Wage Inequality in France: The Role of Education

Oussama Ben Abdelkarim
Ali Skalli

ERMES UMR CNRS 7017
Université Panthéon-Assas (Paris 2), France

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Abstract :

In this paper, we adopt the Mincer-type approach to measure the contribution of education and age to overall wage inequality in France. We, however, do not simply decompose the variance of wages into different components, but rather infer the wage distributions one would observe if individuals differed only in their age or education and then compute the corresponding Gini coefficients. These are then compared to each other as well as to those associated with the actual wage distribution. Inference of theoretical wage distributions is based on a switching regression model with endogenous switching as this framework allows one to account for (i) the endogeneity of schooling, (ii) non-linearities in the earnings-schooling relationship and (iii) cross-level differences in age-earnings profiles. Our results show that endogeneity and non-linearity are indeed crucial issues and that imposing identical age-earnings profiles results in downward biased estimates of the returns to schooling. They also show that education is an important contributor to wage inequality. By influencing both starting wages and age-earnings profiles, education, in line with basic predictions of human capital theory, generates within- as well as between-educational group wage inequality. While the latter increases with age, the former also varies with educational levels, although the pattern is less clear. The highlighted patterns are, however, cohort-specific. In particular, education-related wage inequality is lower among the youngest cohort members.

Keywords: Wage inequality, Returns to schooling, Gini coefficients.
JEL Classification : J21.

1. Introduction

Income inequalities are a common characteristic of market economies (Atkinson *et al*, 1995, Atkinson, 1996). As such, their sources as well as their consequences are of a major concern not only to academia but also to policy makers. Indeed, the identification of inequality sources is more than a requirement if correction mechanisms are to be designed in order to reduce economic inequalities. Obviously, education is an important factor in understanding inequality, but also in designing redistribution policies. On the one hand, by yielding significant returns, individual investments in education necessarily generate some inequality.[1] On the other hand, despite the investment is profitable, a large number of individuals do not undertake it because of limited resources.

Yet, education is a profitable investment not only for individuals but for societies as a whole. Human capital and productive skills accumulation has been given an increasingly important role in endogenous growth theories (Lucas, 1988, Romer, 1989, Azariadis and Drazen, 1990, Mankiw *et al*, 1992 and Jones, 1996). These theories rely on the idea that the knowledge and the skills individuals are endowed with have a direct effect on productivity and hence increase the ability of an economy to develop and adopt new technologies. Empirical evidence supporting this hypothesis has also been given in a large number of well known studies like Baumol *et al* (1989), Barro (1991) and Mankiw *et al* (1992), but also in more recent ones like de la Fuente & Doménech (2000), Krueger & Lindhal (2001), Cohen & Soto (2001) and Bassanini & Scarpetta (2001) among others.[2]

While there exist theoretical as well as empirical support for a positive effect of education on economic growth, the picture is by far less clear regarding the link between inequality and growth. Inequality is traditionally viewed as a means of increasing the returns to education and therefore to provide individuals with higher incentives to improve their standards of living through educational investments. It is therefore expected to have a positive effect on growth; an effect documented in a number of empirical studies.[3] For instance, Forbes (2000) shows that a ten point increase in the Gini coefficient in a year yields a 1.3% increase in the average growth rate over the five following years. This suggests that re-distributive policies aiming at reducing educational inequalities are likely to result in a less efficient level of educational investments and hence to reduce market efficiency and growth.

During the past decade, however, this view has been challenged by a number of new theories aiming at giving rigorous explanations for a negative, rather than a positive effect of inequality on growth. In contrast to the traditional view where markets are assumed to be

[1] See Psacharopoulos (1994), Card (1999) and Harmon *et al* (2001) for comprehensive presentations of empirical evidence on private returns to education.

[2] There are also studies reporting a negative effect of education on productivity growth (Kyriacou, 1991, Benhabib & Spiegel, 1994, Pritchett, 1999, Islam, 1995 and Caselli *et al*, 1996). It has, however, been shown later that the reported results are due to a variety of data limitations or econometric problems, especially misspecification. See de la Fuente (2002) for a discussion.

[3] For discussions of the traditional view, see Aghion *et al* (1999) and Topel (1999).

perfect, these new theories systematically involve some market imperfections. However, as underlined by Asplund (2004), of the several approaches adopted in this literature, those relying on credit market imperfections on the one hand and on political economy considerations on the other, link strongly to the assessed effect of education on inequality and growth.[4] In the former framework, increased equality through a distortion-free redistribution might under some conditions, enhance economic growth. In the latter, more inequality induces more re-distribution and more associated tax finance, which creates more economic distortions and, in the end, less growth. Empirical evidence in favour of these effects is given in a number of studies surveyed in Asplund (2004).

Despite the debate among researchers on the trade-off between efficiency and equality, policy makers seem to agree upon the idea that redistribution should compensate at least for differences in initial endowments, that is, in inequality factors which are out of individuals' control (Piketty, 1997). This means that the pragmatic view is that inequality is not necessarily bad. Some inequality in outcomes might provide individuals with incentives to perform better. In contrast, inequality in opportunities is different as it may result in persistent inequalities in outcomes. This is why the role of education is so important to assess since subsidising education might reduce educational inequalities (inequality in opportunities), not necessarily earnings inequality (inequality in outcomes).

The role of education in earnings inequality has been examined in the literature in two different ways. The first one relies on decomposable overall inequality indexes.[5] In this framework, aggregate inequality in the distribution of earnings is disaggregated into inequality emanating from differences between groups and inequality emanating from differences within groups. For instance, if individuals are sorted according to their educational levels, then one is able to measure within- as well as between-educational groups inequality. The resulting measure will, however, be noisy. Within a given group, the earnings of individuals might differ for a variety of reasons which are not identified. Between groups, the measured differences might be due to other factors which condition the sorting of individuals across groups. Of course, these limitations could be overcome by classifying individuals into smaller and more homogeneous groups. That is, by considering other classification factors

[4] See Bénabou (1996), Aghion *et al* (1999) or Bertola (1999) for a survey.

[5] See Cowell (2000).

than the sole education. In general, however, sample size considerations compel researchers to consider only a few of these factors such as education, sex, age and sector.[6]

An alternative and widely used approach relies on estimating earnings functions which allow one to decompose the variance of earnings into one part which is due to the observable characteristics one can control for and another part that is due to unobservables. In this framework, the coefficient associated with education is interpreted as the extra-earnings an individual would get on average if she/he spends a further year at school. That is, the return to an extra-year of education. It is hence meant to reflect the contribution of the latter to the variance of earnings.

Although this approach leaves more room to account for as many contributive factors as one actually observes, it has important limitations as well. First, no inequality indexes are in general computed so that the contributions of different factors to aggregate earnings-inequality are not easily comparable, especially when these factors are not measured in the same unit. Second, the earnings-schooling relationship is in general assumed to be linear despite the existence of clear evidence that it is not.[7] Third, the results from this approach are very sensitive to possible correlations between unobservables and observed factors. At least, there is clear evidence in the literature showing that when unobserved determinants of schooling decisions are not accounted for, the estimated returns to education turn out to be downward biased (Card, 2001). Last but not least, it is often assumed that the returns to schooling emanate from different starting wages, not from different age-earnings profiles. Indeed, these are in general assumed not to depend on educational attainments. Obviously, this hypothesis is too strong as one would expect the highly educated to be better endowed to "learn by doing" and hence to accumulate general and specific human capital more efficiently than low educated individuals. Even in basic human capital models, individuals undertake a further investment in education if the net present value of the investment is positive even if they expect a lower starting wage. Hence, what determines the decision to invest is not the starting wage only but the expected age-earnings profile, together with individuals' discount rates. Thus, education influences at least the returns to age and possibly the returns to other observable characteristics as well. Therefore, an appropriate measure of the returns to

[6] See Tsakloglou (2004) for an example.

[7] See for instance, Park (1999), Denny and Harmon (2002) and Skalli (2005).

education should capture not only the effect on starting wages but also the effect on the returns to all individual endowments.

In this paper, we adopt the earnings-equation approach to assess the role of education as an earnings inequality factor. However, we propose a testing strategy which allows us to overcome the empirical problems discussed above. We estimate a switching regression model with endogenous switching where each separate regime is associated with an educational grade. Such a testing strategy has many advantages. First, the endogeneity of schooling is explicitly accounted for via an ordered probit schooling decision model so that the resulting estimates of the returns to education are purged from any effect of the possible correlation between unobservables and educational attainments. Second, the switching regression model entails estimation of level-specific earnings functions. This implies that the returns to observable characteristics are no longer restricted to be independent of educational achievements. In particular, seniority- and age-earnings profiles are in this framework allowed to vary across educational groups just like human capital theory predicts. Third, the earnings-schooling relationship is no more assumed to be linear since not only are specific marginal returns to education estimated for each educational group but they are restricted to obey to no specific non-linear scheme.[8]

Perhaps, however, the most innovative implication of our empirical strategy is that we are able to calculate within- and between-inequality indexes which highlight the extent of earnings inequality one would observe if education were the sole source of inequality. Because the process of wage determination is identified for each educational level, we are able to predict the marginal wage distribution across educational groups. Hence, the Gini coefficient of such a distribution measures between group earnings inequality. The same exercise could, however, be conducted for each possible value of age, hence yielding conditional wage distributions. Indeed, the main idea in the paper is that education influences not only earnings *per se*, but also the speed at which these evolve throughout one's working career; that is, age-earnings profiles. Thus, it generates some inequality across educational groups and some inequality within these groups which depends on age. The latter could,

[8] In general, studies assuming a non-linear earnings-schooling relationship rely on the use of qualifications rather than years of schooling as the measure of human capital investments. However, the highlighted non-linearities (sheepskin effects) are interpreted as reflecting signalling effects (see for instance Park, 1999, Denny and Harmon, 2002). As our results show, the latter effects are by far not the only source of non-linearity.

however, differ significantly according to education, simply because a higher level of education goes with a steeper age-earnings profile.

Unfortunately, cross-sectional estimates of age-earnings profiles are in general noised by cohort effects. That is, younger cohorts are better endowed with education and hence face steeper age-earnings profiles. In this paper, we also aim at measuring within-cohort earnings inequality to identify the earnings- as well as the age-profile effects of education.

The paper is organised as follows. A description of the data as well as of the empirical setup is given in section 2. Section 3 reports the main estimates, especially, the returns to schooling. Section 4 infers from the latter within- and between-group inequality measures. Concluding remarks are made in section 5.

2. Data and Empirical Set-up

The conventional IV approach to estimating the returns to schooling consists of the estimation of a two-equations system describing log-earnings, y_i, and the number of years of schooling (NYS), S_i:

$$y_i = X_i'\beta + rS_i + u_i \qquad (1)$$
$$S_i = Z_i'\gamma + v_i \qquad (2)$$

where X and Z are vectors of observed characteristics and where $E(X_i, u_i) = E(Z_i, v_i) = 0$. Only if S_i is exogenous would estimation of (1) yield an unbiased estimate of the return to schooling, *r*. Otherwise, (1) and (2) are to be estimated simultaneously. In general, S_i is treated as a continuous variable and IV methods are therefore used. A problem with this approach, however, is that it treats schooling as a continuous measure though, in general, no information on the date of leaving school in any year is given so that the schooling measure is in fact an integer. Moreover, there is in general a high proportion of individuals who leave school at the compulsory schooling level. Because of this, the nature of the disturbances is such that the resulting estimates are not consistent (see Garen, 1984). Using U.K. data, Harmon and Walker (1995) estimate a selectivity model where (2) is replaced with an ordered probit equation. While this yields an estimate of the returns to schooling of 16.9%, the IV approach suggests such an estimate to be 15.3%.[9] More specifically, Harmon and Walker (1995) use an extension of Heckman's two-step approach which they apply to the estimation of the following model:

$$y_i = X_i'\beta + rS_i + u_i \tag{3}$$
$$S_i^* = Z_i'\gamma + v_i \tag{4}$$
$$S_i = j \quad \text{if} \quad \mu^{j-1} < S_i^* \leq \mu^j \tag{5}$$

where S_i^* is the latent variable corresponding to S_i and where $j = 1, \cdots, J$. The μ's are unknown parameters to be estimated which indicate the threshold values for moving through the schooling participation decision.

A common feature of the two approaches described above is that earnings are assumed to be linear in schooling. Moreover, both specifications assume that the remuneration of the individual endowments captured in the vector X_i does not depend on individuals' schooling grades. One possible alternative approach could consist in estimating an extended version of the switching regression model with endogenous switching, based on the ordered probit model. The alternative model structure would then be:[10]

$$y_i^j = X_i'\beta^j + u_i^j, \quad j = 1, \cdots, J \tag{6}$$
$$S_i^* = Z_i'\gamma + v_i \tag{7}$$
$$S_i = j \quad \text{if} \quad \mu^{j-1} < S_i^* \leq \mu^j \tag{8}$$

Suppose that u_i^j, $j = 1, \cdots, J$, and v_i are distributed as (J+1)-variate normal. It is now a standard result that this model entails the following earnings equations for observed schooling levels $j = 1, \cdots, J$.

$$y_i = X_i'\beta^j + \rho^j \sigma^j \lambda_i^j + \varepsilon_i^j, \qquad j = 1, \cdots, J \tag{9}$$

where

$$\lambda_i^j = \frac{\phi\left(\mu^{j-1} - Z_i'\gamma\right) - \phi\left(\mu^j - Z_i'\gamma\right)}{\Phi\left(\mu^j - Z_i'\gamma\right) - \Phi\left(\mu^{j-1} - Z_i'\gamma\right)}, \tag{10}$$

[9] These figures are to be compared to an OLS estimate of 6.1%.

[10] This is formally close to Vella and Gregory's (1996) approach.

μ^0 and μ^J being taken as $-\infty$ and $+\infty$, respectively and $\Phi(\cdot)$ and $\phi(.)$ denoting the standard normal distribution and density functions, respectively. ρ^j, $j = 1,\cdots,J$, are the correlation coefficients of u_i^j and v_i in their respective marginal distributions. The variances of u_i^j, $j = 1,\cdots,J$, and v_i are σ^j and 1, respectively. ε_i^j, $j = 1,\cdots,J$, are zero mean random variables distributed independently of X_i and λ_i^j.

As in Heckman's (1979) original procedure, while the λ_i^j's are not observed, consistent estimates of them are derived from using consistent estimates of the γ parameter vectors and the corresponding μ^{j-1} and μ^j. The existence of sample selection bias (and therefore the endogeneity of schooling decisions) could then be examined via a test of the null hypothesis that the ρ^j's are zero using the *t*-distribution.

For each schooling level $j = 1,\cdots,J$, estimation of equations (9) yields a specific estimate $\hat{\beta}^j$ which in turn, allows simulation of the earnings distribution one would have observed had all individuals had schooling level *j* as:

$$e_{i|j} = \exp\left\{X_i'\hat{\beta}^j\right\}, \qquad j = 1,\cdots,J \tag{11}$$

Thus, for each individual *i* with schooling level *j*, the (marginal) return to investing a j^{th} year in education is given by:

$$r_{m,i}^j = \frac{e_{i|j}}{e_{i|j-1}} - 1, \qquad j = 2,\cdots,J \tag{12}$$

and the average marginal return, r_m^j, associated with schooling level j is simply the sample mean of individual marginal returns. Likewise, cumulative returns to schooling with reference to the lowest schooling level $(j = 1)$ could be estimated as:

$$r_{c,i}^j = \frac{e_{i|j}}{e_{i|1}} - 1, \qquad j = 2,\cdots,J \tag{13}$$

and the average cumulative return, r_c^j, associated with schooling level *j* as the sample mean of individual cumulative returns.

Among the β coefficients, those associated with age are of particular importance. Not only would one expect age-earnings profiles to be different from one schooling level to another, but also that they be steeper as one moves from one schooling level to a higher one. For individuals in the j^{th} group, $j = 1, \cdots, J$, starting wages, start_i^j, could be estimated using the j^{th} equation in (9) where age is set equal to the number of years of schooling augmented by 6 years and where job seniority is set equal to 0. For the average individual in that group, the starting wage, start^j, is simply the sample mean of start_i^j. Likewise, assuming Equations (9) are quadratic functions of age, the slope of the corresponding age-earnings profile could be estimated as:

$$\text{slope}_i^j = \exp\left\{\hat{y}_i^j\right\} \cdot \left(\hat{a}^j + 2\hat{b}^j \cdot \text{age}_i\right) \tag{14}$$

where $\hat{y}_i^j$ is the predicted wage of individual *i* with schooling level *j* and where $\hat{a}^j$ and $\hat{b}^j$ are the estimated coefficients associated with age and its square, respectively. Again, for the average individual in group *j*, the slope, slope^j, of the age-earnings profile is simply the sample mean of slope_i^j. The age, peak^j, at which the age-earnings profile of individuals in group *j* peaks is then $-\hat{a}^j / 2\hat{b}^j$. Rank correlation coefficients of schooling levels $j = 1, \cdots, J$ with start^j, slope^j and peak^j, together with their significance levels could be used to examine how age-earnings profiles vary with schooling levels and, in a sense, the extent to which they are influenced by education.

One could also infer from the estimation of equations (9), the predicted earnings distribution within each educational group $j = 1, \cdots, J$. Within each group, the components of the *X* vector, including age, are thus the only source of earnings variation. And the role of a given variable in within-educational group earnings inequality could be assessed simply by holding the other variables constant within that group. By assigning each component of the *X* vector, its average value, except age, we get age-earnings distributions, conditional on educational levels. As a matter of fact, schooling-earnings distributions, conditional on age are then also available. To be more specific, let $e_{\bar{x}}^{j,a}$ denote the predicted earnings of individuals aged *a*, $a = 16, \cdots, 64$, with schooling level *j*, $j = 1, \cdots, J$, assuming they are endowed with the sample average characteristics. For a given value of *j*, say $\tilde{j}$, $e_{\bar{x}}^{\tilde{j},a}$, $a = 16, \cdots, 64$, is the age-earnings distribution, conditional on $j = \tilde{j}$. For a given value of *a*, say $\tilde{a}$, $e_{\bar{x}}^{j,\tilde{a}}$, $j = 1, \cdots, J$, is the schooling-earnings distribution, conditional on $a = \tilde{a}$.

Of course, one can also infer from the estimation of equations (9), the marginal schooling-earnings distribution $e_{\bar{x}}^{j,\bullet}$, $j = 1, \cdots, J$, which is simply the mean of the distributions, conditional on age. Similarly, the marginal age-earnings distribution $e_{\bar{x}}^{\bullet,a}$, $a = 16, \cdots, 65$ which is the mean of the distributions, conditional on schooling.

Overall, the earnings distributions predicted from estimation of equations (9) can be summarised as in Table 1 where $f_{\tilde{j},\tilde{a}}$ denotes the proportion of individuals with schooling level $\tilde{j}$, aged $\tilde{a}$. Our assessment of the effect of education on earnings inequality will thus be based on Gini coefficients associated with these various distributions.

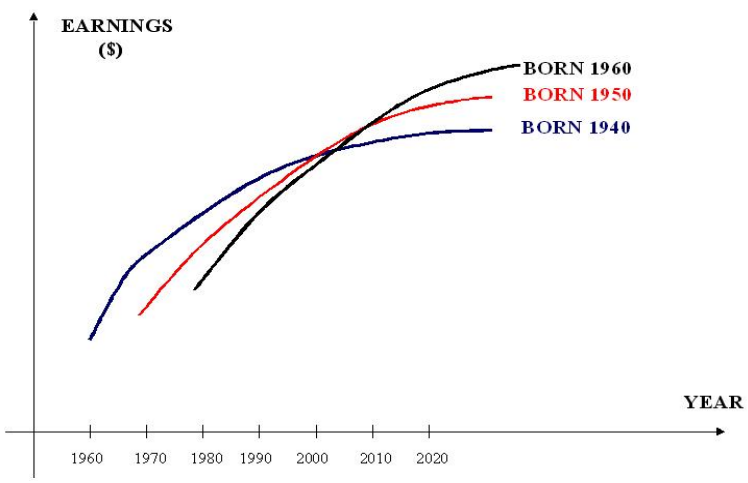
One issue of importance here is that of the definition of average characteristics. If $e_{\bar{x}}^{j,a}$ is inferred using the average characteristics of the sample of individuals aged *a* and with schooling level *j*, then the earnings distribution $e_{\bar{x}}^{\tilde{j},a}$, $a = 16, \cdots, 65$, for instance will obviously reflect the role of age, but also that of differences in observed characteristics across age groups. Likewise, the earnings distribution $e_{\bar{x}}^{j,\tilde{a}}$, $j = 1, \cdots, J$, will reflect the role of education, but also that of differences in observed characteristics across educational groups. In contrast, if $e_{\bar{x}}^{j,a}$ is inferred using the average characteristics of the whole sample of individuals, then the earnings distributions $e_{\bar{x}}^{\tilde{j},a}$, $a = 16, \cdots, 65$, and $e_{\bar{x}}^{j,\tilde{a}}$, $j = 1, \cdots, J$ will reflect exclusively the role of age and education, respectively. When averaging is based on the marginal distribution of characteristics (no conditioning, neither on age nor on education), the resulting earnings distributions will be denoted $e_{\bar{x}_m}^{\tilde{j},a}$, $a = 16, \cdots, 65$, and $e_{\bar{x}_m}^{j,\tilde{a}}$, $j = 1, \cdots, J$, respectively.

One problem with the procedure described above is that the resulting estimates of age-earnings profiles and hence, of the earnings distributions, conditional on schooling levels, are noised by cohort effects. That is, if young cohorts are better endowed with education, then age-earnings profiles of the young will be steeper. In a cross sectional framework, this results in general in age-earnings profiles that are concave, suggesting that at some point of one's working life, earnings reach their maximum level and start decreasing. Figure 1 below illustrates the effect of cohorts on cross-sectional age-earnings profiles.

Table 1. Conditional and Marginal Earnings Distributions Predicted from Equations (9)

j \ a	16		$\cdots$	$a=\tilde{a}$		$\cdots$	65		marginal	
1	$e_{\tilde{x}}^{1,16}$	$f_{1,16}$	$\cdots$	$e_{\tilde{x}}^{1,\tilde{a}}$	$f_{1,\tilde{a}}$	$\cdots$	$e_{\tilde{x}}^{1,65}$	$f_{1,65}$	$e_{\tilde{x}}^{1,\bullet}$	$f_{1,\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$j=\tilde{j}$	$e_{\tilde{x}}^{\tilde{j},16}$	$f_{\tilde{j},16}$	$\cdots$	$e_{\tilde{x}}^{\tilde{j},\tilde{a}}$	$f_{\tilde{j},\tilde{a}}$	$\cdots$	$e_{\tilde{x}}^{\tilde{j},65}$	$f_{\tilde{j},65}$	$e_{\tilde{x}}^{\tilde{j},\bullet}$	$f_{\tilde{j},\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
J	$e_{\tilde{x}}^{J,16}$	$f_{J,16}$	$\cdots$	$e_{\tilde{x}}^{J,\tilde{a}}$	$f_{J,\tilde{a}}$	$\cdots$	$e_{\tilde{x}}^{J,65}$	$f_{J,65}$	$e_{\tilde{x}}^{J,\bullet}$	$f_{J,\bullet}$
marginal	$e_{\tilde{x}}^{\bullet,16}$	$f_{\bullet,16}$	$\cdots$	$e_{\tilde{x}}^{\bullet,\tilde{a}}$	$f_{\bullet,\tilde{a}}$	$\cdots$	$e_{\tilde{x}}^{\bullet,65}$	$f_{\bullet,65}$		

Figure 1. Cohort Effects and Age-Earnings Profiles.



To estimate age-earnings profiles that are free of cohort effects, we simply distinguish between four 10-year cohorts and conduct the estimation strategy described above within each cohort. To be more specific, we consider four birth cohorts: 1934-1943, 1944-1953, 1954-1963 and 1964-1973. Of course, the earnings distributions, conditional on schooling levels, one infers within each cohort are not comparable across cohorts since they do not cover the same age bands. However, once the returns to age and to any other individual characteristic are estimated within a given cohort, one can simulate the earnings distribution one would have observed had all individuals belonged to that cohort.

To conduct this estimation strategy, we use the French Labour Force Survey (LFS). The sample consists of some 300,000 full-time male workers aged 16-65 in the year of interview, obtained from pooling the twelve consecutive annual LFS cross-sections from 1990 to 2001.[11]

The specification we consider for equations (9) has deflated gross monthly wages on the left hand side.[12] In the right hand side, we include age and its square, job tenure and its square, one marital status dummy, the number of children, one citizenship dummy, one capital city dummy, one private sector employment dummy, one permanent labour contract dummy and ten year dummies (those observed in 1990 being the omitted group).

Equation (7) on the other hand is estimated as an ordered probit on the left hand side of which is a qualitative variable with nine possible outcomes. The schooling level of those who attended school up to age 16 (10 years of schooling) is coded 1.[13] That of the others is coded as $j = S - 10 + 1$ where $S = 11, \cdots, 17$ is the actual NYS, and $j = 9$ for those who attended school for more than seventeen years.

In an individual optimising framework, the decision to leave or to invest a further year in education depends on individuals' wage expectations. Therefore, the reduced form probit equations we estimate, include all observable wage determinants. That is, all the regressors in

[11] This is the so-called *Enquête Emploi* which is a rotating panel where individuals are observed thrice. Earnings information in data prior to 1990 is given in earnings bands. Summary statistics are given in Table 1.

[12] Net earnings are not predictable from the data because of the non-neutrality of the French tax system and because taxes are calculated on a household basis. The data provides usually worked hours as well as actually worked hours of the last week, so that one could a priori calculate a proxy of hourly earnings. The resulting variable might, however, suffer from large measurement errors for certain occupational categories such as teachers, white collars, self-employed, seasonal workers, etc.

[13] Compulsory schooling in France has been established at 13 years in 1882, 14 in 1936 and 16 since 1959.

equation (6) are included in the vector *Z*. However, like in the IV approach, identification in the model is provided only if the vector *Z* includes at least one variable that is not included in *X*. That is, there must exist a variable which is a determinant of schooling participation that can legitimately be omitted from the earnings equation. In an IV framework, Dearden (1995) uses parental education and social class while Uusitalo (1999) considers parental income and education. As an indicator of these family background dimensions, we take four dummies describing fathers' occupational status at the time the individual left school (private sector employee, self-employed with no employees, self-employed with less than 10 employees, self-employed with more than 10 employees; those whose father is/was a public sector employee being the omitted group).

3. Non-linear Returns to Schooling and Level-specific Age-Earnings Profiles

In this section, we start by identifying the determinants of schooling decisions. We then report estimations of level-specific earnings functions. Estimates of marginal returns to schooling, assuming a non-linear wage-schooling relationship, are then reported and discussed.

3.1. The Determinants of Schooling Decisions

Table 3 reports estimates of reduced form schooling equations using the ordered probit model. The results in the first four columns are cohort-specific whereas the last column reports results from the whole sample.

While age is not significant, the sign on age squared indicates that old individuals are less likely to reach high levels of education than young ones. This is a cohorts effect suggesting that young cohorts are better endowed with education than older cohorts. Likewise, job tenure seems to have a decreasing and convex impact on the likelihood that individuals reach the highest schooling levels. This is exactly what one would expect since among two equally aged individuals, the one with the shortest schooling duration is more likely to have a longer job tenure. The effect of job tenure is, however, cohort specific. Insignificant for the oldest cohort, it is increasing and concave within the two middle cohorts, hence suggesting that, within these two cohorts, the highly educated are individuals, the less likely are their employers to let them leave. In contrast, for the youngest cohort, the negative effect of seniority is most likely to reflect the idea that the longer youngsters attend school, the less likely to have experienced long seniority spells. For the whole sample as well as for the three most younger cohorts, the negative sign on the number of children indicates either that child care duties limit the likelihood that individuals keep on investing in education or simply that the highly educated have fewer children than individuals with low educational attainments. For the oldest cohort, however, the number of children seems to be positively correlated with educational attainments, probably indicating that for the elderly, access to education was possible only to those with favourable socio-economic background and who could at the same time afford having children. It seems also that, although insignificant within three cohorts out of four, marriage is positively correlated with educational attainments. This might suggest that marriage is more likely to occur among highly educated individuals. Note also that, whatever cohort one considers, the French are much more likely to reach higher educational levels than foreigners. In addition, the proportion of well educated individuals seems to be much higher in the area of Paris than anywhere in France. Also, the results suggest that the private sector employs a higher proportion of low educated people, no matter how old they are. Finally, it is clear from the results that the higher is one's educational level, the more likely he/she is to be in a permanent job position. Note that such a correlation is not significant within the oldest cohort, probably because most of the elderly are in permanent positions.

Turning on to our instrumental set of dummies, it appears that, either on the overall sample or within each of the four cohorts, they are systematically highly significant and have a robust effect on individuals' educational investment decisions. They indicate that, compared to those who's father was a public sector employee, sons of the self employed, employing less than ten employees or of private sector employees are less likely to do attain high educational levels. In contrast, those who's father is a self employed, employing more than ten employees do definitely perform better at school.

3.2. Estimates of the Returns to Schooling: Endogeneity and Non-linearity Taken Together

To simultaneously account for possible non-linearities in the wage-schooling relationship as well as for the endogeneity of schooling levels, we estimate a wage equation for each of the 9 educational levels. This is done for the whole sample first and then within each of the four cohorts we consider. This requires that selectivity be controlled for. Inverse Mill's ratios should therefore be estimated and this is done using the reduced-form ordered probit schooling equations discussed above. Because no significant qualitative differences emerge from the estimations drawn from the whole sample and from cohort-specific samples, Table 4 reports the results from selectivity corrected level-specific wage equations, estimated using the whole sample.[14]

A striking feature of Table 4 is the high significance level of the coefficients associated with inverse Mill's ratios. This is evidence that correction for selectivity is crucial and therefore that the schooling levels individuals reach are indeed endogenous.
Besides, the results are again in line with those usually observed. Age-earnings profiles are systematically increasing and concave. Likewise, tenure-wage profiles are also increasing and concave. In addition, the impact of the number of children seems to be highly level-specific. It is negative for the three lowest educational levels, positive within groups 7 and 9 and insignificant for the other groups. In contrast, being married systematically yields a significant wage premium. Likewise, whatever their educational attainment is, French citizens earn more than foreigners, although the citizenship wage premium is lower for the least educated. Also, no matter what their educational level is, inhabitants of the Great Paris area always earn more than comparable workers of other areas of France. It is, however, worth noting that there is no clear association between the capital-city wage premium and educational levels. Another wage differential the results highlight is that related to private sector employment as, except for the least educated (level 1), private sector employees systematically earn more on average than their public sector counterparts. Even more interesting is the increase of the wage differential between private and public sector employees with educational levels. Also not surprising is the systematically positive sign on the permanent contract dummy, which indicates that employees with permanent positions always earn more than the others. Note finally that the permanent position premium is also positively correlated with educational levels.

Perhaps, the most interesting pattern the results in Table 4 highlight is the importance of the consideration of a specific regime of wage determination for each educational level. It is indeed clear from the outset that despite the apparent cross-regime similarity in the effect of some wage determinants, there are significant differences which might result in a pooling data bias if not accounted for. Although not reported, a number of Chow-type tests rejected the hypothesis of identical regimes of wage determination. In particular, age-earnings as well as seniority-earnings profiles are significantly different, just like human capital theory would predict.

[14] The results from within-cohort analyses can of course be made available from the authors upon request.

The returns to education estimated through the switching regression model with endogenous switching are reported in Table 5. Whether based on the overall sample or on cohort-specific samples, the results show that the marginal returns to education are not constant, hence suggesting that the wage-schooling relationship is not linear. The last column of Table 5 shows for instance that while one further year after compulsory schooling yields a wage increase of almost 22%, the first year of tertiary education (j = 4) yields an extra wage of less than 9% above the salary of those who undertake no further investment after high school graduation. In addition, the wage-schooling relationship is not concave either. For instance, the return to high school graduation (j = 2) is only 7% just as much as the returns to graduation from tertiary education (j = 9). Overall, the estimated marginal returns obey to no specific functional form; rather, they oscillate across educational levels. Overall, marginal returns to education are not correlated to educational levels and this is evidence that not only is the wage-schooling relationship not linear, but marginal returns are neither monotonically increasing nor monotonically decreasing.

4. Age- and Education-Related Earnings Inequality

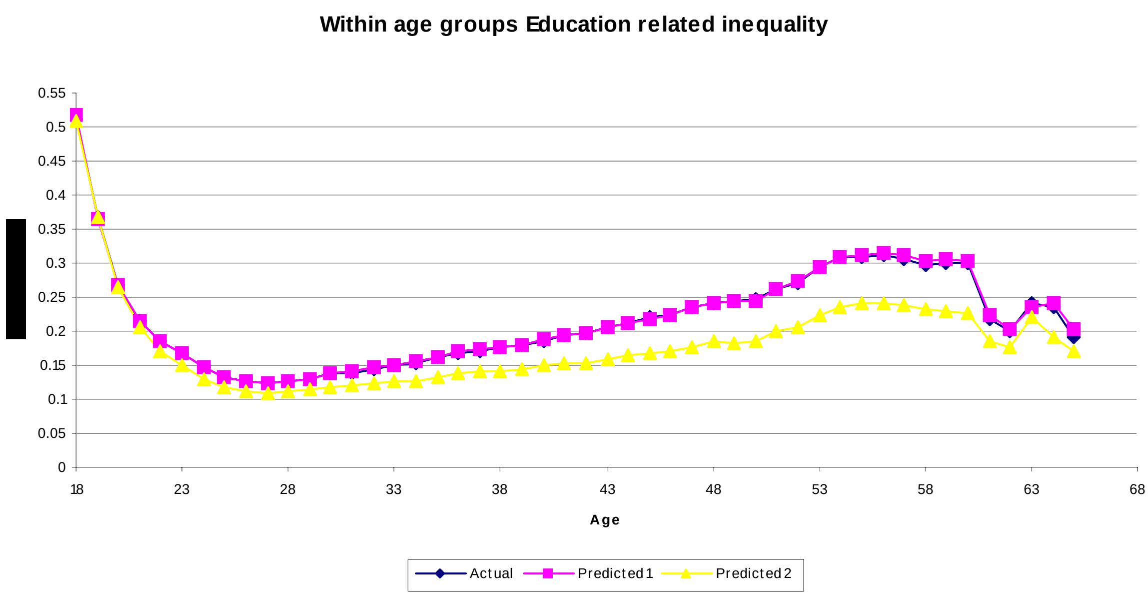
The estimation strategy described above allows one to explicitly account for the prediction of human capital theory; that differently educated people would face different age-earnings profiles. As the estimation results reported in the previous section show, the effects on wages of the variety of observable characteristics we consider are indeed different across educational levels. In particular, the effect of age is level-specific.

What human capital theory actually predicts is that the level as well as the slope of age-earnings profiles are increasing functions of the accumulated amount of human capital. This would mean that within any educational level, there will be some wage inequality that is due to the positive correlation between wages and age and the extent of that inequality would primarily depend on the slope of the corresponding age-earnings profile. As a consequence, if the slopes increase with educational levels, then within educational groups wage inequality would also increase with educational levels. This is the slope effect of education on wage inequality. Likewise, within each age group, there will be some wage inequality that is due to the positive correlation between wages and education and the extent of that inequality would primarily depend on how dispersed are the levels of age-earnings profiles for that age group.

Consequently, if that dispersion increases with age, then within age groups wage inequality would also increase with age. This is the level effect of education on wage inequality.

4.1. The Level Effect of Education on Wage Inequality

Figure 1 reports Gini coefficients associated with two types of predicted wage distributions conditional on age. More specifically, the series labelled "predicted 2" is based on distributions where the only source of variation is age whereas, the one labelled "predicted 1" is based on distributions where all observables are left free to vary across individuals. These curves illustrate the level effect of education on wage inequality. On the same Figure are also reported Gini coefficients associated with within age group actual wage distributions. It can easily be seen that the actual and the predicted series of type 1 of Gini coefficients are very close to each other, hence suggesting that our model predicts pretty well the actual within age groups inequality measures. On the other hand, comparison of predicted series of type 1 and 2 shows that the latter is most of the time below the former. More specifically, the two curves are pretty close to each other for young values of age, which suggests that for young people, the main, if not the sole source of within age groups wage inequality is education, via the level effect. In addition, as one moves along age-earnings profiles, the contribution of education to overall within age groups inequality decreases, although it remains rather important.. This means that as individuals get older, the contribution of inequality sources, other than education increases. Interestingly enough, the contribution of other observable characteristics shrinks again above age 60 and thus suggests that for both the very young and the very old, education is the main contributor to within age group wage inequality.



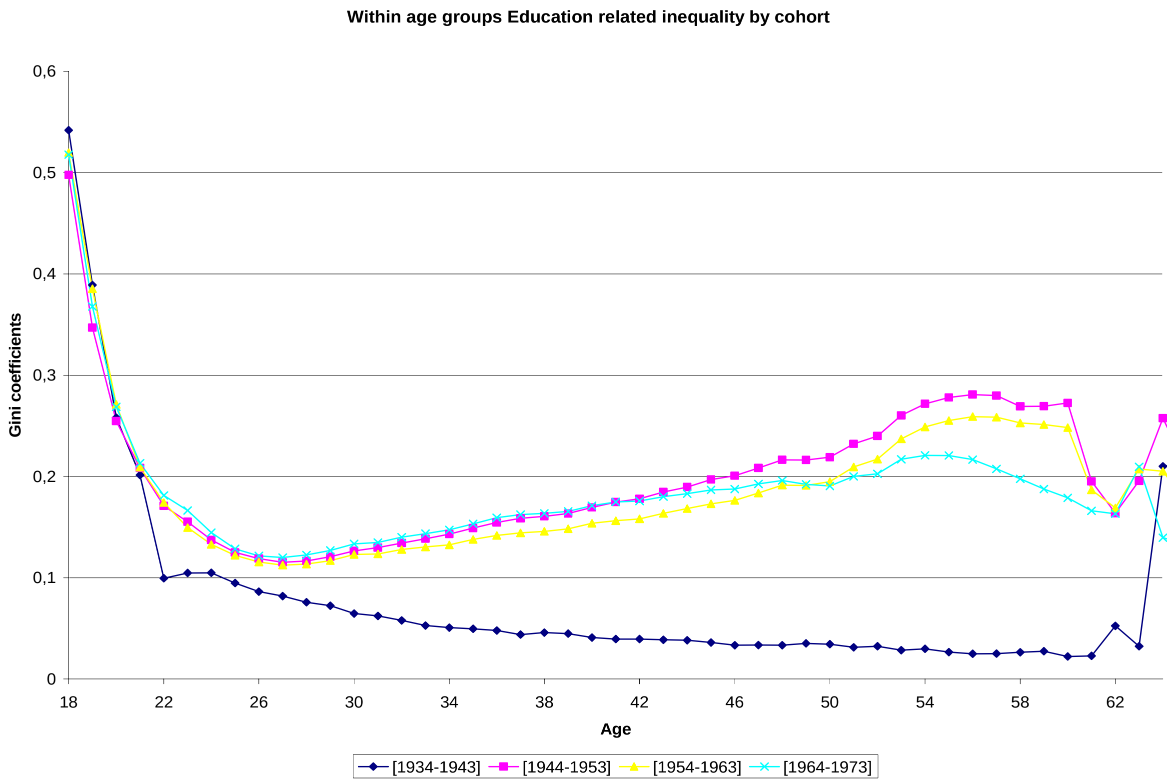
The series of Gini coefficients reported in Fig. 1 could be roughly split into three main parts: from age 18 to 24, from 24 to 60 and then above 60. The first part highlights a decreasing pattern of within age groups wage inequality. More specifically, at age 18 the Gini coefficient is more than 0.5. One interpretation of this is that at age 18, almost no sampled individual has reached tertiary education yet and the proportion of early school leavers and low achievers is the highest among the 18-years-old. For this category of individuals, there are obviously huge wage differences, in line with the very high marginal returns to the two first educational levels reported in Table 5. As one moves to higher age values, the proportion (the weight) of early school leavers decreases and individuals with higher educational levels enter the sub-sample of each age group, hence the decrease in the Gini coefficients series up to age 24.

Starting from age 24 at which the majority has had the opportunity to complete higher education and up to age 60, the series of Gini coefficients in Fig. 1 steadily increases. This reflects the positive correlation between the slope of age-earnings profiles and educational levels. Indeed, such a positive correlation implies that as one moves along the horizontal axis the wage gap between the highly educated and the low educated increases.

Above age 60, the series of Gini coefficients is neither clearly increasing nor clearly decreasing. It is often argued that age-earnings profiles peak at a certain age and that the higher is one's educational level, the later her/his age-earnings profile peaks. If this were true, then the Gini coefficients curve would have remained increasing even after age 60. Clearly, this is not what Fig. 1 suggests. In other words, there is no clear association between peaking ages and educational levels. Skalli (2003) for instance, shows that the correlation between educational levels and peaking ages is not significant, albeit positive.

As underlined in Section 2, one reason why age-earnings profiles estimated from cross-sectional data seem to peak is the existence of cohort effects. If educational attainments of younger cohorts are higher then age-earnings profiles become steeper and steeper as one considers younger cohorts. As a consequence, what one observes in cross-sectional data is young individuals who earn less than older ones (increasing part of age-earnings profiles) not because they are less educated but rather because they entered the labour market later and old individuals who earn less than younger ones (decreasing part of age-earnings profiles) not because they are older but because they are on average less educated.

To overcome this problem, we have split our sample into four cohorts and conducted a similar estimation strategy within each cohort. Once the wage determinants specific to each cohort have been estimated the earnings of all individuals have been predicted as if they all belonged to that specific cohort and corresponding Gini coefficients have been inferred accordingly. Fig 2 plots these and highlights several interesting patterns.



First, between age 18 and age 24, the curves of Gini coefficients are again decreasing, just like when no distinction between cohorts were made. This mean that the early school leavers effect is common to all cohorts.

Second, between age 24 and 60, the series of Gini coefficients are increasing for the three younger cohorts, not for the older one. For the latter, the series are even decreasing, hence suggesting that age-earnings profile converge one to another as age increases. This contradicts the idea of a positive correlation between educational levels and the slopes of age-earnings profiles.

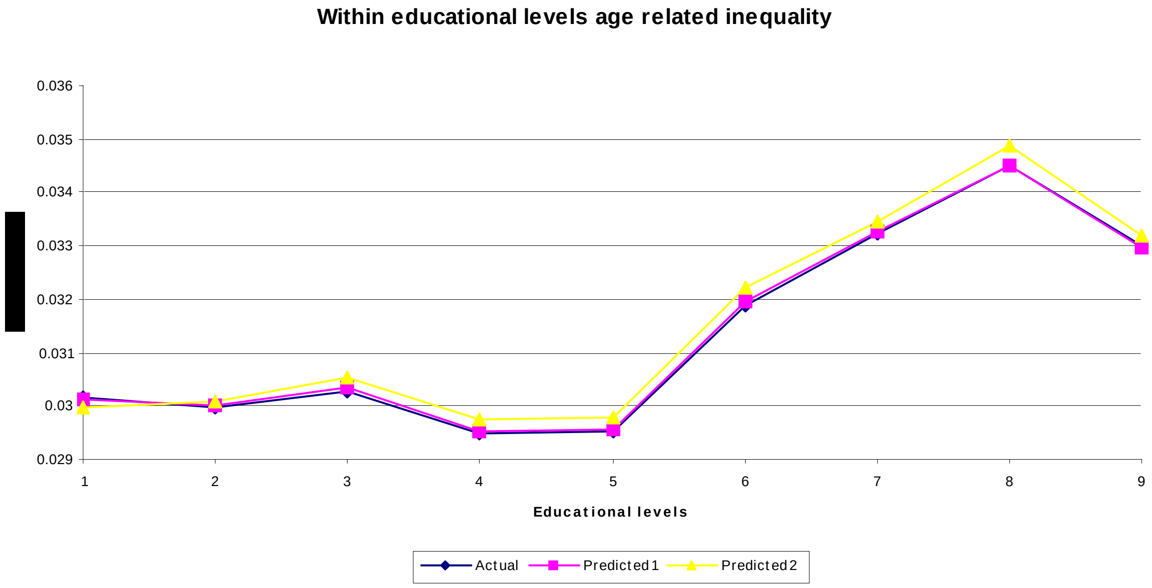
For the three youngest cohorts, the pattern of Gini coefficients is increasing. However, while one would expect that as cohorts get younger the age-earnings profiles would become steeper, hence yielding higher wage inequality, no such a pattern emerges from Fig. 2. Not only are the differences across cohorts in Gini coefficients for each age group very small, but at high age values, there even seems to be less inequality among younger cohorts' members.

Third, above age 60, the series of Gini coefficients fluctuate, again reflecting the peaking age effect. This means that distinction between four cohorts is not enough to cancel it. Note, however, that for every age value above 24, the Gini coefficients in Fig. 2 are lower than their counterparts in Fig. 1, which suggests that part of the inequality measured in the latter is also due to the differences between cohorts.

4.2. The Slope Effect of Education on Wage Inequality

Figure 3 reports Gini coefficients associated with two types of predicted wage distributions conditional on educational levels. The series labelled "predicted 2" is based on distributions where the only source of variation is education whereas, the one labelled "predicted 1" is based on distributions where all observables are left free to vary across individuals. These curves illustrate the slope effect of education on wage inequality. On the same Figure are again also reported Gini coefficients associated with within educational levels actual wage distributions. It can again be seen that the actual and the predicted series of type 1 of Gini coefficients are very close to each other, hence suggesting that our model successfully predicts the actual within educational groups inequality measures. On the other hand, comparison of predicted series of type 1 and 2 shows the two curves are very close to each other, especially for low educational levels. Although we have not tested whether the observed differences are statistically significant, we could obviously conclude that what these results show is that education is again the most important contributor to within educational levels wage inequality. At the extreme, if one assumes that the differences between the two curves are statistically significant for higher levels of education, then the interpretation would be that within educational levels wage inequality would have been even higher if the other observable characteristics did not lower the variance of wages within educational categories. Note, however, that perhaps, the most striking feature of Fig. 3 is the fact that the Gini coefficients it reports are at least ten times lower than the ones reported in Fig. 1. This simply means that the slope effect of education on wage inequality is much weaker that the level effect. Put differently, within age groups wage inequality is much higher than within educational level wage inequality.

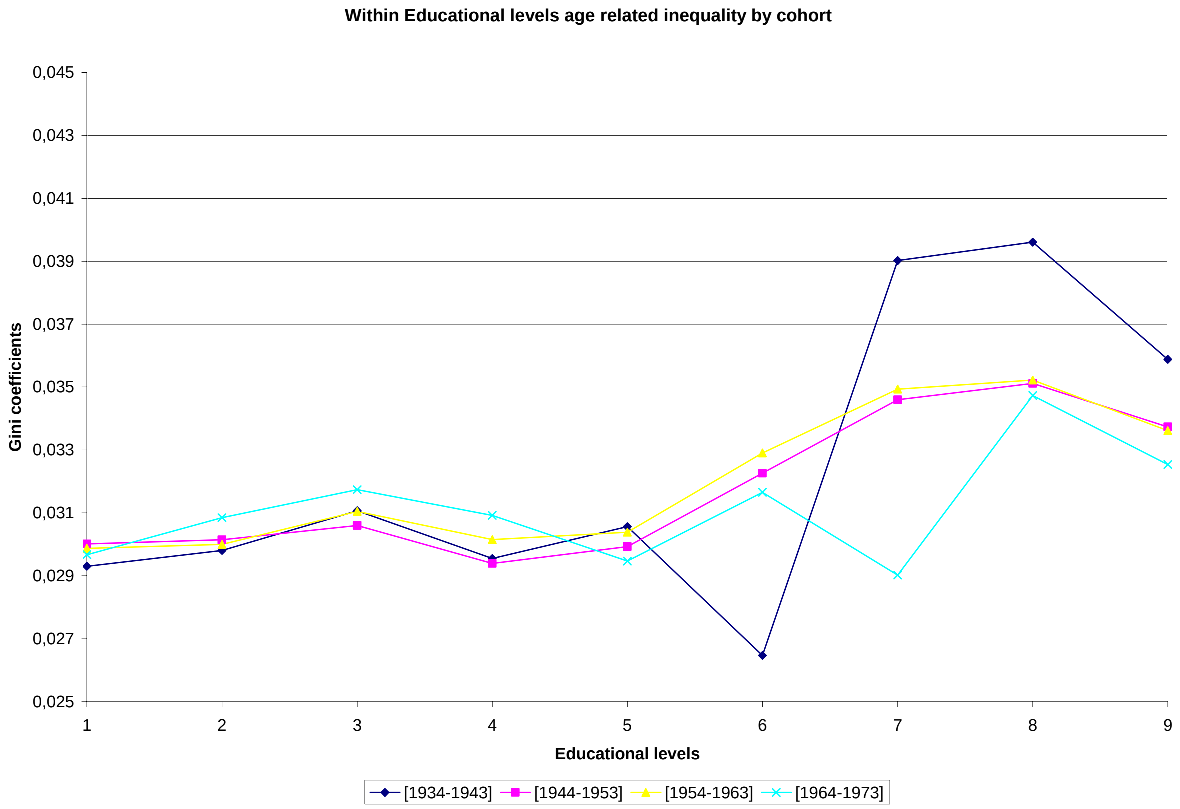
The series of Gini coefficients reported in Fig. 3 could also be roughly split into three main parts: from level 1 to level 5, from level 5 to level 8 and then level 9. The first part highlights a slightly decreasing pattern of within educational levels wage inequality. More specifically, although the differences are not very big, inequality is the highest among level 3 individuals (high school degree level) and the lowest amongst people with one or two years in tertiary education. This suggests that up to level 5, the slopes of age-earnings profiles are not positively correlated with educational levels as one would have expected.



Starting from level 5 (second year of tertiary education) and up to level 8 (graduation from tertiary education), there is a significant increase in wage inequality, suggesting that as one moves along the second and third cycles of tertiary education, the slopes of age-earnings profiles get steeper enough to yield such an increase in within educational levels wage inequality.

Within educational level 9, however, wage inequality seems to be lower than within educational level 7 and 8. The age-earnings profile within the former level is therefore flatter than that of the latter two groups. Nevertheless, it is worth noting that in contrast to its previous counterparts, level 9 corresponds to a rather heterogeneous group as it comprises individuals who have been involved in post graduation studies, but also a significant number of late achievers; that is, individuals to whom it took longer to reach graduation from tertiary education.

The analysis conducted within cohorts yields similar results and highlights the following patterns. First, from level 1 and up to level 5, there is only a very slight difference in within educational levels wage inequality and no cohort ranking is possible. This means that for these first five groups there are almost no cross-cohort changes in the slopes of age-earnings profiles. From level 5 and up to level 8, the Gini coefficients increase with education and there seems to be a clear ranking of the subsequent cohorts. That is, within each educational group, inequality decreases as one moves towards younger cohorts. This means that for these educational groups, age-related inequality tends to decrease over time, albeit very slightly. Within group 9, age-related inequality is systematically lower than within group 7 or 8. Again, this certainly reflects the sample heterogeneity of the ninth group.



5. Concluding Remarks

In this paper, an analysis of the role of education as an important contributor to wage inequality is proposed. The basic idea is that education influences wage inequality via its impact on age-earnings profiles: the higher is one's educational level is, the higher is her/his age earnings profile and the steeper it is. Thus, education increases inequality by yielding a dispersion of wages within each age group, but also by increasing the speed at which one's wages increase throughout her/his working career. It hence generates within age groups wage inequality via its level effect and within educational level inequality via its slope effect.

The analysis is based on wage distributions predicted from estimated Mincer-type equations. However, our estimation strategy relies on a switching regression model with endogenous switching which entails estimation of a specific earnings function for each educational level. It hence allow one to simultaneously account for (i) the endogeneity of schooling decisions via a selectivity model, (ii) non-linearity of the earnings-schooling relationship and (iii) differences across educational groups in the effects on wages of observed earnings determinants. In particular, this approach allows estimation of specific age-earnings profiles for each educational group.

Our results show that (i) endogeneity is indeed a crucial issue, that (ii) not only do the returns to education vary across educational groups, hence suggesting the earnings-schooling relationship is not linear, but they obey to no specific non-linearity scheme and that (iii) there is indeed a specific regime of wage determination for each educational group; in particular, age-earnings profiles are significantly different, just like human capital theory predicts.

The results also show the pattern of wage inequality within age groups as well as within educational levels. Comparison of Gini coefficients estimated from predicted wage distributions where the only source of variation is schooling or age to corresponding figures drawn from the actual wage distribution suggests that education is the main contributor to wage inequality. This is clearly good news as such inequalities are beneficial in the sense that they endow individuals with incentives to do better. But the results also show there are huge inequalities in opportunities as inequality is the highest among the youngest. That is, within those groups where the proportion of early school leavers and low achievers is the highest.

Otherwise, within age groups (level effect) is much higher than inequality within educational groups (slope effect). In addition, inequality increases across age groups, hence suggesting the correlation between education and the slope of age-earnings profiles is positive. However, only for high educational levels does the slope effect increase with education. Finally, distinction between different cohorts did not result in a clear assessment of the effect of cross-cohort differences in educational attainments on age-earnings profiles.

Clearly, further research is needed in order to better assess the level and the slope effects of education on wage inequality. First, real cohort data are clearly better suited to perform this kind of analysis. Second, even if based on cohort data, the results from the Mincer-type approach are to be compared to those based on the conventional inequality indexes approach.

References

Aghion, P., E. Caroli and C. García-Peñalosa (1999), “Inequality and Economic Growth: The Perspective of the New Growth Theories”, *Journal of Economic Literature*, 37(4), 1615–1660.

Angrist, J.D. and A. B. Krueger (1992), “Estimating the Pay to Schooling Using the Vietnam-Era Draft Lottery”, *National Bureau of Economic Research Working Paper*, N° 4067.

Asplund, R. (2004), “A Macroeconomic Perspective on Education and Inequality”, *Etla*, Discussion Papers N° 906.

Atkinson, A.B. (1996), “Income Distribution in Europe and the United States”, *Oxford Review of Economic Policy*, 12 (1), pp.15-28.

Atkinson, A.B., L. Rainwater and T. Smeeding (1995), “Income Distribution in OECD Countries: Evidence from the Luxembourg Income Study (LIS)”, *Social Policy Studies*, 18. Paris: Organization for Economic Cooperation and Development, October.

Azariadis, C. and A. Drazen (1990), “Threshold externalities in development”, *Quarterly Journal of Economics*, 105, 501-526.

Barro, R. J. (1991), “Economic growth in a cross-section of countries”, *Quarterly Journal of Economics*, 106, 407-43.

Bassanini, A. and S. Scarpetta (2001), “The Driving Forces of Economic Growth: Panel Data Evidence for the OECD Countries”, *OECD Economic Studies*, No. 33, 2001/II.

Baumol, W. J., Batey Blackman S. A., and E. N. Wolff (1989), “Productivity and American Leadership: The Long view”, *Cambridge M.A.*, M.I.T. Press.

Bénabou, R. (1996), “Inequality and Growth”, *NBER Macroeconomics Annual*, 11–74.

Benhabib, J. and M. M. Spiegel (1994), “The role of human Capital in Economic Development: Evidence from Aggregate Cross-Country Data”, *Journal of Monetary economics*, 34(2), 143-74.

Bertola, G. (1999), “Macroeconomics of Distribution and Growth”, in Atkinson, A.B. and F. Bourguignon (eds), *Handbook of Income Distribution*, Volume 1, North-Holland, Amsterdam.

Card, D. (1999), “The Causal Effect of Education on Earnings”, in Ashenfelter, O. and D. Card (eds), *The Handbook of Labor Economics*, Volume 3, part 7, 1801-63, Elsevier, Amsterdam.

Card, D. (1993), Using Geographic Variation in College Proximity to Estimate the Return to Schooling, National Bureau of Economic Research Working Paper N° 4483.

Caselli, F., G. Esquivel and F. Lefort (1996), “Reopening the convergence debate: a new look at cross-country growth empirics”, *Journal of Economic Growth*, pp. 363-89.

Cohen, D. and M. Soto (2001), “Growth and human capital: good data, good results”, *CEPR*, Discussion paper no. 3025.

Cowell, F.A. (2000), “Measurement of inequality”, In: Atkinson, Bourguignon (eds.), *Handbook of Income Distribution*, vol. 1, Elsevier Science, B.V., Amsterdam, 87-166.

De la Fuente, A. (2003), “Human capital in a global and knowledge-based economy”, part II: assessment at the EU country level, Final Report, Instituto de Análisis Económico (CSIC).

De la Fuente, A. and R. Doménech (2002), “Human capital in growth regressions: how much difference does data quality make? An update and further results”, *CEPR*, Discussion Paper no. 3587.

Dearden, L. (1995), “Education, Training and Earnings”, PhD Thesis, *University College Dublin*.

Denny, K. J. and C. P. Harmon (2001), “Testing for Sheepskin Effects in Earnings Equations: Evidence from Five Countries”, *Applied Economics Letters*.

Forbes, K.J. (2000), “A Reassessment of the Relationship Between Inequality and Growth”, *American Economic Review*, 90(4), 869–887.

Garen, J. (1984), “The Returns to Schooling: A Selectivity Bias Approach with a Continuous Choice Variable”, *Econometrica*, September, 52(5), pp.1199-1218.

Harmon, C. and I. Walker, “Estimates of the Economic Return to Schooling for the United Kingdom”, *American Economic Review*, 1995, 85(5), pp.1278-86.

Harmon, C., I. Walker and N. Westergaard-Nielsen (2001), “Education and Earnings in Europe: A Cross Country Analysis of the Returns to Education”, *Edward Elgar Publishing*, Cheltenham, UK.

Heckman, J. J. (1979), “Sample Selection Bias as a Specification Error”, *Econometrica*, January, 47(1), pp. 153-61.

Islam, N. (1995), “Growth empirics: a panel data approach”, *Quarterly Journal of Economics*, 110, pp.1127-70.

Jones, C. I. (1996), “Human Capital, Ideas and Economic Growth”, Paper presented to the VIII Villa Mondragone, *International Economic Seminar on Finance, Research, Education and Growth*, Rome, Italy, (June).

Kane, T. J. and C. E. Rouse (1995), “Labour Market Returns to Two and Four Year College: Is a Credit a Credit and do Degrees Matter?”, *American Economic Review*, 85, pp. 600-14.

Krueger, A.B. and M. Lindahl (2001), “Education for Growth: Why and for Whom?”, *Journal of Economic Literature*, 39, 1101–1136.

Kyriacou, G. (1991), “Level and Growth Effects of Human Capital: A Cross-Country Study of the Convergence Hypothesis”, *New York: C.V. Starr Centre*, Working Paper 91-26.

Lucas, R.E. (1988), “On the mechanics of economic development”, *Journal of Monetary Economics*, 22, 3-42.

Mankiw, N.G., Romer D. and Weil D. N. (1992), “A contribution to the empirics of economic growth”, *Quarterly Journal of Economics*, 107, 407-37.

Park, J. H. (1999), “Estimation of Sheepskin Effects using the Old and New Measures of Educational Attainment in the Current Population Survey”, *Economics Letters*, 62(12), pp. 237-40.

Piketty, T. (1997), “L’économie des inégalités”, *Editions La Découverte, Collection Repères*, (2ème édition, 1999 ; 3ème édition, 2001 ; 4ème édition, 2002).

Pritchett, L. (1999), “Where has all the education gone?”, Mimeo, *World Bank*.

Psacharopoulos, G. (1994), “Returns to Investment in Education: A Global Update”, *World Development*, 22(9), 1325–1343.

Romer, P.M. (1989), “Capital Accumulation in the Theory of Long-run Growth”, in R.J. Barro (ed.), *Modern Business Cycle Theory*.

Skalli, A. (2003), “Are Successive Investments in Education Equally Worthwhile? Endogenous Schooling Decisions and Non-linearities in the Earnings-Schooling Relationship”, *ERMES*, Working Papers Number 03-18.

Topel, R. (1999), “Labor Markets and Economic Growth”, in Ashenfelter, O. & D. Card (eds), *Handbook of Labor Economics*, Volume 3. Elsevier, Amsterdam.

Tsakloglou, P. and I. Cholezas (2004), “Earnings inequality in Europe: structure and inter-temporal change”, mimeo, *Athens University of Economics and Business*, Department of International and European Economic Studies.

Uusitalo, R. (1999), “Returns to Education in Finland”, *Labour Economics*, November, 6(4), pp.569-80.

Vella, F. and R.G. Gregory (1996), “Selection Bias and Human Capital Investment: Estimating the Rates of Return to Education for Young Males”, *Labour Economics*, September, 3(2), pp. 197-219.

Appendix

Table 2: Descriptive Statistics

	S = 1	***S = 2***	***S = 3***	***S = 4***	***S = 5***	***S = 6***	***S = 7***	***S = 8***	***S = 9***	***All***
Mean and standard deviation of continuous variables										
Monthly wages	7322.06 (2580.91)	7957.77 (2870.48)	8176.33 (3193.49)	8584.67 (3496.97)	9230.42 (3827.44)	9659.72 (4073.37)	10454.15 (4507.10)	11544.66 (4951.97)	12391.09 (5177.01)	8506.64 (3686.60)
Number of years of schooling	8.7509 (1.2840)	11 -	12 -	13 -	14 -	15 -	16 -	17 -	19.5980 (1.9496)	11.91036 (3.2983)
Age	42.1742 (9.2524)	38.9548 (8.9943)	37.1054 (8.9525)	36.3204 (9.1727)	36.7001 (9.2550)	35.4013 (8.9922)	35.7310 (8.8558)	36.1297 (9.0284)	38.2486 (8.9423)	38.9753 (9.4465)
Job tenure	13.3305 (10.0801)	12.4947 (9.7316)	11.1461 (9.1841)	10.6216 (9.0472)	10.3632 (8.9680)	9.1372 (8.4929)	8.5351 (8.1716)	8.3827 (8.2546)	8.0844 (8.0060)	11.5131 (9.5625)
Number of children	1.4627 (1.2748)	1.3655 (1.1353)	1.3388 (1.1227)	1.2608 (1.1239)	1.2202 (1.1186)	1.1406 (1.1188)	1.1237 (1.1288)	1.0881 (1.1423)	1.1271 (1.1701)	1.3319 (1.1905)
Frequencies of qualitative variables										
Married	0.7256	0.6883	0.6328	0.6026	0.5951	0.5563	0.5515	0.5616	0.6000	0.6570
French citizen	0.9024	0.9684	0.9638	0.9656	0.9647	0.9714	0.9702	0.9703	0.9385	0.9421
Resident in Paris	0.1493	0.1340	0.1518	0.1681	0.1872	0.1970	0.2321	0.2730	0.3113	0.1731
Private	0.8377	0.7991	0.7872	0.7455	0.7371	0.7437	0.7507	0.7233	0.6455	0.7849
Permanent contract	0.9410	0.9416	0.9346	0.9238	0.9223	0.9127	0.9161	0.9189	0.9125	0.9324
Father was private sector emp.	0.6428	0.6401	0.6242	0.5914	0.5646	0.5510	0.5452	0.5178	0.5001	0.6080
Father self-employed, no emp.	0.1725	0.1392	0.1308	0.1289	0.1237	0.1240	0.1161	0.1143	0.1082	0.1430
Father self-emp., - than 10 emp.	0.0617	0.0544	0.0617	0.0687	0.0799	0.0796	0.0958	0.0954	0.1045	0.0687
Father self-emp.,+ than 10 emp.	0.0028	0.0047	0.0057	0.0067	0.0101	0.0110	0.0154	0.0204	0.02013	0.0070
Number of observations	112095	44481	56982	24099	21145	14099	13172	10551	21849	318473

Table 3: Reduced form schooling equations

	Ordered Probit model				
	1934 – 1943 cohort 1	**1944 – 1953 cohort 2**	**1954 – 1963 cohort 3**	**1964 – 1973 cohort 4**	**Whole sample**
Age	- -	- -	- -	- -	0.0011 (0.0019)
Age squared / 100	- -	- -	- -	- -	-0.0340 (0.0024)
Job tenure	-0.0016 (0.0021)	0.0226 (0.0014)	0.0204 (0.0017)	-0.0443 (0.0035)	-0.0232 (0.0007)
Job tenure squared / 100	0.0059 (0.0052)	-0.0960 (0.0044)	-0. 2090 (0.0076)	-0.2990 (0.0026)	0.0396 (0.0024)
Number of children	0.0329 (0.0056)	-0.0077 (0.0033)	-0.1169 (0.0032)	-0.1233 (0.0035)	-0.0719 (0.0018)
Married	0.0147 (0.0173)	0.0108 (0.0099)	0.0888 (0.0077)	-0.0108 (0.0083)	0.0308 (0.0047)
French citizen	0.6422 (0.0272)	0.5878 (0.0171)	0.2950 (0.0151)	0.4204 (0.0180)	0.4321 (0.0089)
Resident in Paris	0.2996 (0.0152)	0.2830 (0.0097)	0.3459 (0.0087)	0.2764 (0.0099)	0.3120 (0.0051)
Private	-0.4446 (0.0137)	-0.3762 (0.0083)	-0.3683 (0.0081)	-0.3558 (0.0110)	-0.3940 (0.0048)
Permanent contract	-0.0383 (0.0419)	0.0774 (0.0219)	0.1460 (0.0154)	0.0805 (0.0115)	0.0756 (0.0080)
Father was private sector emp.	-0.4119 (0.0160)	-0.3845 (0.0096)	-0.3055 (0.0088)	-0.1934 (0.0102)	-0.3190 (0.0052)
Father self-employed, no emp.	-0.6627 (0.0198)	-0.3590 (0.0121)	-0.2616 (0.0120)	-0.1323 (0.0148)	-0.3175 (0.0069)
Father self-emp., - than 10 emp.	-0.1645 (0.0233)	-0.0072 (0.0158)	0.0499 (0.0149)	-0.0341 (0.0173)	-0.0008 (0.0085)
Father self-emp.,+ than 10 emp.	0.6790 (0.0679)	0.5001 (0.0450)	0.5088 (0.0388)	0.2752 (0.0412)	0.4621 (0.0226)
Intercept	-1.3466 (0.0635)	-1.6846 (0.0321)	-1.1957 (0.0259)	-0.8578 (0.0269)	-0.6035 (0.0377)
Cut 2	-1.1948 (0.0634)	-1.4850 (0.0319)	-0.9936 (0.0258)	-0.5222 (0.0268)	-0.3759 (0.0377)
Cut 3	-1.0516 (0.0633)	-1.2969 (0.0319)	-0.7847 (0.0257)	-0.2162 (0.0267)	-0.1558 (0.0377)
Cut 4	-0.9346 (0.0632)	-1.1324 (0.0318)	-0.6005 (0.0257)	0.0523 (0.0267)	0.0378 (0.0377)
Cut 5	-0.7361 (0.0632)	-0.8915 (0.0317)	-0.3677 (0.0256)	0.3470 (0.0267)	0.2822 (0.0377)
Cut 6	-0.5498 (0.0632)	-0.6914 (0.0317)	-0.1099 (0.0256)	0.6451 (0.0267)	0.5231 (0.0377)
Cut 7	-0.1591 (0.0631)	-0.2816 (0.0317)	0.4720 (0.0256)	1.2412 (0.0269)	1.0289 (0.0377)
Cut 8	0.1707 (0.0631)	0.0923 (0.0317)	0.9225 (0.0257)	1.6413 (0.0271)	1.4235 (0.0377)
Likelihood ratio	-4212.5595	-8230.0140	-11263.9161	-12972.7613	-48019.9162
Number of observation	38314	95833	106856	77470	318473

Note: The coefficients on 10 year dummies are not reported in the table although included in the regressions. Standard deviations in parentheses.

Table 4: Selectivity corrected earnings equations (Overall)

	J = 1	*J = 2*	*J = 3*	*J = 4*	*J = 5*	*J = 6*	*J = 7*	J = 8	*J = 9*
Intercept	7.7961 (0.0203)	7.7570 0.0264)	7.6643 (0.0240)	7.5089 (0.0372)	7.1681 (0.0439)	7.1371 (0.0577)	6.8554 (0.0675)	7.2069 (0.0847)	7.4340 (0.0697)
Age	0.0293 (0.0008)	0.0327 (0.0013)	0.0375 (0.0012)	0.0444 (0.0020)	0.0573 (0.0023)	0.0628 (0.0030)	0.0798 (0.0035)	0.0652 (0.0042)	0.0605 (0.0031)
Age squared / 100	-0.0303 (0.0009)	-0.0272 (0.0017)	-0.0300 (0.0016)	-0.0359 (0.0026)	-0.0522 (0.0030)	-0.0549 (0.0040)	-0.0761 (0.0045)	-0.0578 (0.0054)	-0.0546 (0.0038)
Job tenure	0.0065 (0.0003)	0.0096 (0.0005)	0.0099 (0.0005)	0.0101 (0.0009)	0.0085 (0.0010)	0.0107 (0.0013)	0.0076 (0.0015)	0.0094 (0.0018)	0.0082 (0.0013)
Job tenure sq. / 100	-0.0015 (0.0009)	-0.0023 (0.0016)	-0.0072 (0.0016)	-0.0094 (0.0027)	-0.0053 (0.0032)	-0.0221 (0.0044)	-0.0076 (0.0050)	-0.0156 (0.0059)	-0.0111 (0.0044)
Number of children	-0.0110 (0.0008)	-0.0026 (0.0014)	-0.0056 (0.0013)	-0.0003 (0.0020)	-0.0021 (0.0023)	-0.0008 (0.0027)	0.0110 (0.0030)	-0.0019 (0.0036)	0.0137 (0.0026)
Married	0.0963 (0.0021)	0.0702 (0.0032)	0.0804 (0.0029)	0.0866 (0.0046)	0.0978 (0.0052)	0.1033 (0.0063)	0.0915 (0.0068)	0.1292 (0.0082)	0.1290 (0.0058)
French citizen	0.0855 (0.0036)	0.0535 (0.0086)	0.0661 (0.0075)	0.1062 (0.0119)	0.2374 (0.0131)	0.1757 (0.0169)	0.2161 (0.0181)	0.2013 (0.0213)	0.1749 (0.0119)
Resident in Paris	0.1607 (0.0029)	0.1435 (0.0048)	0.1490 (0.0043)	0.1275 (0.0063)	0.1271 (0.0068)	0.1183 (0.0081)	0.1407 (0.0085)	0.1469 (0.0095)	0.1251 (0.0068)
Private	0.0052 (0.0033)	0.0358 (0.0052)	0.0333 (0.0047)	0.0522 (0.0070)	0.0817 (0.0075)	0.1052 (0.0090)	0.1398 (0.0095)	0.1561 (0.0109)	0.1440 (0.0078)
Permanent contract	0.0924 (0.0038)	0.0895 (0.0059)	0.0914 (0.0052)	0.1032 (0.0077)	0.1074 (0.0086)	0.1360 (0.0098)	0.1620 (0.0109)	0.2011 (0.0130)	0.1829 (0.0091)
Lambda	-0.0950 (0.0112)	-0.0912 (0.0093)	-0.0779 (0.0083)	-0.0788 (0.0124)	-0.0782 (0.0132)	-0.0725 (0.0157)	-0.1100 (0.0167)	-0.1055 (0.0188)	-0.0914 (0.0153)
N. of observations	112094	44480	56981	24098	21144	14098	13171	10550	21848
Adjusted R squared	0.1988	0.2940	0.3307	0.3816	0.3787	0.4194	0.4022	0.3758	0.2939

Note: The coefficients on 10 year dummies are not reported in the table although included in the regressions. Standard deviations in parentheses.

Table 5: Marginal returns to schooling

	1934 – 1943 cohort 1	1944 – 1953 cohort 2	1954 – 1963 cohort 3	1964 – 1973 cohort 4	***Overall***
J = 2	0.2518 (0.0002)	0.1757 (0.0001)	0.1602 (0.0001)	0.1533 (0.0001)	0.2154 (0.0001)
J = 3	0.0976 (0.0003)	0.0927 (0.0002)	0.0608 (0.0001)	0.0398 (0.0001)	0.0746 (0.0000)
J = 4	0.0900 (0.0003)	0.0857 (0.0001)	0.0944 (0.0001)	0.0609 (0.0001)	0.0822 (0.0000)
J = 5	0.0294 (0.0003)	0.0910 (0.0002)	0.0905 (0.0002)	0.1028 (0.0004)	0.0813 (0.0001)
J = 6	0.1336 (0.0006)	0.1145 (0.0003)	0.0715 (0.0002)	0.1239 (0.0002)	0.1040 (0.0001)
J = 7	0.1990 (0.0008)	-0.0021 (0.0003)	0.2705 (0.0005)	0.1510 (0.0002)	0.1404 (0.0001)
J = 8	0.1698 (0.0006)	0.1899 (0.0003)	0.1325 (0.0002)	0.0598 (0.0004)	0.1347 (0.0001)
J = 9	0.1260 (0.0006)	-0.0709 (0.0002)	0.2265 (0.0002)	0.3154 (0.0004)	0.0751 (0.0001)
M	0.1335 (0.0014)	0.0732 (0.0006)	0.1270 (0.0007)	0.1130 (0.0008)	0.1135 (0.0002)

Note: Standard errors in parentheses. The M row reports the mean of the corresponding column.