2006).
22. Namely: Italy, Spain, France, Ireland, Belgium and the UK. In our sample, the increase in the immigrant share has been particularly pronounced in the UK and Ireland.

effect. Moreover, note that, according to tab.3, the marginal effect of being immigrant on the probability of getting a tertiary degree can be either positive or negative.

Another classical issue at stake in the literature on intergenerational transmission of educational attainments is whether parents mainly affect child outcomes in the transition from upper secondary to tertiary education or if this influence is inherited from previous stages of the educational sequence. A standard way of answering this question consists in looking at the transition from upper secondary to tertiary education only (e.g. Mare 1980). With this purpose, I recomputed the predicted inter-quintile differences conditioned to the fact of having successfully completed upper secondary education. In line with previous findings (Mare 1980, Cameron and Heckman 1998, 2001, and Blanden and Machin 2004), the magnitude of the association between parental background and higher education attainment declines at a later stage of the educational carrier[23]. Table 6 (col. 3-5) shows that the Q5-Q1 inter-quintile difference is cut by more than 1/3 and appears significant only at 90%. Specifically, top inequality begins to decline when the fraction of college educated reaches the level of 0.35 compared to 0.40 in the unconditioned model. The size of the coefficient for bottom inequality is now reduced by 32% and 38% for respectively real and predicted inter-quintile differences.

6. Discussion and Conclusions

This paper analyses the evolution of the relationship between family background and higher education attainments in 12 European countries. The novel measure of background used here makes it possible to differentiate out the effect of changes in the composition of parental characteristics and to assess the effect of higher education expansion at various points of the distribution of parental origins. Looking at educational inequality in various parts of the background distribution is important to shed light on the way in which the expansion of higher education trickles down to the subsequent layers of the offspring population.

Consistently with previous works (Acemoglu and Pischke 2001, Chevalier et al. 2003, Blanden and Machin 2004, Breen et al. 2009), this paper casts serious doubts on the validity of the modernization hypothesis, which implies a mechanical reduction of inequality triggered by expanding attainments. Similar patterns of higher educational attainments often hide large differences in the association between home background and attainments, and reflect only partially the usual ranking of countries in terms of intergenerational inequality. Over the long time span considered, an increased level of higher education inequality is observed in most countries and has emerged especially in the last 10 years.

When examining education inequality at different points of the background distribution, it appears evident that the raise of inequality has been mainly concentrated in the bottom half of this distribution. Conversely, an inversely U-shaped relationship tends to characterize the evolution of inequality at the top, especially if considering only the transition from upper secondary to tertiary education. This implies that the benefits of higher education expansion spilled over at most to the middle class.

23. This is consistent with the fact that diversification at the upper secondary level allowed to expand attainments but, at the same time, brought the majority of working class pupils to enter the vocational stream, which does not provide the general skills needed to enter university education (e.g. Duru-Bellat et al. 2008, Dustmann 2004).

The particularly high level of college graduates (around 40%) for which the inversion of the pattern occurs can explain why the increasing branch of the relationship between education inequality and expansion prevails also for top-end inequality. Likewise, the fact that still the majority of countries considered are far from reaching 'universal' higher education attainments might explain the prevalence of an increasing relationship on aggregate. If well-off offspring do not have yet saturated their maximum level of higher education attainment, the increase in tertiary attainments should be faster for them than for disadvantaged offspring.

Nonetheless, a large fraction of inequality should be brought about by educational policies and structural factors. In this respect, the increased offer of higher education programs might have eased the access to higher education to well-off offspring with lower initial abilities. Concerning higher education policies, countries characterized by generous and universal (or quasi-universal) grants, i.e. Finland, Netherlands and to a less extent Ireland, are also those that managed to keep inequality low or decreasing (Usher and Cervenan 2005)[24]. In contrast, countries where costs of education are relatively higher and the mix grant-loan is more oriented towards the latter, i.e. the UK, do not succeed in achieving both objectives of higher education expansion and of inequality reduction. Note that the grant mix is important because those from worse background are less likely to be engaged in risky investment and to commit themselves to long-lasting repayments. As a result, the increased inequality in the UK can be partially explained by reforms reducing the grant component of student aids during the 80s (see references in Blanden and Machin 2004).

The implications of the results for intergenerational income inequality are also of great policy relevance. Blanden and Machin (2004) discuss the relationship between educational and income inequality using the model of Solon (2004). In this model, intergenerational income inequality increases the higher the effect of parental background on child education and the larger returns to education, being the 'labour market lottery' more risky. They conclude that, since both returns to college and higher education inequality increased in last four decades, intergenerational inequality should have increased too. In a paper with Michele Raitano (Raitano and Vona 2011), we suggest a further source of intergenerational inequality. Using also the EU-SILC dataset, we show that a significant residual correlation between parental occupation and earnings might persist after having controlled for child education and occupation. In addition, these correlations are higher in countries where educational immobility is also higher but returns to education differ, i.e. the UK, Spain, Italy. In line with decompositions of the intergenerational income elasticity where a large fractionof inequality remains unexplained (e.g. Bowles and Gintis 2003), our analysis suggests that educational attainments and average returns to education are not sufficient statistics to understand intergenerational inequality. Further researches are required to identify the source of this residual background effect. Of particular interest is to understand whether family background explains residual within-group inequality because well-off people attend better schools or because they have better labour market contacts.

24. According to data presented by Usher and Cervenan (2005) Netherlands and Finland are the countries with larger grant per capita in our sample. Considering that these grants are often means-tested, the poor will benefit relatively more from them. These two countries are also those with the lowest affordability cost, also compared with OECD countries not included in our analysis.

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Tables and Figures

Table 1: General Descriptive Statistics

	Spain	Italy	Portugal	Greece	Finland	Denmark	France	Netherl.	Belgium	Austria	UK	Ireland
Variable												
Parents												
Low. Sec.	6.61	18.88	3.73	10.61	34.01	40.62	8.08	36.90	16.10	53.14	11.45	14.87
Upper Sec.	6.93	13.36	3.04	9.79	20.89	41.48	23.69	19.63	23.49	40.65	20.32	13.43
Tertiary	10.18	4.22	4.61	7.58	17.63	17.90	10.06	17.80	19.57	6.06	17.80	11.23
Isei (occ. status)	35.05	36.35	33.16	33.76	40.31	42.75	40.15	45.91	42.78	37.30	43.60	42.89
Children												
Low. Sec.	21.22	32.78	13.78	11.2	18.9	24.95	14.31	19.62	13.89	17.77	18.49	19.56
Upper Sec.	21.74	37.07	13.01	35.72	44.47	45.24	44.22	38.57	33.45	61.28	43.78	29.52
Tertiary	27.73	13.38	13.31	21.35	35.64	28.08	24.61	34.63	37.51	20.43	37.67	31.47
immigrant	4.03	4.34	2.69	5.11	1.46	4.63	6.53	1.91	8.36	7.56	5.48	7.13
both parents	91.86	95.11	90.29	95.8	86.28	85.19	84.73	95.37	91.45	86.4	89.15	94.4
siblings	2.71	2.24	2.85	2.25	2.22	1.73	2.69	2.79	2.43	2.16	2.11	4.18
female	49.73	50.32	50.92	50.18	49.37	49.81	51.12	51.42	49.54	50.47	52.29	57.74
age	42.26	43.46	43.09	43.57	44.28	44.43	44.18	44.53	43.58	44.04	45.00	44.46
Observations	18,680	26,716	6,277	7,684	7,309	4,110	11,736	5,571	5,378	6,689	8,462	4,956

Table 2: Descriptive Statistics by cohort

Changes over Time in Parental ISEI

Cohort	Spain	Italy	Portugal	Greece	Finland	Denmark	France	Netherl.	Belgium	Austria	UK	Ireland
1 (older)	31.3	32.9	29.1	30.1	34.6	37.0	36.8	43.1	39.2	35.3	39.0	41.3
2	32.8	34.6	30.7	31.5	36.4	40.6	38.1	44.2	40.8	35.2	41.8	41.4
3	35.1	37.0	32.8	34.4	41.9	43.5	40.6	46.7	43.4	37.5	44.5	42.7
4 (younger)	38.4	39.5	37.7	37.5	47.1	48.2	44.1	49.2	46.5	39.9	48.9	45.7
Average change	1.77	1.65	2.14	1.84	3.13	2.81	1.82	1.53	1.81	1.14	2.47	1.11

Changes over Time in Parental Edu. Attainment, Upper secondary and more

Cohort	Spain	Italy	Portugal	Greece	Finland	Denmark	France	Netherl.	Belgium	Austria	UK	Ireland
1 (older)	10.3	9.7	3.8	8.3	10.3	42.5	19.2	24.1	25.3	39.3	25.6	14.5
2	11.7	11.8	3.5	9.5	21.6	51.4	23.3	28.9	35.1	39.9	33.2	16.9
3	15.9	17.0	6.7	16.6	45.9	61.0	35.4	40.9	44.4	47.3	42.2	25.2
4 (younger)	25.0	27.4	14.0	30.3	69.2	78.2	52.6	53.8	61.4	56.3	51.0	39.4
Average change	3.67	4.43	2.55	5.52	14.72	8.93	8.33	7.43	9.02	4.23	6.34	6.24

Changes over Time in Tertiary Edu. Attainment

Cohort	Spain	Italy	Portugal	Greece	Finland	Denmark	France	Netherl.	Belgium	Austria	UK	Ireland
1 (older)	14.1	9.1	8.4	13.2	28.2	18.7	14.4	26.0	28.1	16.5	24.2	19.4
2	19.8	12.7	10.5	17.0	34.7	29.0	18.6	30.9	31.8	19.0	35.8	23.7
3	28.0	13.5	11.5	25.3	40.1	28.5	23.6	37.3	38.4	21.9	39.5	30.8
4 (younger)	39.5	17.1	19.8	26.8	44.8	36.0	38.9	43.1	48.3	23.6	51.4	48.8
Average change	6.33	1.99	2.84	3.42	4.13	4.33	6.13	4.26	5.04	1.79	6.79	7.34

Changes over Time in the fraction of Immigrants

Cohort	Spain	Italy	Portugal	Greece	Finland	Denmark	France	Netherl.	Belgium	Austria	UK	Ireland
1 (older)	1.3	0.7	0.7	1.6	0.5	2.2	5.8	1.5	5.1	5.1	3.0	4.5
2	2.2	2.6	1.8	4.3	1.3	4.2	5.9	1.0	7.0	6.7	3.7	4.2
3	4.6	5.3	2.4	6.8	2.1	7.1	7.2	1.8	8.7	8.3	4.3	5.1
4 (younger)	6.1	7.5	4.6	6.7	2.3	5.2	7.0	3.3	11.6	9.8	11.1	13.7
Average change	1.19	1.69	0.97	1.27	0.45	0.77	0.32	0.45	1.62	1.19	2.03	2.29

Table 3a: Finland, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
	Background Variable			
Education:				
- Lower. Sec.	0.1286***	0.1171***	0.0291	0.0008
	[0.0389]	[0.0331]	[0.0822]	[0.1632]
- Upper. Sec.	0.1413**	0.2047***	0.1271	0.1266
	[0.0637]	[0.0456]	[0.0850]	[0.1643]
- Tertiary	0.2993***	0.3235***	0.3027***	0.2574***
	[0.0940]	[0.0644]	[0.0902]	[0.1681]
Occupation:				
- Q2 isei	0.0642	-0.0333	0.0273	-0.0687
	[0.0416]	[0.0437]	[0.0397]	[0.0470]
- Q3 isei	0.1550***	0.0598	0.0693*	0.0303
	[0.0424]	[0.0419]	[0.0394]	[0.0483]
- Q4 isei	0.1840***	0.1070**	0.1031**	0.0755*
	[0.0430]	[0.0412]	[0.0412]	[0.0491]
- Q5 isei	0.2966***	0.0824*	0.1969***	0.1401**
	[0.0525]	[0.0499]	[0.0538]	[0.0633]
Isei°	0.0059***	0.0037***	0.0039	0.0031***
	[0.0009]	[0.0009]	[0.0009]	[0.0011]
Fin. Prob.	-0.0596**	-0.0746***	0.0182	-0.0696
	[0.0260]	[0.0282]	[0.0344]	[0.0450]
Immigrant	0.0337	-0.1481	-0.2884**	-0.2719**
	[0.1713]	[0.1216]	[0.1166]	[0.1115]
Obs.	1615	2057	1787	1238
Pseudo R^2	0.1443	0.1004	0.1026	0.1201
Log-Lik.	-272006	-421080	-401138	-296395
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3b: Netherlands, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
	Background Variable			
Education:				
- Lower. Sec.	0.0741***	0.0943***	0.1065***	0.0166
	[0.0276]	[0.0341]	[0.0351]	[0.0699]
- Upper. Sec.	0.2031***	0.1764***	0.1775***	0.0792
	[0.0469]	[0.0466]	[0.0414]	[0.0713]
- Tertiary	0.3083***	0.4018***	0.3823***	0.2686***
	[0.0573]	[0.0603]	[0.0497]	[0.0755]
Occupation:				
- Q2 isei	0.0426	-0.0488	0.0189	-0.0435
	[0.0357]	[0.0452]	[0.04185]	[0.0486]
- Q3 isei	0.0932**	0.0750	0.1167***	0.0698
	[0.0380]	[0.0491]	[0.0426]	[0.0513]
- Q4 isei	0.1470***	0.0808*	0.0945**	0.0844*
	[0.0390]	[0.0494]	[0.0441]	[0.0492]
- Q5 isei	0.2341***	0.1167**	0.2147***	0.2119***
	[0.0502]	[0.0572]	[0.0510]	[0.0638]
Isei°	0.0053***	0.0044***	0.0053***	0.0046***
	[0.0009]	[0.0011]	[0.0010]	[0.0011]
Fin. Prob.	-0.0254	-0.0307	-0.0165	-0.0373
	[0.0321]	[0.03992]	[0.0457]	[0.0541]
Immigrant	-0.2547**	-0.1424	-0.1467*	-0.0880
	[0.1137]	[0.1246]	[0.0917]	[0.0931]
Obs.	1162	1250	1574	1389
Pseudo R^2	0.2052	0.1444	0.1191	0.0922
Log-Lik.	-621290	-917010	-1093422	-1078968
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3c: Ireland, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
	Background Variable			
Education:				
- Lower. Sec.	0.1901***	0.2313***	0.1308***	0.2312***
	[0.0526]	[0.0496]	[0.0416]	[0.0520]
- Upper. Sec.	0.2746***	0.3805***	0.2658***	0.3078***
	[0.0664]	[0.0509]	[0.0443]	[0.0543]
- Tertiary	0.4612***	0.3745***	0.5331***	0.3865***
	[0.0792]	[0.0748]	[0.0552]	[0.0653]
Occupation:				
- Q2 isei	0.0867**	0.0278	0.0628	0.1037*
	[0.0235]	[0.0298]	[0.0398]	[0.0423]
- Q3 isei	0.0884**	0.1314***	0.1123**	0.1153*
	[0.0286]	[0.0300]	[0.0357]	[0.0431]
- Q4 isei	0.0894**	0.1398***	0.0730*	0.1702***
	0.0275]	[0.0305]	[0.0402]	[0.0397]
- Q5 isei	0.1394***	0.1420***	0.1122**	0.1678**
	[0.0304]	[0.0310]	[0.0410]	[0.0447]
Isei°	0.0030***	0.0039***	0.0020**	0.0032**
	[0.0008]	[0.0008]	[0.0009]	[0.0010]
Fin. Prob.	-0.0260	-0.0399	-0.0463	-0.1094*
	[0.0321]	[0.0322]	[0.0378]	[0.0583]
Immigrant	0.0558	0.1366**	0.1017*	0.0881
	[0.0611]	[0.0574]	[0.0639]	[0.0597]
Obs.	1186	1388	1430	886
Pseudo R^2	0.2116	0.1948	0.1948	0.1633
Log-Lik.	-137569	-225981	-225981	-305836
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3d: United Kingdom, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
	Background Variable			
Education:				
- Lower. Sec.	0.1690***	0.1796***	0.0973***	0.0904***
	[0.0452]	[0.0449]	[0.0346]	[0.0346]
- Upper. Sec.	0.1256***	0.1640***	0.1102***	0.1054***
	[0.0281]	[0.0299]	[0.0283]	[0.0339]
- Tertiary	0.1983***	0.3120***	0.2954***	0.2694***
	[0.0437]	[0.0410]	[0.0351]	[0.0355]
Occupation:				
- Q2 isei	0.0604**	-0.0236	-0.0080	0.0133
	[0.0269]	[0.0345]	[0.0344]	[0.0369]
- Q3 isei	0.0981***	-0.0278	0.0271	0.0715*
	[0.0279]	[0.0339]	[0.0353]	[0.0386]
- Q4 isei	0.1493***	0.0438	0.0489	0.1962***
	[0.0299]	[0.0339]	[0.0356]	[0.0393]
- Q5 isei	0.2367***	0.1781***	0.1390***	0.2443***
	[0.0329]	[0.0419]	[0.0428]	[0.0464]
Isei°	0.0050	0.0045	0.0030	0.0058
	[0.0006]	[0.0008]	[0.0008]	[0.0008]
Fin. Prob.	-0.0242	-0.0241	0.0325	-0.0054
	[0.0221]	[0.0262]	[0.0270]	[0.0307]
Immigrant	0.0100	0.0353	0.1417**	0.0185
	[0.0584]	[0.0553]	[0.0576]	[0.0384]
Obs.	1880	1885	1874	1874
Pseudo R^2	0.1318	0.1119	0.0691	0.1042
Log-Lik.	-1920782	-2563191	-3118923	-2790130
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3e: Spain, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Background Variable				
Education:				
- Lower. Sec.	0.0404 [0.0391]	0.0813** [0.0399]	0.0834** [0.0335]	0.0464* [0.0264]
- Upper. Sec.	0.1504*** [0.0381]	0.1440*** [0.0399]	0.1499*** [0.0341]	0.1533*** [0.0291]
- Tertiary	0.2413*** [0.0535]	0.2529*** [0.0431]	0.3220*** [0.0384]	0.2806*** [0.0326]
Occupation:				
- Q2 isei	0.0219 [0.0183]	0.0486** [0.0191]	0.0460** [0.0224]	0.0782*** [0.0258]
- Q3 isei	0.0691*** [0.0205]	0.0864*** [0.0196]	0.0726*** [0.0224]	0.1061*** [0.0257]
- Q4 isei	0.0546*** [0.0176]	0.1350*** [0.0209]	0.1355*** [0.0224]	0.1676*** [0.0289]
- Q5 isei	0.1678*** [0.0256]	0.2403*** [0.0265]	0.2066*** [0.0302]	0.1962*** [0.0318]
Isei°	0.0034*** [0.0005]	0.0054*** [0.0005]	0.0054*** [0.0006]	0.0051*** [0.0007]
Fin. Prob.	-0.0329** [0.0148]	-0.0364** [0.0164]	-0.0273 [0.0202]	-0.0796*** [0.0254]
Immigrant	0.0736* [0.0448]	-0.0438 [0.0576]	-0.0188 [0.0433]	-0.0983** [0.0417]
Obs.	3387	4444	5236	5242
Pseudo R^2	0.217	0.1713	0.1549	0.116
Log-Lik.	-1064809	-2001469	-3129701	-4507398
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3f: France, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Background Variable				
Education:				
- Lower. Sec.	0.1239*** [0.0309]	0.0631** [0.0262]	0.0873*** [0.0281]	0.0895** [0.0354]
- Upper. Sec.	0.0931*** [0.0227]	0.0562*** [0.0184]	0.1279*** [0.0211]	0.1036*** [0.0234]
- Tertiary	0.3579*** [0.0522]	0.3858*** [0.0488]	0.3189*** [0.0400]	0.2935*** [0.0371]
Occupation:				
- Q2 isei	0.0219 [0.0201]	0.0078 [0.0217]	0.0177 [0.0217]	0.0379 [0.0302]
- Q3 isei	0.0216 [0.0194]	-0.0196 [0.0204]	0.0127 [0.0239]	0.0798** [0.0310]
- Q4 isei	0.0682*** [0.0222]	0.0700*** [0.0241]	0.0794*** [0.0255]	0.1588*** [0.0319]
- Q5 isei	0.1202*** [0.0258]	0.1510*** [0.0274]	0.1636*** [0.0297]	0.2714*** [0.0393]
Isei°	0.0031*** [0.0005]	0.0045*** [0.0006]	0.0039*** [0.0007]	0.0059*** [0.0007]
Fin. Prob.	-	-	-	-
Immigrant	-0.0563* [0.0320]	0.0048 [0.0268]	0.0069 [0.0311]	-0.0277 [0.0408]
Obs.	2372	3071	3235	2931
Pseudo R^2	0.2091	0.191	0.1454	0.1495
Log-Lik.	-1963690	-2702307	-3656040	-4607335
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3g: Belgium, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Background Variable				
Education:				
- Lower. Sec.	0.1214*** [0.0407]	0.1368*** [0.0349]	0.1635*** [0.0357]	0.0168 [0.0436]
- Upper. Sec.	0.2925*** [0.0639]	0.2692*** [0.0358]	0.2337*** [0.0335]	0.1979*** [0.0404]
- Tertiary	0.5159*** [0.0639]	0.4708*** [0.0507]	0.3969*** [0.0471]	0.4294*** [0.0484]
Occupation:				
- Q2 isei	-0.0403 [0.0399]	-0.0290 [0.0375]	-0.0443 [0.0380]	0.0269 [0.0416]
- Q3 isei	-0.0252 [0.0420]	0.0654* [0.0391]	0.0706* [0.0392]	0.1222*** [0.0461]
- Q4 isei	0.0637 [0.0469]	0.0947** [0.0406]	0.0860** [0.0418]	0.0737* [0.0449]
- Q5 isei	0.1040** [0.0529]	0.0993** [0.0464]	0.1984*** [0.0529]	0.2109*** [0.0570]
Isei°	0.0034*** [0.0009]	0.0026*** [0.0008]	0.0039*** [0.0009]	0.0033*** [0.0009]
Fin. Prob.	-0.0254 [0.0403]	-0.0059 [0.0388]	-0.0345 [0.0441]	-0.1122** [0.0488]
Immigrant	-0.0672 [0.0574]	-0.0633 [0.0477]	-0.0129 [0.0411]	-0.0678 [0.0487]
Obs.	996	1390	1600	1366
Pseudo R^2	0.2091	0.154	0.1636	0.1894
Log-Lik.	-361451	-600740	-718184	-676914
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3h: Denmark, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
Background Variable				
Education:				
- Lower. Sec.	-	-	-	-
- Upper. Sec.	-0.0147 [0.0243]	0.0312 [0.0298]	0.0712** [0.0288]	0.0089 [0.0419]
- Tertiary	0.0985 [0.0749]	0.2007*** [0.0643]	0.1967*** [0.0474]	0.2335*** [0.0531]
Occupation:				
- Q2 isei	-0.0425 [0.0308]	-0.0018 [0.0422]	-0.0594 [0.0411]	0.0841* [0.0511]
- Q3 isei	0.0278 [0.0371]	0.0606 [0.0482]	-0.0008 [0.0430]	0.1552*** [0.0529]
- Q4 isei	0.1271*** [0.0462]	0.1009** [0.0506]	0.1087** [0.0483]	0.1438*** [0.0518]
- Q5 isei	0.2480*** [0.0475]	0.2106*** [0.0551]	0.1371** [0.0549]	0.2270*** [0.0626]
Isei°	0.0059*** [0.0007]	0.0050*** [0.0009]	0.0039*** [0.0009]	0.0039*** [0.0012]
Fin. Prob.	-0.037 [0.0397]	0.0370 [0.0537]	-0.0856* [0.0485]	0.0081 [0.0700]
Immigrant	0.0965 [0.0668]	-0.0803 [0.0759]	0.0831 [0.0556]	0.0556 [0.0785]
Obs.	894	999	1198	848
Pseudo R^2	0.127	0.086	0.091	0.091
Log-Lik.	-250552	-362206	-425907	-357472
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3i: Italy, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 26]
	Background Variable			
Education:				
- Lower. Sec.	0.0734*** [0.0192]	0.0693*** [0.0160]	0.0507*** [0.0136]	0.0430*** [0.0121]
- Upper. Sec.	0.2075*** [0.0337]	0.2588*** [0.0292]	0.1612*** [0.0216]	0.1505*** [0.0176]
- Tertiary	0.3760*** [0.0735]	0.2957*** [0.0514]	0.3761*** [0.0463]	0.3426*** [0.0410]
Occupation:				
- Q2 isei	0.0030 [0.0142]	0.0301** [0.0145]	0.0173 [0.0173]	-0.0211 [0.0152]
- Q3 isei	0.0011 [0.0145]	0.0306** [0.0153]	0.0185 [0.0168]	0.0201 [0.0163]
- Q4 isei	0.0238 [0.0164]	0.0602*** [0.0153]	0.0493*** [0.0171]	0.0758*** [0.0194]
- Q5 isei	0.0755*** [0.0198]	0.1400*** [0.0201]	0.1026*** [0.0196]	0.1303*** [0.0225]
Isei°	0.0018*** [0.0004]	0.0031*** [0.0004]	0.0026*** [0.0004]	0.0037*** [0.0005]
Fin. Prob.	-0.0390*** [0.0098]	-0.0384*** [0.0106]	-0.0263** [0.0124]	-0.0456*** [0.0142]
Immigrant	0.0011 [0.0616]	0.0553 [0.0357]	0.0310 [0.0322]	-0.1505 [0.0369]
Obs.	5534	6348	7428	6859
Pseudo R^2	0.2596	0.2357	0.1859	0.1771
Log-Lik.	-1169745	-1916937	-2434941	-2854144
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3j: Portugal, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 26]
	Background Variable			
Education:				
- Lower. Sec.	0.1156 [0.0908]	0.1123** [0.0567]	0.1074** [0.0424]	0.0791* [0.0501]
- Upper. Sec.	0.3712*** [0.1234]	0.2447** [0.0943]	0.1325** [0.0624]	0.2152*** [0.0599]
- Tertiary	0.2227** [0.1142]	0.1810** [0.0879]	0.1572*** [0.0556]	0.2477*** [0.0613]
Occupation:				
- Q2 isei	0.0131 [0.0253]	-0.0097 [0.0169]	-0.0057 [0.0193]	0.0870*** [0.0314]
- Q3 isei	0.0073 [0.0188]	-0.0021 [0.0168]	0.0695*** [0.0252]	0.0654** [0.0297]
- Q4 isei	0.0234 [0.0217]	0.0450** [0.0215]	0.0601*** [0.0226]	0.1583*** [0.0345]
- Q5 isei	0.1486*** [0.0282]	0.2206*** [0.0322]	0.1348*** [0.0284]	0.2283*** [0.0383]
Isei°	0.0035*** [0.0006]	0.0056*** [0.0006]	0.0039*** [0.0006]	0.0044*** [0.0009]
Fin. Prob.	-	-	-	-
Immigrant	-0.0037 [0.0564]	0.0350 [0.0575]	0.1364*** [0.0395]	-0.2480** [0.1198]
Obs.	1349	1606	1716	1454
Pseudo R^2	0.2969	0.3208	0.2894	0.2229
Log-Lik.	-205642	-282351	-365710	-613653
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3k: Greece, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
	Background Variable			
Education:				
- Lower. Sec.	0.1647*** [0.0455]	0.2041*** [0.0426]	0.1789*** [0.0433]	0.0646** [0.0323]
- Upper. Sec.	0.2163*** [0.0731]	0.3035*** [0.0691]	0.2215*** [0.0501]	0.1665*** [0.0334]
- Tertiary	0.2960*** [0.0900]	0.2009*** [0.0766]	0.3960*** [0.0661]	0.2929*** [0.0512]
Occupation:				
- Q2 isei	-0.0079 [0.0271]	-0.0087 [0.0279]	0.0235 [0.0348]	0.0040 [0.0331]
- Q3 isei	-0.0046 [0.0300]	0.0714** [0.0349]	0.0615* [0.0364]	0.0827** [0.0370]
- Q4 isei	0.0773** [0.0343]	0.0738** [0.0333]	0.0654* [0.0375]	0.1452*** [0.0390]
- Q5 isei	0.1052*** [0.0384]	0.1369*** [0.0383]	0.1142*** [0.0422]	0.1156*** [0.0426]
Isei°	0.0029*** [0.0007]	0.0035*** [0.0008]	0.0033*** [0.0009]	0.0046*** [0.0008]
Fin. Prob.	-	-	-	-
Immigrant	0.0219 [0.0736]	0.0675 [0.0500]	-0.0937 [0.0509]	-0.0526 [0.0460]
Obs.	1592	1905	2061	2126
Pseudo R^2	0.255	0.1583	0.1326	0.1508
Log-Lik.	-323302	-521639	-785336	-855519
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 3l: Austria, Marginal Effects				
Age Cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
	Background Variable			
Education:				
- High edu. (upsec+tert	0.0758*** [0.0244]	0.0388* [0.0252]	0.0239 [0.0243]	0.0804*** [0.0284]
Occupation:				
- Q2 isei	0.0196 [0.0306]	0.0110 [0.0304]	-0.0501 [0.0312]	0.0219 [0.0353]
- Q3 isei	0.0657* [0.0348]	0.0499* [0.0314]	-0.0140 [0.0309]	0.0463 [0.0384]
- Q4 isei	0.0841** [0.0362]	0.0845** [0.0361]	0.0703* [0.0415]	0.1136** [0.0441]
- Q5 isei	0.0756** [0.0387]	0.1209*** [0.0428]	0.1579*** [0.0480]	0.1202** [0.0464]
Isei°	0.0035*** [0.0008]	0.0057*** [0.0008]	0.0055*** [0.0008]	0.0055*** [0.0009]
Fin. Prob.	-	-	-	-
Immigrant	-0.0266 [0.0553]	0.0115 [0.0391]	0.0305 [0.0383]	0.1159*** [0.0401]
Obs.	1452	1661	1934	1369
Pseudo R^2	0.1395	0.101	0.066	0.0898
Log-Lik.	-321944	-419217	-605284	-470755
Ref. Group: primary edu., Q1 isei				
Other controls: age, sex, both parents, num. siblings, chronic ill.				
° This coefficient refers to a linear spec. of the impact of par. Isei				
§: Robust standard errors, observations are population weighted				

Table 4a. Finland: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.124	0.176	0.270	0.326
Q2	0.192	0.296	0.308	0.359
Q3	0.253	0.298	0.350	0.445
Q4	0.332	0.382	0.453	0.513
Q5	0.580	0.560	0.661	0.645
Std. dev.	0.191	0.168	0.180	0.195
Coeff. of Var.	0.646	0.492	0.444	0.436
Predicted Inter-quintile differences				
Q5-Q3	0.327	0.262	0.311	0.201
Q3-Q1	0.128	0.122	0.080	0.118
Q5-Q1	0.455	0.384	0.391	0.319
Real Inter-quintile differences				
Q5-Q3	0.276	0.216	0.306	0.213
Q3-Q1	0.190	0.141	0.086	0.090
Q5-Q1	0.466	0.356	0.392	0.303
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.284	0.268	0.312	0.192
Q3-Q1	0.162	0.120	0.086	0.120
Q5-Q1	0.446	0.388	0.398	0.312

Table 4b. Netherlands: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.099	0.161	0.196	0.263
Q2	0.150	0.211	0.269	0.325
Q3	0.265	0.320	0.352	0.413
Q4	0.271	0.328	0.432	0.484
Q5	0.525	0.564	0.621	0.677
Std. dev.	0.211	0.196	0.190	0.173
Coeff. of Var.	0.827	0.615	0.503	0.398
Predicted Inter-quintile differences				
Q5-Q3	0.260	0.244	0.269	0.265
Q3-Q1	0.165	0.159	0.156	0.150
Q5-Q1	0.425	0.403	0.426	0.414
Real Inter-quintile differences				
Q5-Q3	0.246	0.191	0.257	0.273
Q3-Q1	0.176	0.158	0.180	0.146
Q5-Q1	0.422	0.350	0.437	0.419
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.223	0.183	0.236	0.241
Q3-Q1	0.191	0.124	0.156	0.142
Q5-Q1	0.415	0.308	0.392	0.383

Table 4c. Ireland: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.058	0.088	0.167	0.292
Q2	0.111	0.153	0.237	0.362
Q3	0.130	0.159	0.296	0.511
Q4	0.202	0.256	0.318	0.538
Q5	0.422	0.543	0.573	0.722
Std. dev.	0.190	0.217	0.224	0.228
Coeff. of Var.	1.002	0.909	0.737	0.466
Predicted Inter-quintile differences				
Q5-Q3	0.292	0.384	0.277	0.211
Q3-Q1	0.072	0.071	0.129	0.218
Q5-Q1	0.364	0.455	0.406	0.430
Real Inter-quintile differences				
Q5-Q3	0.207	0.209	0.194	0.151
Q3-Q1	0.193	0.231	0.218	0.301
Q5-Q1	0.400	0.440	0.412	0.452
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.162	0.309	0.221	0.190
Q3-Q1	0.121	0.076	0.074	0.187
Q5-Q1	0.283	0.385	0.295	0.377

Table 4d. United Kingdom: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.200	0.334	0.213	0.245
Q2	0.247	0.367	0.272	0.324
Q3	0.289	0.394	0.339	0.467
Q4	0.354	0.464	0.424	0.616
Q5	0.457	0.625	0.610	0.760
Std. dev.	0.166	0.182	0.148	0.189
Coeff. of Var.	0.684	0.512	0.373	0.361
Predicted Inter-quintile differences				
Q5-Q3	0.168	0.231	0.271	0.294
Q3-Q1	0.089	0.060	0.126	0.221
Q5-Q1	0.257	0.291	0.396	0.515
Real Inter-quintile differences				
Q5-Q3	0.239	0.355	0.243	0.275
Q3-Q1	0.107	0.021	0.069	0.166
Q5-Q1	0.346	0.375	0.312	0.441
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.224	0.236	0.207	0.235
Q3-Q1	0.076	0.070	0.065	0.171
Q5-Q1	0.300	0.306	0.272	0.406

Table 4e. Spain: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1 pred.	0.043	0.068	0.121	0.228
Q2 pred.	0.066	0.106	0.182	0.312
Q3 pred.	0.090	0.141	0.230	0.340
Q4 pred.	0.133	0.177	0.292	0.467
Q5 pred.	0.332	0.444	0.548	0.629
Std. dev.	0.158	0.172	0.194	0.188
Coeff. of Var.	1.181	0.913	0.699	0.478
Predicted Inter-quintile differences				
Q5-Q3	0.242	0.304	0.318	0.289
Q3-Q1	0.047	0.073	0.109	0.112
Q5-Q1	0.290	0.377	0.427	0.401
Real Inter-quintile differences				
Q5-Q3	0.253	0.294	0.328	0.271
Q3-Q1	0.069	0.095	0.104	0.140
Q5-Q1	0.322	0.389	0.433	0.411
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.062	0.142	0.166	0.152
Q3-Q1	0.009	0.029	0.065	0.064
Q5-Q1	0.071	0.171	0.231	0.216

Table 4f. France: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.049	0.015	0.115	0.120
Q2	0.071	0.032	0.158	0.197
Q3	0.105	0.065	0.233	0.316
Q4	0.188	0.161	0.312	0.444
Q5	0.370	0.436	0.489	0.695
Std. dev.	0.162	0.177	0.172	0.211
Coeff. of Var.	1.119	0.960	0.728	0.541
Predicted Inter-quintile differences				
Q5-Q3	0.265	0.371	0.256	0.379
Q3-Q1	0.056	0.049	0.118	0.196
Q5-Q1	0.320	0.420	0.374	0.575
Real Inter-quintile differences				
Q5-Q3	0.279	0.337	0.301	0.358
Q3-Q1	0.038	0.014	0.069	0.151
Q5-Q1	0.317	0.351	0.369	0.509
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.290	0.315	0.273	0.323
Q3-Q1	0.065	0.064	0.105	0.164
Q5-Q1	0.354	0.379	0.377	0.487

Table 4g. Belgium: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.125	0.164	0.200	0.254
Q2	0.169	0.197	0.227	0.318
Q3	0.201	0.267	0.335	0.500
Q4	0.366	0.381	0.476	0.563
Q5	0.588	0.577	0.692	0.777
Std. dev.	0.230	0.204	0.221	0.246
Coeff. of Var.	0.796	0.643	0.574	0.508
Predicted Inter-quintile differences				
Q5-Q3	0.387	0.310	0.357	0.277
Q3-Q1	0.076	0.103	0.135	0.246
Q5-Q1	0.463	0.413	0.492	0.523
Real Inter-quintile differences				
Q5-Q3	0.421	0.269	0.341	0.258
Q3-Q1	-0.001	0.131	0.138	0.296
Q5-Q1	0.420	0.399	0.478	0.554
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.334	0.254	0.336	0.260
Q3-Q1	0.098	0.076	0.132	0.231
Q5-Q1	0.432	0.331	0.468	0.491

Table 4h. Denmark: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.124	0.176	0.270	0.326
Q2	0.192	0.296	0.308	0.359
Q3	0.253	0.298	0.350	0.445
Q4	0.332	0.382	0.453	0.513
Q5	0.580	0.560	0.661	0.645
Std. dev.	0.147	0.145	0.149	0.164
Coeff. of Var.	0.765	0.521	0.519	0.454
Predicted Inter-quintile differences				
Q5-Q3	0.30	0.26	0.25	0.23
Q3-Q1	0.05	0.09	0.08	0.12
Q5-Q1	0.35	0.35	0.33	0.35
Real Inter-quintile differences				
Q5-Q3	0.295	0.239	0.263	0.210 -- 0.2
Q3-Q1	0.008	0.090	0.021	.185 -- 0.14
Q5-Q1	0.303	0.330	0.284	.396 -- 0.35
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.300	0.256	0.251	0.234
Q3-Q1	0.049	0.094	0.083	0.116
Q5-Q1	0.349	0.350	0.334	0.350

** The first value corresponds to cohort 27-25, the second to 25-35*

Table 4i. Italy: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 26]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.019	0.029	0.048	0.062
Q2	0.040	0.060	0.063	0.089
Q3	0.048	0.068	0.087	0.119
Q4	0.080	0.135	0.164	0.211
Q5	0.256	0.319	0.309	0.389
Std. dev.	0.140	0.160	0.147	0.160
Coeff. of Var.	1.533	1.284	1.086	0.938
Predicted Inter-quintile differences				
Q5-Q3	0.208	0.251	0.222	0.270
Q3-Q1	0.030	0.039	0.038	0.057
Q5-Q1	0.238	0.289	0.261	0.327
Real Inter-quintile differences				
Q5-Q3	0.231	0.273	0.240	0.269
Q3-Q1	0.022	0.039	0.031	0.045
Q5-Q1	0.253	0.312	0.271	0.314
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.220	0.276	0.223	0.251
Q3-Q1	0.048	0.058	0.042	0.060
Q5-Q1	0.268	0.334	0.264	0.311

Table 4j. Portugal: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 26]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.021	0.011	0.017	0.070
Q2	0.027	0.025	0.055	0.103
Q3	0.043	0.046	0.069	0.134
Q4	0.068	0.083	0.104	0.246
Q5	0.240	0.350	0.337	0.428
Std. dev.	0.142	0.164	0.161	0.189
Coeff. of Var.	1.714	1.593	1.415	0.957
Predicted Inter-quintile differences				
Q5-Q3	0.197	0.304	0.268	0.294
Q3-Q1	0.022	0.036	0.052	0.065
Q5-Q1	0.219	0.339	0.320	0.358
Real Inter-quintile differences				
Q5-Q3	0.253	0.329	0.241	0.326
Q3-Q1	0.013	0.014	0.076	0.066
Q5-Q1	0.266	0.343	0.317	0.392
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.025	0.173	0.207	0.197
Q3-Q1	0.042	0.096	0.121	0.073
Q5-Q1	0.067	0.270	0.328	0.270

Table 4k. Greece: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 25]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.041	0.074	0.116	0.103
Q2	0.053	0.090	0.174	0.157
Q3	0.069	0.139	0.197	0.220
Q4	0.134	0.183	0.294	0.325
Q5	0.319	0.364	0.449	0.517
Std. dev.	0.168	0.156	0.175	0.187
Coefficient of	1.306	0.904	0.689	0.699
Predicted Inter-quintile differences				
Q5-Q3	0.250	0.225	0.253	0.297
Q3-Q1	0.028	0.065	0.081	0.118
Q5-Q1	0.278	0.290	0.333	0.414
Real Inter-quintile differences				
Q5-Q3	0.284	0.187	0.231	0.221
Q3-Q1	0.013	0.112	0.122	0.157
Q5-Q1	0.298	0.299	0.353	0.378
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.196	0.166	0.193	0.256
Q3-Q1	0.006	0.037	0.060	0.106
Q5-Q1	0.202	0.203	0.253	0.363

Table 4l. Austria: Predicted, real and transition inter-quintile differences				
Age cohort	[65, 55)	[55-45)	[45-35)	[35, 27]
Predicted Prob. for each quintile of parental ISEI				
Q1	0.065	0.075	0.109	0.096
Q2	0.110	0.104	0.153	0.156
Q3	0.155	0.153	0.194	0.209
Q4	0.194	0.224	0.268	0.319
Q5	0.306	0.361	0.367	0.390
Std. dev.	0.137	0.125	0.109	0.132
Coeff. of Var.	0.816	0.676	0.498	0.554
Predicted Inter-quintile differences				
Q5-Q3	0.151	0.208	0.173	0.181
Q3-Q1	0.091	0.078	0.085	0.112
Q5-Q1	0.241	0.286	0.258	0.294
Real Inter-quintile differences				
Q5-Q3	0.117	0.193	0.239	0.184
Q3-Q1	0.118	0.077	0.015	0.099
Q5-Q1	0.236	0.270	0.254	0.283
Transition upper secondary-tertiary Inter-quintile diff.				
Q5-Q3	0.143	0.195	0.168	0.174
Q3-Q1	0.084	0.075	0.081	0.112
Q5-Q1	0.227	0.269	0.249	0.286

Table 5: Testing the Modernization Hypothesis									
Measures of Inequality	Q5-Q1 pred	Q5-Q3 pred	Q5-Q3 pred	Q3-Q1 pred	Q5-Q1 real	Q5-Q3 real	Q5-Q3 real	Q3-Q1 real	Dummy Q5
college graduate	.6601*** [.1279]	.2823** [.1269]	.9108** [.2759]	.3778*** [.0455]	.6228*** [.1377]	.2033 [.1308]	.1797 [.3666]	.4198** [.1346]	.2392** [.1055]
college graduate^2	-	-	-1.152** [.4338]	-	-	-	.0433 [.4855]	-	-
age track: voc. vs. gen.	.0137** [.0044]	.0157** [.0051]	.01555** [.0053]	-0.0021 [.0024]	.0149** [.0045]	.0163** [.0058]	.0163** [.0059]	-.0015 [.0052]	.0138** [.0041]
country*cohort effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
obs.	48	48	48	48	48	48	48	48	48
R^2	0.68	0.38	0.46	0.79	0.65	0.30	0.30	0.41	0.27
std. errors clustered for countries in parenthesis									
*, **, *** resp. 90%, 95%, 99% sign. levels									

Table 6: Testing the Modern. Hyp., alternative specifications							
Measures of Inequality	Q5-Q4 pred	Q5-Q4 real	Q5-Q1 trans	Q5-Q3 trans	Q3-Q1 trans	Q5-Q3 real no young	Q3-Q1 real no young
college graduate	.1294 [.1374]	-3.826 [2.9758]	.4176* [.2209]	.7387* [.4681]	.2589** [.1033]	.3058 [.2028]	.4181* [.2388]
college graduate^2	-	-	-	-1.063* [.6901]	-	-	-
age track: voc. vs. gen.	.0141** [.0047]	-.0308 [.0273]	.0068 [.0101]	.0089 [.0087]	-.0024 [.0033]	0.0169** [0.0055]	-.0017 [.0048]
country*cohort effects	yes	yes	yes	yes	yes	yes	yes
obs.	48	48	48	48	48	36	36
R^2	0.28	0.28	0.43	0.24	0.54	0.28	0.26
std. errors clustered for countries in parenthesis							
*, **, *** resp. 90%, 95%, 99% sign. levels							

Table 7: Real inter-quintile differences of the native popuation, selected countries

cohort	[65, 55)	[55-45)	[45-35)	[35, 26]	cohort	[65, 55)	[55-45)	[45-35)	[35, 26]
Italy					***Ireland***				
Q5-Q3	0.231	0.269	0.245	0.282	Q5-Q3	0.203	0.212	0.206	0.203
Q3-Q1	0.024	0.043	0.023	0.036	Q3-Q1	0.179	0.213	0.195	0.263
Q5-Q1	0.255	0.312	0.267	0.318	Q5-Q1	0.382	0.426	0.401	0.469
Spain					***United Kingdom***				
Q5-Q3	0.256	0.294	0.328	0.276	Q5-Q3	0.239	0.346	0.238	0.266
Q3-Q1	0.070	0.098	0.112	0.136	Q3-Q1	0.107	0.024	0.086	0.160
Q5-Q1	0.326	0.392	0.440	0.412	Q5-Q1	0.346	0.370	0.324	0.426
France					***Belgium***				
Q5-Q3	0.279	0.335	0.295	0.352	Q5-Q3	0.419	0.263	0.356	0.273
Q3-Q1	0.036	0.005	0.055	0.146	Q3-Q1	0.004	0.125	0.125	0.244
Q5-Q1	0.314	0.340	0.349	0.498	Q5-Q1	0.423	0.388	0.481	0.517

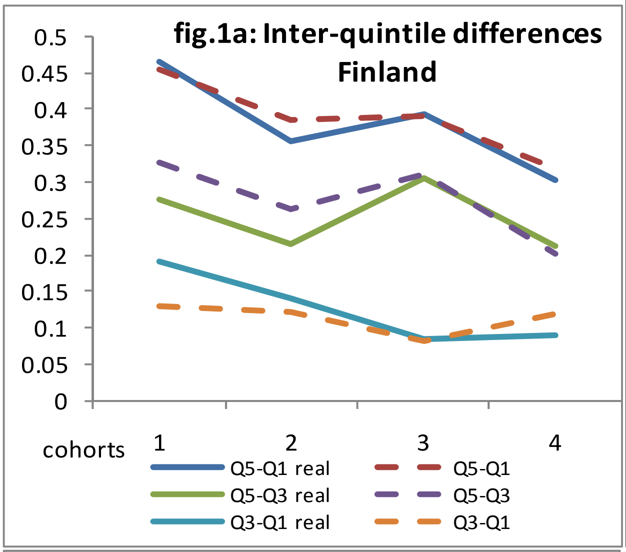
fig.1a: Inter-quintile differences Finland
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

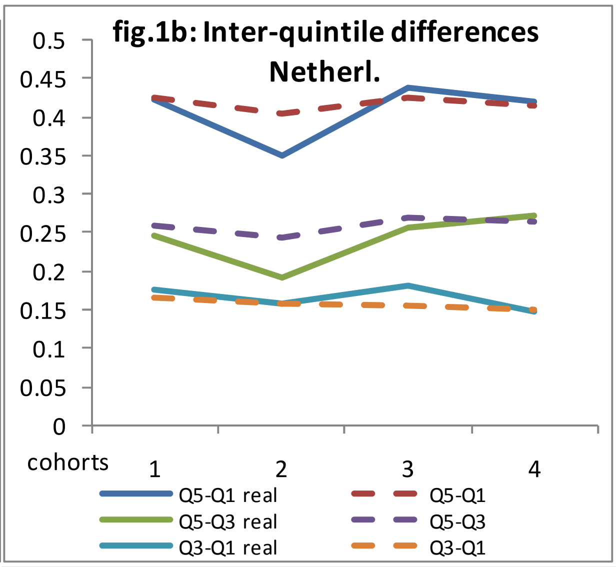
fig.1b: Inter-quintile differences Netherl.
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

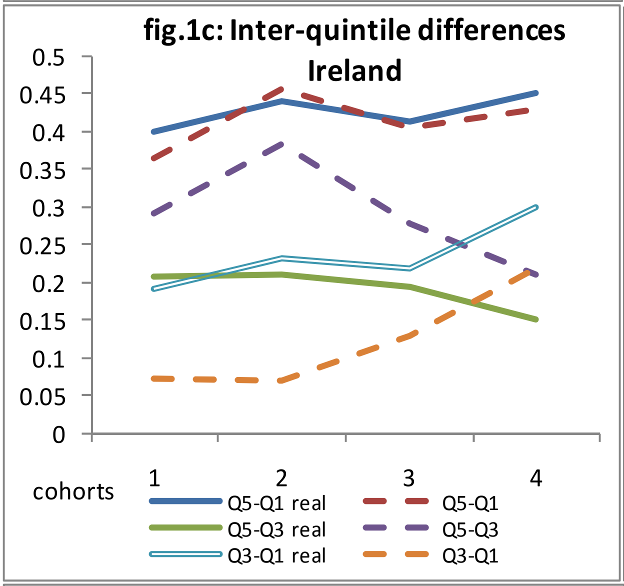
fig.1c: Inter-quintile differences Ireland
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

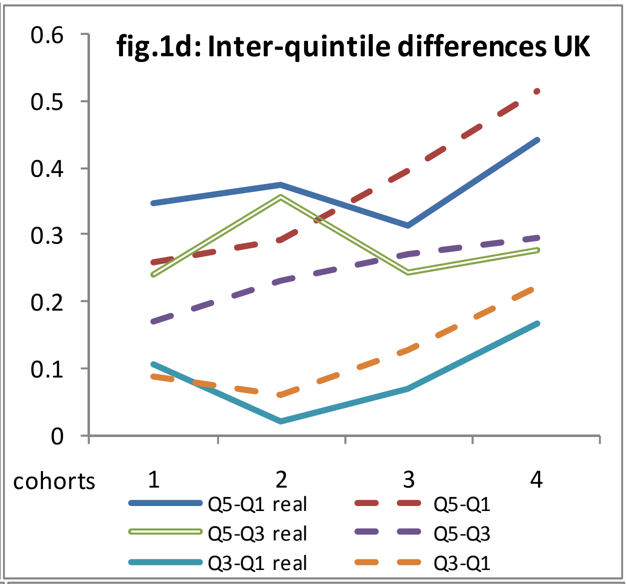
fig.1d: Inter-quintile differences UK
0.6
0.5
0.4
0.3
0.2
0.1
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

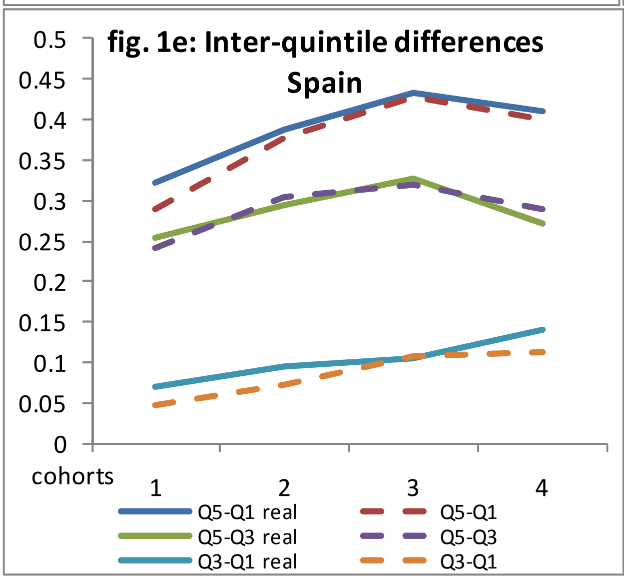
fig. 1e: Inter-quintile differences Spain
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

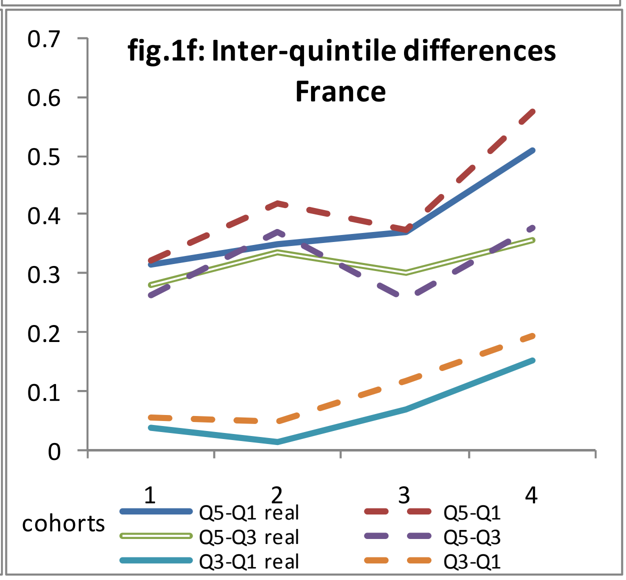
fig.1f: Inter-quintile differences France
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
cohorts
1
2
3
4
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

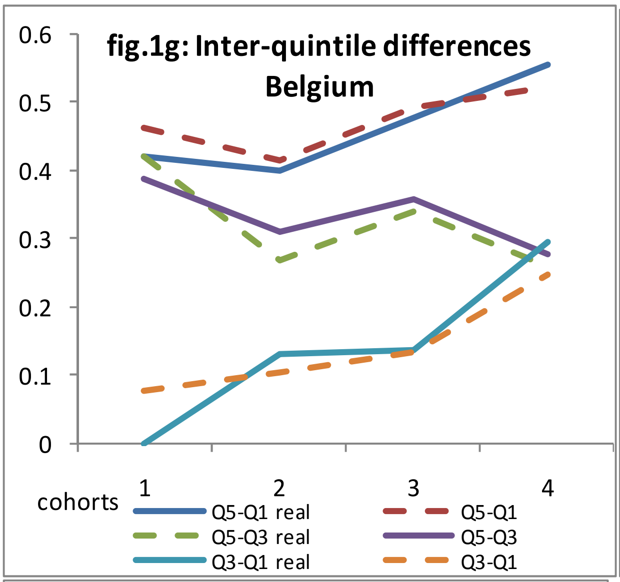
fig.1g: Inter-quintile differences Belgium
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

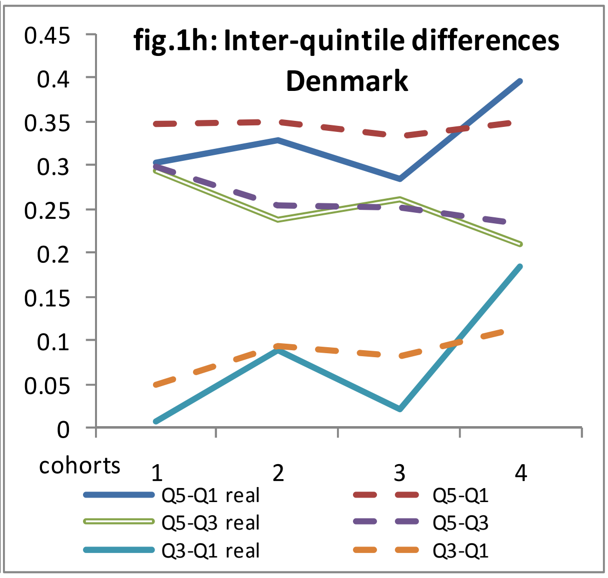
fig.1h: Inter-quintile differences Denmark
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

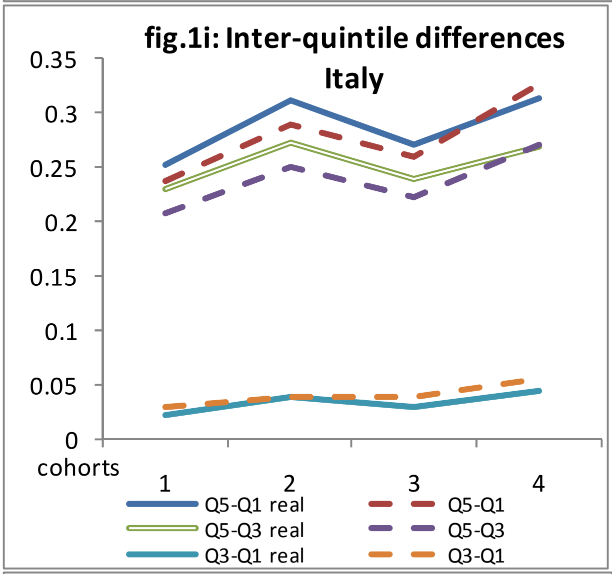
fig.1i: Inter-quintile differences Italy
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

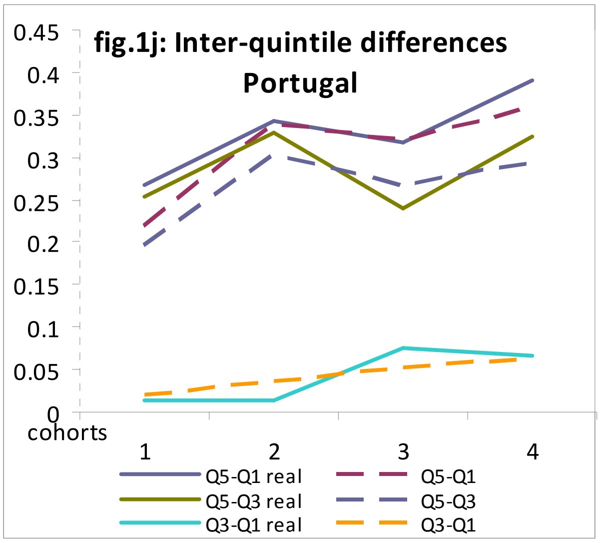
fig.1j: Inter-quintile differences Portugal
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

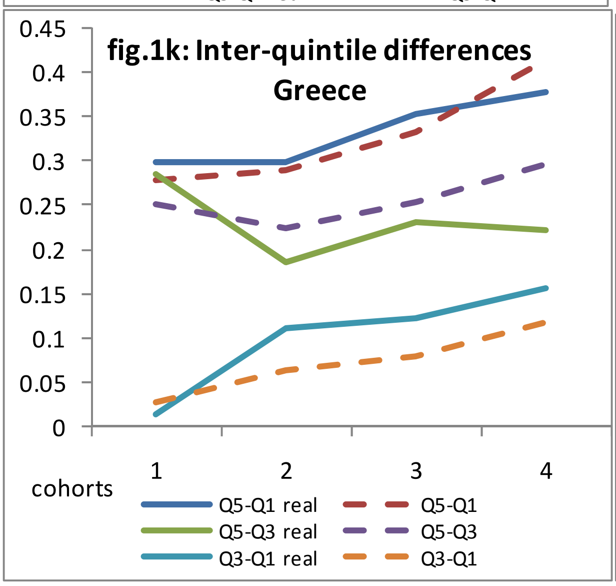
fig.1k: Inter-quintile differences Greece
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1

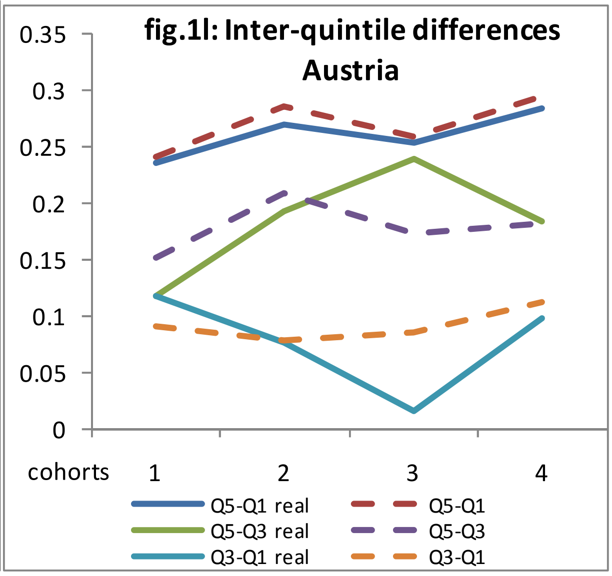
fig.1l: Inter-quintile differences Austria
cohorts
Q5-Q1 real
Q5-Q3 real
Q3-Q1 real
Q5-Q1
Q5-Q3
Q3-Q1