Intergenerational earnings persistence and economic inequality in the long-run : Evidence from French cohorts, 1931-1975

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Abstract

This paper analyzes long-term trends in intergenerational earnings persistence in France for male cohorts born between 1931 and 1975. This time period has witnessed important changes in the French labor market and educational system, in particular an important compression of earnings differentials as well as a large expansion in access to secondary and higher education. Using a two-sample instrumental variables approach, I estimate two measures of intergenerational economic persistence: the intergenerational earnings elasticity (IGE) and the intergenerational correlation (IGC). Over the period, the IGE exhibits a V-shaped pattern. It falls from a high of value of .6 for cohorts born in the 1930s to around .4 for those born in the 1950s, but subsequently rises to a level close to the beginning of the period. In contrast, the IGC remains relatively stable over the period. This suggests that changes in the IGE are partly driven by transitory responses to changes in cross-sectional inequality rather than long-term changes in the degree of intergenerational persistence.

JEL Codes: D1, D3, J3

Keywords: Intergenerational mobility, intergenerational persistence, earnings, inequality, trends, elasticity, correlation, education, France.

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1 Introduction

Recent public debates have echoed growing concern that, in modern democratic societies, a sizable share of economic inequality remains inherited within families.[1] Over the last fifteen years, an important body of empirical research has investigated the extent of the intergenerational transmission of earnings inequality. Two key results stands out from this literature. First, individual earnings are strongly influenced by family background: On average, in developed economies, between 20 and 60% of economic advantage is transmitted, within families, from one generation to the next (Solon 1999, Black & Devereux 2010). Second, the transmission of economic inequality varies considerably across countries (Björklund & Jäntti 2009).

From a theoretical perspective, the determinants of intergenerational economic persistence are now well established (Becker & Tomes 1979, Solon 2004). However, beyond the above stylized facts, the factors that empirically contribute to the intergenerational transmission of inequality are still largely to be explored. Why does the degree of intergenerational persistence vary across countries ? To what extent does it change over time ? How does the level of economic inequality relate to the persistence of inequality across generations ? The so-called "Great Gatsby Curve" has provided striking evidence that more equal countries also generally exhibit lower intergenerational persistence (Corak 2013). However, it remains difficult to draw firm conclusions from cross-sectional correlations among heterogenous countries.

The objective of this paper is to analyze long-term changes in the intergenerational persistence of earnings in France, over the second half of the twentieth century. This period appears particularly interesting for the study of intergenerational economic persistence, since it witnessed a considerable reduction in the degree of earnings inequality, as well as a massive expansion of access to secondary and higher education. In particular, given the large reduction in earnings inequality that occurred throughout the 1960s and early 1970s, recent cohorts were exposed to much less inequality of family environment than older ones. Hence, assessing historical changes in intergenerational persistence, within the context of a single country, may help understand how the overall economic and social

[1] Reactions to Piketty (2014) or Krueger (2012) are emblematic of this concern.

environment (e.g. labor market institutions, educational and redistributive policies) affects the intergenerational transmission of inequality.

In this paper, I estimate two measures of intergenerational economic persistence. The first one is the intergenerational earnings elasticity (IGE) on which most of the economic literature has focused. It can be obtained by regressing the log of individual earnings on the log of their father's earnings. The second one is the intergenerational earnings correlation (IGC). The IGE and IGC capture different aspects of intergenerational persistence. The IGE can be understood as a measure of the degree of transmission of parental economic advantage to their children. The IGC, instead, measures to what extent inequality among children is inherited from their parents. Although the two measures coincide in the steady-state, they might respond differently to changes in cross-sectional inequality. This underlines that in a period of long-run changes in economic inequality, assessing patterns in both the IGE and the IGC is necessary to understand changes in intergenerational persistence.

I estimate cohort-specific IGEs and IGCs for male cohorts born between 1931 and 1975. In the absence of linked parent-child data sets measuring earnings over such a long period, I use a two-sample instrumental variables approach (Arellano & Meghir 1992, Angrist & Krueger 1995). The estimation exploits a labor force survey covering the period 1964-2003 that contains information on both individual earnings and several parental characteristics, including father's education which is used to form a prediction of father's earnings.

As is now well understood, estimating intergenerational economic persistence, and assessing trends therein, is vulnerable to various statistical issues, including what has been referred to as the life-cycle bias. This bias arises from the fact that current earnings measured early (resp. late) in the life-cycle tend to underestimate (resp. overestimate) the extent of permanent earnings inequality among fathers or sons (Jenkins 1987, Grawe 2006, Haider & Solon 2006). In this paper, I use the specification of Lee & Solon (2009) to provide estimates of the average and cohort-specific IGE (and IGC) in France that correct for life-cycle bias.

The last contribution of this paper is to assess how the large educational expansion that took place in France over the twentieth century contributed to changes in intergenerational economic persistence. I rely on a decomposition approach to disentangle two factors: changes in the association between parental earnings and child's human capital, on the one hand, and changes in the returns to human capital, on the other hand.

This paper relates to a series of recent contributions that have examined changes over time in intergenerational mobility in various countries. The most extensively studied country is by far the United States. Early studies based the Panel Study of Income Dynamics (PSID) concluded to a fall in intergenerational earnings persistence in the recent period (Fertig 2003, Mayer & Lopoo 2005). One of the limitations of these studies, as shown in subsequent work (Hertz 2007, Lee & Solon 2009), is that life-cycle bias leads to underestimate the IGE for the most recent cohorts. The current conclusion that arises from the PSID data is that between the late 1970s and the early 2000s, the IGE has remained roughly constant for males in the US. A further limitation of these studies is that they cover a relatively narrow interval of cohorts and a small sample. Aaronson & Mazumder (2008) take a longer-run perspective, which is closer to the perspective of the present paper. They estimate changes in the IGE between 1940 and 2000, using census data and relying, as I do here, on a two-sample instrumental variables approach. Their conclusion is that the IGE exhibits a large fall between 1950 and 1980 and a sharp rise in the recent period.

The assessment of trends in intergenerational economic persistence has also attracted researchers' attention in several other countries, including Britain - where no consensus has been reached on trends at work (Ermisch & Francesconi 2004, Blanden, Goodman, Gregg & Machin 2004, Nicoletti & Ermisch 2007, Erikson & Goldthorpe 2010)-, Finland (Pekkala & Lucas 2007), Italy (Piraino 2007), Norway (Bratberg, Nilsen & Vaage 2005) and Sweden (Björklund, Jäntti & Lindquist 2009).

With respect to the existing literature on trends in the IGE, the contribution of the present paper is twofold. First, I analyze a country that has not been studied so far, over a long time period. Second, I am able to provide a more detailed account of the sources of change in the IGE using multiple measures of persistence and relying on an original decomposition.

Four main results emerge from this paper. First, taking into account life-cycle biases and using an estimation procedure comparable to state-of-the-art estimates reveals that the average IGE in France is around .5, a value higher than what was originally found.[2] Second the IGE has fallen from a high of value of .6 for cohorts born in the 1930s to slightly above .4 for those born in the 1950s, but has subsequently risen to a level close to the beginning of the period. Third, in contrast, the IGC appears much more stable over time with a small fall at the beginning of the period and not marked trend thereafter. Fourth, the initial fall in the IGE results both from a fall in labor market inequality and a rise in the degree of openness of the educational system; the recent rise partly reflects a rise in the association between parental earnings and child's education.

The rest of the paper is organized as follows. I first discuss the estimation procedure and the data used in the analysis (section 2). Then I present the results of the first-step estimation (section 3) and analyze the main trends in the IGE across cohorts (section 4). In section 5, I examine long-term changes in the IGC and in cross-sectional earnings inequality. Section 6 discusses the role the educational expansion to changes in intergenerational earnings persistence. Section 7 concludes.

2 Estimation method and data

2.1 Two measures of intergenerational economic persistence

In the economics literature, the most commonly used measure of persistence is the intergenerational elasticity (IGE) in permanent earnings. The IGE is given by the coefficient β in the following intergenerational regression model:

$$Y_i = \beta_0 + \beta X_i + \epsilon_i \tag{1}$$

where Y_i denotes individual i's permanent earnings and X_i the permanent earnings of his father, both in logarithm.

An alternative measure of intergenerational persistence is given by the intergenerational correlation (IGC) in permanent earnings, which is the standard Pearson correlation coefficient between the log of permanent earnings of children and fathers.

The IGE and the IGC are summary measures of the joint distribution of fathers and

[2] See Lefranc & Trannoy (2005) for previous estimates.

children's earnings. They should not be regarded as structural parameters of the intergenerational transmission process. In particular, β should not be seen as a measure of the causal effect of parental resources on child's earnings. It is a "catch-all" measure of the intergenerational association that encompasses a variety of transmission mechanisms including ability and genetic transmission, socialization, preference formation as well as economic resource constraints, as discussed for instance in Black & Devereux (2010).

The IGE and the IGC capture different aspects of intergenerational persistence. The IGE can be interpreted as a measure of *degree of transmitted inequality*. It is the share of parental advantage transmitted to their children. For instance, a value of the IGE of 0.3 indicates that if the father earned 10% more than the mean earnings in his generation, his child will, on average, earn 3% more than the mean earnings in his or her generation.

In contrast, the IGC can be interpreted as a measure of the *degree of inherited inequality*. Consider the coefficient of determination in the regression model of equation 1. This coefficient measures the share of the variance of log children's earnings -a crude inequality measure- that is inherited from the parents, in the sense that it is correlated to differences in father's earnings. Since the IGC is equal to the square root of this coefficient of determination, it can be similarly interpreted as a measure of the degree of inheritance.

The link between the IGC and the IGE is given by:

$$\beta = \rho \frac{\sigma_Y}{\sigma_X} \tag{2}$$

Equation 2 makes clear that the two measures of persistence will coincide only in the steady-state, when the variance of earnings of children and fathers are equal ($\sigma_Y = \sigma_X$).

Out of the steady-state, the IGE has often been criticized for being sensitive to changes in cross-sectional inequality, in a way that only partially reflects variations in the degree of intergenerational persistence. This sensitivity can be illustrated by a simple example. Assume that log earnings are fully determined by the market value of the individual stock of human capital and that intergenerational persistence is entirely driven by parental decisions to invest in their children's human capital. Consider an unexpected rise in the market returns to human capital among children, occurring after human capital investment decisions have been made. This rise in the returns to skills would increase inequality among children and the value of the IGE would rise. Since the IGC controls for changes in the standard deviation of log-earnings in both generations, it would be unaffected by such a shock.

This calls for several comments. First, one should not conclude from this example that the IGE is not a suitable measure of persistence. Indeed, the linear increase in log earnings implies that the degree of transmission of parental advantage has increased. However, it illustrates that the IGE only provides a partial view on intergenerational persistence: In the above example, the degree of inheritance of inequality, as measured by the IGC, remains constant.

Second, the constancy of the IGC occurs here under specific assumptions, namely a linear change in log earnings. More complex changes in the distribution of children's earnings might also affect the IGC. The reason for this is that the IGC controls for changes in inequality in the marginal distributions of earnings in a very specific way, i.e. through the standard deviation of log earnings. The use of rank correlation measures, such as the Spearman coefficient, would allow controlling fully for differences in the marginal distributions in the measure of persistence. Their use in the analysis of intergenerational persistence is however quite rare and raises significant empirical challenges.

Third, several analysts have raised concerns that changes in the IGE in response to transitory variations in the ratio $\frac{\sigma_Y}{\sigma_X}$ may not adequately reflect long-run changes in intergenerational persistence (e.g. Checchi 2006). Solon (2004) examines the evolution of the IGE out of the steady-state in response to a rise in the returns to human capital. His results indicate that the short-run increase in the IGE in response to such a shock will overstate variation in the steady-state value of the IGE.[3] Hence, as discussed in Jäntti & Jenkins (2015), in the presence of transitory changes in earnings inequality, one should be cautious in interpreting changes over time or differences across countries in the value of the IGE. In comparison, the IGC seems empirically less sensitive to these transitory dynamics

[3]The interested reader can refer to the discussion in Solon (2004), p. 44 sq. Solon considers the effect of a permanent increase in the returns to human capital. This shock leads to an increase in the steady-value of the IGE. At the onset of the shock, the short-run IGE will however differ from the steady-state values of the IGE (both before and after the permanent shock). Solon shows that the short-run IGE will be higher than the steady-state IGE observed before the rise in the returns to human capital. His results can be easily extended to show that the dynamics exhibits overshooting: in the short-run, the IGE will also rise above the new steady-state value.

(Björklund & Jäntti 2009).

Despite these limitations, the majority of studies of intergenerational persistence exclusively focuses on the IGE. In the present of the paper, I assess trends in persistence using both the IGC and the IGE.

2.2 Estimation method

To assess trends in the IGE, one can rely on the following extension of the intergenerational regression model, allowing for cohort heterogeneity in the parameters:

$$Y_{ic} = \beta_{0c} + \beta_c X_{ic} + \epsilon_{ic} \tag{3}$$

where c is an index of the birth cohort of the child and β_c is the IGE for cohort c.

The direct estimation of equation 3 for a large interval of cohorts requires a considerable wealth of information. Not only does it call for linked data on both father's and child's earnings , but for each generation one needs to observe a time-series of earnings in order to measure long-term earnings. Very few data sets satisfy this requisite. There are of course some exceptions, for instance the PSID data set. But even this fairly rich and long panel data set fails to cover a wide range of children's cohorts. In France, as in many countries, there exists no linked father-child data set that conveys information on long-term earnings over a long historical period.

Estimation of the IGE using TSIV In this paper, I estimate the β_cs using a two-sample instrumental variables (TSIV) approach as first applied to the estimation of the IGE by Björklund & Jäntti (1997). The basic principle is to replace X_{ic} in equation 3 by a prediction $\hat{X}_{ic}$ formed on the basis of some observable father's characteristics, Z_{ic}.[4] Here, I use father's education to predict father's earnings.

The data requirements for TSIV estimation are significantly less stringent than for

[4]This estimation procedure should be more accurately described as a regression with generated regressors, as discussed in Murphy & Topel (1985), rather than TSIV. IV estimation requires that all exogenous regressors are included in the first-step estimation. In my case, child's age appears in the second step but not in the first step. This is also the case in many IGE estimates commonly referred to as TSIV estimates, which is the reason why I use this terminology. Furthermore, omitting child's age from the first-step is in fact likely to be of minor consequences to the first-step estimation, once cohort effect have been properly modelled.

the direct estimation. The estimation of the first-step equation requires a sample that is representative of the fathers' population, and in which one observes both earnings and the characteristics Z_{ic}. Given the first-step estimates, the data requirement for the estimation of β_c is to observe both child's earnings and father's characteristics.

TSIV has been extensively used for the estimation of the IGE and its properties are discussed in several papers (e.g. Solon 1999, Nicoletti & Ermisch 2007). These properties depend on the choice of the instrument. If the instrument only affects child's earnings through its effect on father's earnings, TSIV estimates of the β_cs are consistent.[5] However, if the instrument has a direct effect on the child's outcome, the TSIV estimate is biased in a way that depends on the sign of the direct effect. When using father's education as an instrument, the expectation is that the direct effect is positive, resulting in an overestimation of the IGE. In practice, available evidence suggests that the order of magnitude of this overestimation is small.[6]

Another important source of bias in the estimation of the IGE is the so-called *life-cycle bias* (Jenkins 1987, Grawe 2006, Haider & Solon 2006). This bias arises when using current annual earnings instead of permanent earnings in the estimation of the IGE. In the presence of individual heterogeneity in earnings growth over the life-cycle, current earnings measure permanent earnings with error. Furthermore, the error is not of the classical type and is correlated with both true permanent earnings and age.[7] As a result, differences in current earnings across individuals will in general provide a biased estimate of permanent earnings differentials. Since age-earnings profiles are steeper for high-earnings individuals, current earnings differentials, measured at an early (resp. late) stage of the life-cycle, will underestimate (resp. overestimate) permanent earnings differentials.

This introduces an asymmetric bias in the estimation of β, depending on whether child or father's earnings are affected by this bias. Using current earnings early (resp. late) in

[5]In this case, indeed, TSIV estimation offers the significant advantage of over-riding the *attenuation bias* that typically arises, because of classical measurement errors, when estimating equation 3 with long-term earnings replaced by current earnings (Solon 1992, Zimmerman 1992, Mazumder 2005b)).

[6]For instance, for the US case Björklund & Jäntti (1997) report IGE estimates in the interval .33-.39 when using five-year averages of father's earnings and in the interval .42-.52 when using TSIV estimation. However, Mazumder (2005b) shows that using five-year averages of father's earnings still leaves room for downward attenuation bias and provides estimates of the IGE above .5 when using ten years averages.

[7]The classical measurement error case refer to the situation where measurement error is independent of the true value

the life-cycle, as a proxy for *child*'s permanent earnings will lead to underestimate (resp. overestimate) β. Conversely, using current earnings early (resp. late) in the life-cycle, as a proxy for *father*'s permanent earnings will lead to overestimate (resp. underestimate) the IGE.

Accounting for life-cycle biases is of paramount importance when assessing trends over time in the IGE. Mechanically, younger cohorts will be observed at an earlier stage of their life-cycle than older cohorts, resulting in a lower IGE. Inadequate treatment of life-cycle bias will thus induce a spurious downward trend across cohorts in the value of the IGE (Hertz 2007, Lee & Solon 2009, Nicoletti & Ermisch 2007).[8] To account for this bias, I follow Hertz and Lee & Solon and allows the IGE to vary with child's age by introducing an interaction term between child's age and father's predicted earnings. By focusing on the main effect of father's earnings one can wipe out the effect of child's age on the cross-cohort comparison. The reference age for children used in the estimation of the IGE is the age of 40, as suggested by the rule of thumb of Haider & Solon (2006). Similarly, for all cohorts I predict father's earnings at the age of 40, eliminating life-cycle bias in the dependent variable as well.

In the end, I use the following specification for the second-step equation:

$$Y_{ict} = \alpha_t + \beta_c \hat{X}_{ic} + g(age_{ict}) \times \hat{X}_{ic} + f_C(age_{ict}) + e_{ict} \tag{4}$$

where i and t are indices for individual and time. c denotes the five-year birth cohort of individual i. The α_ts denote time dummies and f and g are fourth order polynomial functions in individual age. I allow the age profile to vary with year of birth and consider four "super cohorts" indexed by C. The birth cohorts of these four groups are the following: 1931-1942, 1943-1949, 1950-1959, 1960-1975.[9] $\hat{X}_{ic}$ is predicted father's earnings at age 40; the variable *age* is normalized to zero at age 40 and I impose the constraint that $g(0) = 0$. Consequently β_c denotes the IGE for cohort c if, as suggested in Haider & Solon (2006) the life-cycle bias is zero at age 40. Since equation 4 includes a predicted regressor, I correct

[8] As a result, the use of different sample selection criteria (for fathers' and children's ages) jeopardizes the comparability of IGE estimates across countries, as discussed in Grawe (2006).

[9] The cutoff years are chosen to balance group size. Since I am using multiple year cohorts, cohort dummies could in principle be added to this specification. Cohort dummies however turn out to be insignificant when added to this specification and their inclusion does not affect the results.

standard errors using the procedure of Murphy & Topel (1985) and Inoue & Solon (2010).

A final point should be made pertaining to the validity of the second-step model. As previously argued, the inclusion of age interactions should minimize the incidence of life-cycle biases.[10] Besides, biases arising from the use of father's education are expected to be small. If some biases remain, the identification of trends in the IGE can nevertheless be achieved if biases are constant over time. Unfortunately, this assumption cannot be tested or relaxed given data availability.[11]

First-step specification Let us now turn to the specification of the first-step equation. Its purpose is to predict father's earnings at the age of 40, based on information on father's education. One of the difficulties is that for some of the children cohorts, in particular the oldest ones, the relevant fathers cohorts are observed late in their work career. For these cohorts, earnings differentials in mid-career have to be predicted on the basis of end-of-career differentials by education group. Hence, one needs to take away the earnings growth that occurred in between. Furthermore, for the prediction of earnings differentials by education to be consistent, one needs to account for heterogeneity in earnings growth by education. This is done by estimating parametric, yet flexible, education-specific age-earnings profiles.

Formally, the first-step model I estimate is the following:

$$X_{ict} = \alpha_t + \sum_j \gamma_c^j Educ_{ic}^j + f(age_{ict}, Educ_{ic}) + e_i \tag{5}$$

where $Educ_{ic}^j$ is a set of education dummies; $f(age_{ict}, Educ_{ic})$ is a fourth polynomial in age, specific to each level of education[12]; age_{ict} is centered at age 40. This equation is used to predict father's earnings at age 40 as:

$$\hat{X}_{ic} = \sum_j \hat{\gamma}_c^j Educ_{ic}^j$$

[10]Results in Nybom & Stuhler (forthcoming) suggests that, in the case of Sweden, the Lee & Solon (2009) correction might not entirely purge estimates from life-cycle biases.

[11]Aaronson & Mazumder (2008) investigate this issue using panel data on earnings that partially overlap with (the end of) their observation period. No such data are available to conduct a similar exercise in my case.

[12]In variants of this model, I also allowed for cohort heterogeneity in the function f, without any significant impact on the results.

Estimation of the IGC Following equation 2, IGC estimates can be obtained as the product of the IGE estimates of equation 4 multiplied by the ratio of the standard deviation of log permanent earnings in the father's and children's generation, $\frac{\sigma_X}{\sigma_Y}$. The main difficulty is that permanent earnings are not observed. Hence, the ratio of their standard deviations has to be estimated. I defer to section 5 the discussion of the methods used.

2.3 Data

Data sets and main variables The data are taken from the FQP (*Formation, Qualification, Profession*, i.e. Education, Training and Occupation) surveys conducted by INSEE in 1964, 1970, 1977, 1985, 1993 and 2003. The number of individuals surveyed varies across waves : 25 000 individuals in 1964, 38 000 from 1970 to 1985 and in 2003, and 19 000 in 1993. The FQP surveys offer a representative sample of the French population of working age. The FQP surveys focus on the description of individual labor market outcomes, earnings, education and social and family background.[13]

For all individuals surveyed, the data contain detailed information on education, as well as training, labor market experience, 4-digits occupation and industry when relevant. Individual annual earnings (excluding unemployment benefits) in the previous year and number of months worked full- and part-time are also collected in all waves.[14] Earnings refer to pre-tax labor earnings and are only recorded for salaried workers.

All surveys provide information about the respondent's current family (marital status, number of children) and family of origin (number of siblings, respondent's birth rank). Waves 1970 through 2003 also contain a detailed description of the educational attainment of the father of the respondent. This information is reported *a posteriori* by survey respondents and refer to the time when the respondent left the schooling system.

I recoded education using a consistent classification across survey waves.[15] The classification is based on the highest degree achieved by the individual and distinguishes between six different categories that reflect key stages in the French educational system. The first

[13] See INSEE (2010) for a presentation.

[14] In 1964, annual earnings are recorded in interval form, using 9 intervals. Hence, all estimations results reported using wave 1964 are based on interval regression.

[15] In all waves, education is recorded using a 10 levels education classification that distinguishes between general and vocational education but the categories changed several time over the five waves.

one gathers individuals with no degree. The second one corresponds to individuals who passed the certification exam organized at the end of primary education (*certificat d'études primaires.*) This was the major degree taken in older cohorts, among children of the lower and middle class.[16] Next, I consider intermediate secondary education degrees, for the general and vocational tracks. The last two categories correspond respectively to upper secondary degrees (*baccalauréat*) and higher education degrees.

Sample selection In the analysis, I use two distinct samples. The *main sample* is the sample of children, on which the second-step equation (equation 4) is estimated. For this sample, I use waves 1970 to 2003 of the survey. The sample is restricted to male heads of household, born between 1931 and 1975 and aged 28 to 50 years old at the date of the survey. I exclude self-employed children as well as children whose father was self-employed from the sample, since earnings are not reported for these individuals.[17] I test for the sensitivity of the results to this exclusion. The main sample is also restricted to individuals who were granted French nationality at birth. This includes individuals born of French parents, as well as second-generation immigrants born in France of foreign parents. The reason for imposing this restriction is that father's earnings cannot be adequately predicted for foreign-born individuals.[18]

The second sample used in the analysis is the *auxiliary sample* of "pseudo-fathers" on which the first-step equation (5) is estimated. This sample should be representative of the population of the fathers of the individual sampled in the children sample. For this sample, I use all waves of the survey, from 1964 to 2003, and restrict the sample to male heads of household, aged 25 to 60 years old as of the survey date, who report at least one child, and are not self-employed.

[16]Starting in 1972, the *certificat d'études primaires* was only taken by adults, in the context of adult education programs. It was abandoned in 1989.

[17]For cohorts 1931 to 1955, about 10% of the children sample are self-employed. This percentage falls to less than 5% in the youngest cohort. On average, 26.7% of salaried children have a self-employed father. This varies from a high value of 33% in the oldest children cohort to a low value of 18% in the youngest one, as described in table 1.

[18]First-generation immigrants and naturalized French citizen account for about 8% of the population of children and their father's earnings cannot be adequately estimated using a survey of individuals living in France. It would, however, be relevant to analyze differences in intergenerational persistence between second-generation migrants and other French-born individuals, along the lines of Aydemir, Chen & Corak (2009). This cannot, however, be investigated here since only the last wave of FQP allows identifying second-generation migrants. For a discussion of the intergenerational mobility of second-generation migrants in France, see Lefranc (2010)

As previously discussed, estimations allow for heterogeneity by cohort in the effect of the explanatory variables. For the first-step equation, I use three-year cohorts to warrant large enough groups in each cohorts.[19] For the second-step equation, where the sample relies on a smaller number of survey waves, I use five-year cohorts.

The matching of individuals from the children and the pseudo-fathers samples is based on the father's characteristics used in the prediction of father's earnings (as discussed above), as well as on reports, provided in the children sample, of the year of birth of the father. Given the age restriction imposed in the children and pseudo-fathers samples, the oldest children cohort observed in the sample was born in 1931 and the oldest cohort of pseudo-fathers from which to predict fathers' earnings was born in 1904. This 27 years gap is reasonable given that the mean age of the fathers at the birth of their children was slightly above 30 in 1933 (Daguet 2002). For children whose father was born before 1904, I assign the predicted father's earnings of the cohort born in 1904. When information on father's birth year is missing the prediction of father's earnings is based on the distribution of birth age computed from non-missing observations, as discussed in appendix A.2.

The main summary statistics are given in table 1. We now turn to the discussion of the results.

3 First-step estimates and trends in educational attainment and returns to education

Before presenting the results of the first-step equation, it is useful to document the main historical trends in educational enrollment in France over the twentieth century. They are described in figure 1. The main evolution is the large rise in access to secondary and higher education. Among cohorts born at the beginning of the century, a very large share of about 70% of the population exhibits a very low level of education, with at most a primary education degree. At this time, mass-education is confined to primary school. Secondary education is to a large extent a privilege of the upper class. The degree of tracking is extremely high at this time. At the level of primary education, two tracks co-exist. The

[19] I group the first two cohorts, 1903-1905 and 1906-1908.

first one offers regular primary education, as well as the possibility of two extra-years of advanced primary training (*classes primaires supérieures*). The second track is integrated into high-schools (*lycées)*, which at the time concurrently offer primary education from the age of six. The two tracks are entirely disconnected and only the children who attended the second track can reach secondary education degrees.

The opening up of access to secondary education took place gradually after 1930 and led to a steady rise in the share of individuals with secondary degrees. This was the result of several reforms occurring between 1936 and 1977. Important stages of educational reform in France in the twentieth century, were, first, the extension of compulsory education from 13 to 14 (Zay, 1936)[20] then 16 years old (Berthoin, 1959) and two key reforms undertaken to reduce tracking in secondary education (Fouquet, 1966; Haby, 1977). The rise in access to higher education started in the 1950s, for cohorts born before WWII. It developed throughout the 1960s among the baby-boom cohorts. It peaks up for cohorts born in the late 1960s and early 1970s. This rise resulted from policies undertaken in the late 1980s and throughout the 1990s.[21] Lastly, it is worth emphasizing that while trends are somewhat similar to other developed countries, educational attainment in France was, throughout the period, markedly lower than in comparable industrialized countries. On the face of the educational attainment of the 1930s cohort, the OECD ranks France as having a "historically low educational attainment" compared to other Western countries (OECD 2011). At the end of the period, the enrollment rate in tertiary education in France amounts to 54.9% which is lower than the EU average (58.1%) or the US rate (88.6%).[22]

Let us now turn to the analysis of earnings differentials by level of education. The analysis is based on the estimation of equation 5. The detailed estimation results are provided in the appendix table A1 and summarized in figures 2 to 4.

Figure 2 presents the evolution over time of the earnings structure, by level of education. The earnings premia attached to each of the six levels of education correspond to the coefficients γ_cs in equation 5. In panel A, premia are expressed in deviation from the mean earnings in each cohort and are predicted at age 40, using estimated age-earnings profiles.

[20]The name in parenthesis is the name of the Minister of Education responsible for the reform mentioned, the date is the date when the reform was enacted.

[21]See Gurgand & Maurin (2006) for a related analysis of educational expansion in France.

[22]Source: World Bank EdStats database.

The figure indicates a convergence of all education group towards mean earnings over the period. Panel B presents earnings premia relative to individuals without any degree. Again, the figure shows a marked decline in the returns to education over the twentieth century. The largest fall occurs between cohorts born at the beginning of the century and early baby-boomers born around 1940.

Whether this compression of education earnings premia led to a reduction of the overall degree of earnings inequality cannot be deducted directly from figure 2. This is because the evolution of earnings dispersion also depends on changes in the distribution of education in the population over time. In fact, at the beginning of the century, a very small share of the population was earning the high earnings premia attached to tertiary and upper secondary degrees. I now directly examine trends in earnings inequality over time, as measured by the Gini coefficient. The major difficulty for assessing the evolution of earnings inequality across cohorts, is that cohorts are observed at different points of their life-cycle. To account for that I subtract education and cohort-specific age-effects to predict mid-career earnings for each cohort and compare earnings inequality by cohort.

Results are displayed in figure 3. The figure gives within-cohort Gini coefficients for annual earnings computed at age 40. Three main findings emerge from this figure. First, cohorts born in the 1920s and the 1930s experienced a high degree of wage inequality. Second, inequality fell markedly in the post WWII period between the 1940 and the 1955 birth cohorts. Lastly, within-cohort earnings inequality stayed approximately constant across cohorts born after 1955.

These results on long-term trends in earnings inequality are consistent those derived from alternative data sources and methodologies. Selz & Thélot (2004) estimate Mincer equations for the period 1964 to 1998 and show that the returns to education has fallen over time in France. Based on fiscal data, the results reported by Piketty indicate a significant fall, throughout the 1970s and early 1980s, in the ratio between the average wage of higher-grade professionals and the average wage of manual workers in the manufacturing sector (Piketty (2001), figure 3-7). Piketty (2003) also reports that the 1930s, 1950s and the 1960s where periods of historically high earnings inequality.

Two main factors lie behind the fall in earnings inequality displayed in figure 3. The first one is the massive wage compression that occurred at the end of the 1960s (in particular in 1968, after the one third rise in the minimum wage) and in the early 1970's. The second one is the competitive wage adjustment that followed the rise in the supply of highly educated workers (Goux & Maurin 2000).

Lastly, figure 4 presents age-earnings profiles by level of education, estimated in equation 5. Following Murphy & Welch (1990), the age profile is captured by a fourth-degree polynomial. The results are consistent with evidence reported elsewhere of a fanning out of earnings profiles as the level of education increases. In particular, the age-earnings profiles of workers with lower secondary vocational degrees or lower are markedly flatter than the age profiles of individuals with other secondary degrees (upper secondary or lower secondary general degree). The steepest profile corresponds, as expected, to individuals with tertiary education.

To summarize, the extent of earnings and educational inequality has varied considerably across cohorts over the last century. We now investigate how much of this inequality has been transmitted across generations and the extent to which this intergenerational transmission has varied over time.

4 Changes in the intergenerational earnings elasticity

4.1 Main results

Table 2 reports estimates of the IGE for various specifications of the intergenerational regression model. Column 1 gives the average IGE across all cohorts. Over the full sample, the average elasticity amounts to .511. This value appears high compared to estimates obtained for other developed countries and surveyed for instance in Björklund & Jäntti (2009). IGEs of comparable magnitude are only found in the United States (Mazumder 2005a), Italy (Mocetti 2007, Piraino 2007), and the United Kingdom (Dearden, Machin & Reed 1997). This confirms that a large fraction of inequality is transmitted across generations in France. This elasticity is higher than the value of .4 reported in Lefranc & Trannoy (2005). Two factors account for this discrepancy. First, Lefranc & Trannoy (2005) do not control for life-cycle bias and rely on a sample in which children are aged 30 to 40 years old which leads to underestimate the value of the IGE. Second, I use a broader sample of children and include both older and younger cohorts than in Lefranc & Trannoy (2005). Given the trends in the IGE described in the rest of this section, this also accounts for the higher IGE estimated here.

Column 2 of table 2 and figure 5 show the main estimates of the IGE for each of the nine five-year cohorts. The IGE exhibits a V-shaped evolution over the period. The degree of intergenerational transmission decreases across cohorts until cohorts born in the late 1950s but rises at the end of the period. The Wald test indicates that differences across cohorts in IGE estimates are jointly significant. Table 3 also presents pair-wise comparisons of IGE estimates across cohorts. Tests indicate that the IGE is significantly lower for the middle cohorts than for the younger and older ones.

The value estimated for the two cohorts born in the 1930s is around .6, which is very high, compared to values reported elsewhere. By comparison, Aaronson & Mazumder (2008) report a value of the IGE around .35 for US cohorts born in the same decade and Pekkala & Lucas (2007) report a similar figure for Finland. The finding of a high degree of intergenerational economic persistence in France among the oldest cohorts is consistent with findings reported elsewhere. First, historical sociological evidence indicates that the degree of educational mobility was very low in France among cohorts born at the beginning of the twentieth century and only started falling for cohorts born in the late 1930s and early 1940s (Thélot & Vallet 2000). Second, these cohorts also experienced the high degree of labor market inequality at work in France in the 1950s and the 1960s. In fact, over this period, the degree of earnings inequality appears markedly higher than in the rest of Western Europe and the US (Atkinson & Morelli 2014, Atkinson 2015).

The decline in the IGE occurs for the first part of the baby-boom cohorts, i.e. individuals born in the second half of the 1940s and in the 1950s. In these cohorts, the IGE reaches a low value of .421. This represents a sizable decline in the IGE, although the level is still relatively high by international standards. The IGE subsequently rises for cohorts born in the 1960s and in the early 1970s to reach .57. The value found for the younger cohorts turns out to be close to and not significantly different from the value found among cohorts born before WWII.

An important caveat should be kept in mind when commenting on the value of the IGE for the cohorts of children born in the 1930s. For the two earliest cohorts of children, predicted father's earnings partly rely on out-of-sample extrapolation. I use the 1964 wave of the FQP survey to predict father's earnings. In this wave, pseudo-fathers of the 1930s children are typically observed late in their life-cycle, around age 60.[23] Age-forty predicted father's earnings for these cohorts are obtained from earnings differentials by education observed in 1964 for these pseudo-fathers cohorts, after correcting for education-specific age-earnings profiles. Note however, that age-earnings profile specific to the earliest fathers cohort cannot be estimated due to data availability. Inconsistent estimation of earnings differentials among father's would lead to inconsistent estimation of the IGE for these cohorts. In this respect, two issues should be considered: First, whether age 60 earnings differentials for these early father cohorts are representative; second, whether the returns to experience used to correct for life-cycle earnings growth are representative. On the first issue, it is worth emphasizing that earnings inequality was historically high in the 1960s (Atkinson & Morelli 2014); using 1964 as the observation year should, thus, lead to over-estimate earnings differentials among fathers in the early cohorts. Regarding the second issue, estimates of changes in the returns to experience suggest that the returns were roughly stable from 1962 onward (Selz & Thélot 2004). Hence, all in all, it seems that out-of-sample extrapolation may lead to over-estimate earnings differentials among fathers, which would lead to *under*-estimate the IGE for the earliest two cohorts.

Beyond the above discussion, it is also worth emphasizing that starting from the 1941-1945 cohort, the estimation relies only to a small extent, if at all, on out-of-sample extrapolation and trends from these date are more strongly established. In the rest of the paper, I investigate the determinants of this fall and rise of intergenerational earnings persistence in France, after performing some sensitivity analysis.

4.2 Sensitivity analysis

As suggested by Hertz (2007) and Lee & Solon (2009), it is important to examine the incidence of life-cycle effects on the estimated trends in intergenerational persistence. Fur-

[23] The fathers of these child cohorts were born in the early twentieth century.

thermore, Bohlmark & Lindquist (2006) suggests that the life-cycle bias might not be constant across cohorts. To address this issue, figure 6 compares the main estimates discussed in the previous section with the results one would obtain without controlling for life-cycle biases. Omitting the interaction between father's earnings and age leads on average to underestimate the IGE. Three main points need to be emphasized. First, for all cohorts, the bias is negative. The finding of a negative bias, despite having imposed an age restriction centered on the mid-career (28-50 years old) can be easily explained by the concavity of the interaction effect, as shown in figure 7. Second, the bias is for most cohorts relatively small, around -.04, with the notable exception of the last cohort. For individuals born in the early 1970s, who are surveyed earlier in their life-cycle, the bias is more important and close to -.08. Third, the V-shaped trend in the intergenerational persistence of inequality is largely present even without controlling for life-cycle effects. Including the interaction term between child's age and father's earnings slightly reinforces the estimated upward trend in the IGE in the most recent period.

The second robustness check investigates the influence of excluding self-employed workers. Since labor earnings are not reported by self-employed workers, I excluded from my samples both self-employed children and the children of self-employed fathers. The latter group represents about 27% of the children's sample while the former one amounts to 10%. There is no way to satisfactorily predict the incidence of this exclusion. To explore this question, I imputed father's earnings for the children of self-employed workers on the basis of the Mincer equation estimated for salaried fathers. This allows me to include the children of self-employed fathers in the estimation, as long as they are themselves salaried.[24] Results are given in table 2, column 4 and in figure 8. The level and time trends are very similar to those previously discussed. Of course, the validity of this robustness check hinges upon stringent restrictions. It requires that the relationship between schooling and earnings is similar for salaried and self-employed workers. Or at least that the bias induced by the use of a Mincer equation estimated on the sole sample of salaried workers stays constant over time. Both hypothesis are of course open to discussion. One additional point to keep in mind is that a large fraction of self-employed workers, especially at the beginning of the

[24] In my sample, this is the case for 75% of the children of self-employed fathers.

period, were farmers. As is well-known, earnings in agriculture tend to be relatively low (e.g. Lefranc, Pistolesi & Trannoy 2009) and occupational inheritance is particularly strong among farmers. This may suggest that the IGE is underestimated, in particular among early cohorts.

5 Changes in earnings inequality and the intergenerational correlation coefficient

Changes in the IGE are of course deeply connected to the evolution of earnings inequality, as discussed in section 2.1. We now turn to the analysis of the intergenerational correlation, which is less dependent on changes in the cross-sectional dispersion of earnings.

As equation 2 shows, a simple way to derive IGC estimates is to rescale IGE estimates by the ratio of the standard deviation of log *permanent* earnings in the father's and children's generation, $\frac{\sigma_X}{\sigma_Y}$. The main challenge is to obtain an estimate of this ratio. As already discussed, I do not observe permanent earnings for children and fathers. The earnings measure available for fathers is the predicted log-earnings at age 40. Given data availability, I develop two approaches to estimating the standard deviations ratio and the IGC.

The first approach is to use predicted earnings, based on education, in both children and fathers' generations to estimate the ratio $\frac{\sigma_X}{\sigma_Y}$. Under the assumption that the standard deviation of predicted earnings is a constant fraction of the standard deviation of permanent earnings across cohorts, this approach yields a consistent estimator of the IGC.[25] To implement this procedure, I replicate the model used in the first-step model (equation 5) to form a prediction of child's earnings based on education, age and cohort. I then compute the standard deviation of predicted earnings among children and fathers for all birth cohorts. This provides me with the ratio $\frac{\sigma_{\hat{X}}}{\sigma_{\hat{Y}}}$, where hats denote predictions based on education. This ratio can be combined with estimates of the IGE obtained in the previous section to form a first estimator of the IGC for each cohort c:

$$IGC1_c = \beta_c \times \frac{\sigma_{\hat{X}_c}}{\sigma_{\hat{Y}_c}} \tag{6}$$

[25] This assumption is implicit in Aaronson & Mazumder (2008)

Of course the standard deviation of predicted earnings will under-estimate the standard deviation of permanent earnings, in both children and fathers' generations. However $\frac{\sigma_{\hat{X}}}{\sigma_{\hat{Y}}}$ will provide a consistent estimator of $\frac{\sigma_X}{\sigma_Y}$ if the biases $\frac{\sigma_X}{\sigma_{\hat{X}}}$ and $\frac{\sigma_Y}{\sigma_{\hat{Y}}}$ are constant over time.

The second approach is to use *current* earnings to estimate the ratio of *permanent* earnings standard deviation. Under the assumption that the standard deviation of permanent earnings is a constant fraction of the standard deviation of current earnings across cohorts, this approach provides a consistent estimator of the IGC. Implementing this approach raises three issues. First, the point in the individual life-cycle where current earnings are observed varies across cohorts. Since the dispersion of earnings varies over the life-cycle, the standard deviation of current earnings will not be comparable across cohorts. This problem is addressed by removing life-cycle effects, in order to estimate, for each cohort the standard deviation of current earnings at age 40. I denote this standard deviation $\sigma_{\tilde{X}}$, where tilde indicates that current earnings have been purged from life-cycle variation.[26] The second issue is that current earnings are only observed for children and not for fathers. For any particular child cohort, I thus form a synthetic sample of fathers which is representative of the population of fathers of this specific child cohort.[27] I then estimate the dispersion of earnings at age 40 for this synthetic sample, $\sigma_{\tilde{Y}}$. These estimates can be combined to produce an alternative estimator of the IGC given by:

$$IGC2_c = \beta_c \times \frac{\sigma_{\tilde{X}_c}}{\sigma_{\tilde{Y}_c}} \tag{7}$$

The third issue pertains to the range of cohorts for which this procedure can be implemented. When estimating the standard deviation of earnings, I cannot rely on the earliest data wave (1964) since earnings are only available in bracketed form. Thus, I cannot estimate the standard deviation of earnings for any cohort born before 1910.[28] As a result, this second approach is only implemented for child cohorts born after 1951. Whether the

[26]Specifically, individual earnings are regressed on year effects and a fourth order polynomial function in age-40, interacted with birth cohort and education. I then remove any earnings variation arising from age by setting age-40 and year dummies equal to zero. This preserves any earnings variation arising from differences in education and idiosyncratic residuals.

[27]To form a representative synthetic sample of fathers, for each child cohort, I simply draw individuals from the entire sample of salaried workers, with drawing weights given by the distribution of father's birth cohort for the particular child cohort under consideration.

[28]This corresponds to individuals aged 60 in 1970.

assumption that the share of permanent and transitory components in earnings dispersion stayed constant over the range of cohorts considered in this paper is of course open to discussion. Moffitt & Gottschalk (2011) provide supportive evidence for the US. To my knowledge this issue has not been investigated using French data. I provide supportive evidence on this assumption for the French case in appendix A.3.

Levels and trends in the IGC are given in figure 9 and table 4. The first point to emphasize from these results is the high value of the IGC found on average across all cohorts: the average value of IGC1 over all cohorts is around .68; the average value of IGC2 over the cohorts 1951-1975 is around .60. Furthermore, both measures provide consistent results for the average level of the IGC in the second half of the period.

Since estimates of the IGC are the product of the IGE and of the ratio of standard deviations, two ingredients contribute to this high value of the IGC. The first is the high value of the IGE found on average for France over the period. The second contribution is the high value of the ratio of standard deviations of earnings. Both $\frac{\sigma_{\hat{X}}}{\sigma_{\hat{Y}}}$ and $\frac{\sigma_{\tilde{X}}}{\sigma_{\tilde{Y}}}$ are above one. This indicates that the dispersion of earnings was higher among fathers than among children, for every cohort. As a result, the IGC is sizably higher than the IGE throughout the period. For instance, in the middle cohorts, estimates indicate that the IGC is 30% (IGC2) to 50% (IGC1) higher than the IGE.

The second lesson drawn from these results pertains to the change in the intergenerational transmission of inequality across cohorts. Between the 1930s cohort and the early 1950s cohort, both the IGC and the IGE follow a decreasing trend. Note however that the relative fall in the IGC (-20%) is lower than the fall in the IGE (-30%). Furthermore, the fall in the IGC is not statistically significant over this period.[29] This indicates that the large fall in the IGE is also partly driven by changes in cross-section earnings inequality among children and fathers, as captured by the ratio $\frac{\sigma_X}{\sigma_Y}$. In fact, over the first half of the period, this ratio increases markedly as a result of the large fall in earnings inequality among children already noted in figure 3. In summary, the fall in the transmission of parental advantage to children over this period reflects both a decline in the extent to

[29]The overall χ^2 score for the global test of equality of the IGC is equal to 15.97 (36 degrees of freedom). The scores for the joint equality test is equal to 9.75 over the first five cohorts and 1.04 over the last five cohorts. None of these tests reject the null hypothesis of equality of the IGC across cohorts.

which children outcomes are determined by their parental background (lower IGC) and a fall in the degree of inequality between children (lower σ_Y).

Over the second half of the period, the IGC does not exhibit any clear trend. The first estimates, IGC1, exhibit a small decline of -8% from .65 to .60. The second ones, IGC2, increase by +16% from .55 to .64. In both cases, the differences across cohorts in the value of the IGC are not statistically significant over the period. In either case, the magnitude of the change appears small compared to the change in the IGE, over the same period (+35%). Analyzing the evolution of the ratio of standard deviations of earnings among fathers and children allows reconciling these discrepant evolutions. Over the second half of the period this ratio falls by about 20 to 40% (depending on the estimator). This fall indicates a convergence in the dispersion of earnings in the fathers and children's generations. This convergence results from the slowdown in the reduction in cross-sectional earnings apparent in figure 3. The largest fall in inequality occurs between cohorts born in the late 1930s and cohorts born in the early 1950s. Among children born after 1950, earnings inequality appears roughly constant. Earnings inequality among fathers follows the same path, but with a lag of about 25 years. As a result, the ratio $\frac{\sigma_X}{\sigma_Y}$ falls between the 1950s and the 1970s cohorts due largely to a fall in the numerator, while the denominator varies much less.

Overall, this analysis sheds new light on the evolution of intergenerational persistence in the long-run in France. On the one hand, the fall in the IGE noted in the previous section results from two distinct evolutions. The first one is a fall in the relative contribution of parental earnings to inequality among children. The second one is the reduction in cross-sectional inequality among children, which implies that a smaller share of parental earnings advantage gets transmitted to the next generation. On the other hand, the later rise in the IGE appears, to a large extent, as the delayed effect of this fall in cross-sectional inequality and could be seen as a convergence of the IGE to its steady-state value.

6 The contribution of educational expansion

Educational policy is often seen as the means *par excellence* of equalizing life-chances and fostering social mobility. Educational investment, however, is also often considered as one of the main channels of the intergenerational transmission of ability. In this perspective, the rise in access to upper secondary and higher education that occurred after World War II may have contributed to the evolution of intergenerational mobility. I investigate this contribution in this section.

The contribution of education acquisition to the intergenerational earnings elasticity can be summarized by the following system of equations:

$$H_{ic} = \beta_c^1 X_{ic} + u_{ic} \tag{8}$$

$$Y_{ic} = \gamma_c H_{ic} + \beta_c^2 X_{ic} + e_{ic} \tag{9}$$

where H denotes the human capital of the child. Equation 8 captures the relationship between parental earnings and human capital accumulation, as discussed for instance in Becker & Tomes (1979) and Solon (2004). In equation 9, child's earnings are determined by child's human capital and, residually, parental earnings. Using this system, the IGE can be expressed as:

$$\beta_c = \beta_c^1 \gamma_c + \beta_c^2 \tag{10}$$

As this equation makes clear, the intergenerational earnings elasticity can be decomposed as a function of three parameters: the effect of parental earnings on the human capital of the child (β_c^1), the returns to human capital (γ_c) and the residual effect of parental earnings on child's earnings, conditional on human capital (β_c^2).

To implement this decomposition, I first estimate equation 9 by regressing child's earnings on child's number of years of education and predicted father's earnings. As for the main IGE estimates, the coefficient on father's earnings should not be interpreted in a causal sense but as a catch-all measure of the residual impact of all family attributes related to earnings, once educational attainment has been taken into account. Estimates are given in table 5 and in figure 10.[30] Several results emerge from this estimation. First, similar to the results found for the US (Aaronson & Mazumder 2008) and Sweden (Björklund et al. 2009), I find that the residual effect of father's earnings β_c^2 accounts for 50 to 70%

[30] The econometric model also allows for year and age effects, as well as age $\times$ father's earnings interactions. Table 5, column 1, re-estimates the main IGE model on the sub-sample with non-missing education data.

of the total IGE. In other terms, education acquisition accounts for at most half of the intergenerational transmission of earnings inequality. Second, the time trend followed by the residual elasticity is roughly similar to that of the base IGE: it falls for intermediate cohorts and rises again for the most recent ones. Interestingly, while the overall IGE at the end of the period is lower than for cohorts born in the 1930s, it is no longer the case for the residual elasticity: For cohorts born in the 1970s, the residual transmission of earnings inequality is actually higher than for cohorts born in the 1930s.

The contribution of education acquisition to the intergenerational transmission of earnings can be computed as the gap between the overall IGE, β_c, and the residual elasticity β_c^2. This contribution is represented in figure 10. It falls over the period, from .24 for the 1930s cohorts to about .16 for cohorts born in the 1970s. Most of the fall occurs at the beginning of the period. Between the 1941 and the 1966, the contribution of educational acquisition to the intergenerational persistence in earnings is roughly stable, around .19.

This evolution results from changes in two parameters: the semi-elasticity of human capital to parental earnings and the returns to human capital. The evolution of the latter component is given in table 5, column 2. The returns to education fall over time from .057 to .032. This occurs in two steps, with a first drop between the early 1930s and the early 1940s cohorts and a second one for cohorts born in the late 1960s and early 1970s. These values of the returns to education lay on the low end of estimates reported in other studies, probably owing to the inclusion of father's earnings as an additional regressor. However trends are consistent with previous results (Selz & Thélot 2004).

This fall in the returns to education should induce, other things equal, a decrease in the IGE. But the overall evolution of the contribution of education to the intergenerational transmission of earnings also depends on the semi-elasticity β_c^1 of years of schooling with respect to father's earnings. This semi-elasticity is reported in column 3, table 5 and in figure 11. The statistical association between years of education and parental earnings falls over time between the 1930s cohorts and the early 1960s cohorts but subsequently rises to reach an even higher level than at the beginning of the period.

The secular rise in educational mobility that occurs until the very end of the period is relatively well-known. It has also been consistently noted in several studies that have focused on the association between parents' and child's education (e.g. Thélot & Vallet 2000). What is less well-known, however, is the reversal of the trend in the recent decades, although the results reported here are confirmed by those of Vallet & Selz (2007). This decrease in educational mobility, occurring at the end of the period can be characterized by a rise in the influence of family background on educational attainment. Of course, it contributes to the rise in the intergenerational transmission of inequality as we now discuss.

To isolate the contribution of the educational mobility parameter β_c^1 to the intergenerational transmission of earnings, I compute how the contribution of education to the IGE would have evolved, in the long run, if the earnings returns to education had stayed constant. This contribution is computed as $\beta_c^1\overline{\gamma}$, where $\overline{\gamma}$ denotes the average return to education across cohorts. Since it amounts to hold constant any evolution that might have occurred on the labor market, this comes closer to measuring the contribution of changes that have taken place in the educational system. The evolution of $\beta_c^1\overline{\gamma}$ is plotted in figure 10. The simulated values decline at a much slower pace over the 1930s to 1950s cohorts. Among the most recent cohorts the simulated values exhibit an increasing trend. This simulation casts a different light on the contribution of education to the intergenerational transmission of inequality, as it indicates a rise in persistence, even beyond the initially high levels of the 1930s. Once again, this indicates that changes in cross-sectional labor market inequality have played a key role in the decrease in the intergenerational transmission of economic inequality over the twentieth century. On the contrary educational mobility, as captured by β_c^1, had a modest contribution to the change in the intergenerational elasticity, although it may explain the recent upsurge in intergenerational economic persistence. Of course, the fall in the returns to education might itself reflect the wide educational expansion that took place over this period in France. In the end, this suggests that educational "massification" mostly favored mobility by decreasing labor market inequality rather than by decreasing the influence of family background on educational differentials.

7 Conclusion

In this paper, I have estimated trends in intergenerational mobility in France for cohorts of children born between the 1930s and the mid-1970s. The first result arising from this analysis pertains to the overall level of intergenerational mobility in France. Once life-cycle effects are taken into account, the intergenerational earnings elasticity in France amounts to an average value of .51. This value can be directly compared to estimates obtained for other countries. It indicates that intergenerational mobility in France is very low by international standards. Second, I show that the intergenerational earnings elasticity followed a V-shaped patterns across birth cohorts. From a high value of .6 for cohorts born in the 1930s, the intergenerational elasticity falls to a low value of about .43 for cohorts born in the late 1940s and the 1950s. It subsequently rises to reach a value of .57 for cohorts born in the early 1970s. Over the same period, the IGC exhibits smaller changes, in relative terms. It also displays a different time pattern: the IGC falls between the earliest two cohorts and the rest of the period but does not exhibit any clear change afterwards.

The fall in the intergenerational transmission of earnings inequality experienced by the cohorts born after World War II seems largely related to the decrease in earnings inequality and the fall in the returns to education that occurred mostly in the 1970s and early 1980s. This reduction in inequality has brought closer together the earnings prospects of individuals whose parents had experienced very different earnings levels, at a time of high earnings inequality. At the same time, the degree of inheritance, as captured by the intergenerational earnings correlation has remained roughly unchanged.

In the end, this rise in mobility captured by the IGE turns out to be short-lived and limited to the generational transition between two societies: the unequal society experienced by pre- baby-boom cohorts and the more equal one enjoyed by the baby-boomers. The early baby-boomers appeared more mobile than their parents only because they enjoyed more *intra*-generational equality. As the early baby-boomers became parents themselves, their children also experienced this less unequal society. Yet, since the degree of inheritance did not improve, this led the intergenerational elasticity to fall back toward its initial level.

All in all, these results empirically demonstrate that the intergenerational elasticity is very sensitive to inequality dynamics and that its evolution, outside the steady-state, could provide a misleading characterization of the long-run evolution of intergenerational mobility. This contrasts with the greater stability of the intergenerational earnings correlation.

Whether intergenerational persistence in France will get back, in the near future, to the high level experienced by the cohorts born in the 1930s is an open question. There are reasons, however to be pessimistic. First, intergenerational inheritance seems to have only slightly decreased. Second, while intergenerational transmission initially benefited from the large educational expansion of the post-WWII era, the association between parents' earnings and child's educational achievement has also risen recently. If earnings inequality was to rise among recent cohorts, the degree to which economic inequality is transmitted across generations, as captured by the IGE, could well rise to unprecedented levels.

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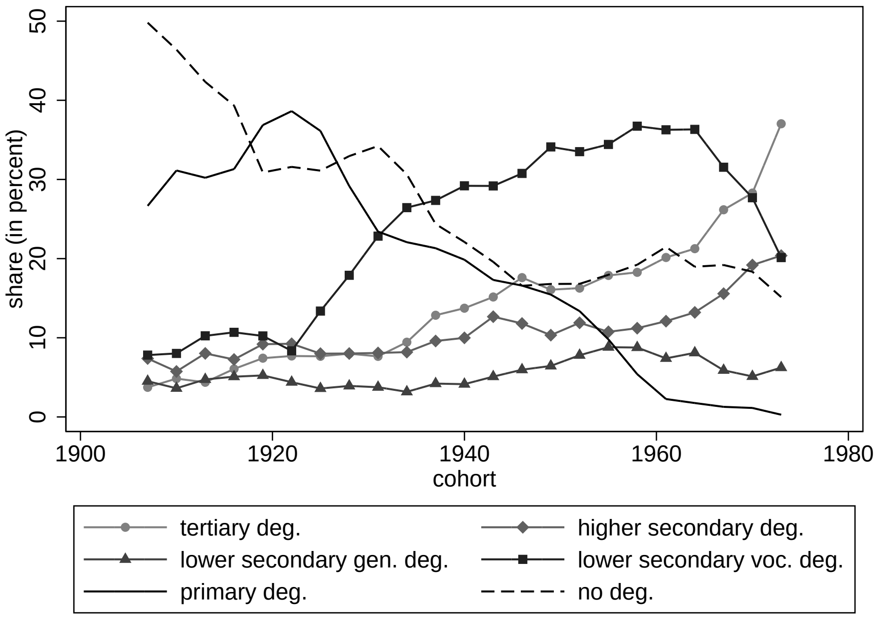
Table 1: Summary statistics

		cohort								
	all	1931-35	1936-40	1941-45	1946-50	1951-56	1956-60	1961-65	1966-70	1971-75
Observations	26932	2276	4328	3933	4548	3680	2816	2338	1623	1390
1970 survey (share)	0.128	0.509	0.387	0.170	0	0	0	0	0	0
1977 survey (share)	0.215	0.376	0.329	0.430	0.405	0	0	0	0	0
1985 survey (share)	0.283	0.115	0.283	0.319	0.433	0.596	0.244	0	0	0
1993 survey (share)	0.119	0	0	0.0814	0.162	0.192	0.255	0.299	0	0
2003 survey (share)	0.255	0	0	0	0	0.212	0.501	0.701	1	1
labor earnings (current Francs)	90466.7	40458.6	54553.2	71997.1	81879.6	110231.8	122337.6	131846.0	135105.3	122048.4
	(63488.0)	(39193.8)	(51091.7)	(60667.5)	(54876.1)	(55098.7)	(60764.1)	(63598.6)	(57424.1)	(49551.8)
highest degree (distribution)										
tertiary degree	0.212	0.135	0.178	0.218	0.227	0.214	0.189	0.198	0.267	0.368
higher secondary degree	0.139	0.113	0.129	0.158	0.139	0.133	0.125	0.130	0.163	0.193
lower sec. voc degree	0.314	0.254	0.287	0.287	0.328	0.345	0.357	0.372	0.340	0.230
lower sec. gen. degree	0.0648	0.0390	0.0410	0.0546	0.0632	0.0797	0.0982	0.0934	0.0588	0.0644
primary degree	0.122	0.203	0.199	0.163	0.140	0.116	0.0713	0.0134	0.00689	0.00650
no degree	0.148	0.255	0.166	0.119	0.102	0.111	0.159	0.193	0.164	0.137
father's predicted earnings (normalized)	1.275	1.102	1.157	1.235	1.262	1.327	1.354	1.372	1.402	1.459
	(0.537)	(0.474)	(0.510)	(0.556)	(0.553)	(0.569)	(0.560)	(0.501)	(0.449)	(0.433)
father's year of birth	1918.7	1901.6	1906.8	1910.8	1916.4	1922.0	1927.0	1932.4	1937.9	1943.9
	(12.053)	(6.954)	(6.749)	(7.582)	(7.337)	(7.207)	(6.750)	(6.808)	(7.146)	(6.686)
father self-employed (share)	0.267	0.340	0.338	0.295	0.263	0.244	0.214	0.224	0.203	0.182
	(0.442)	(0.474)	(0.473)	(0.456)	(0.440)	(0.429)	(0.410)	(0.417)	(0.403)	(0.386)
father's highest degree (distribution)										
tertiary degree	0.0705	0.0428	0.0539	0.0700	0.0611	0.0699	0.0791	0.0846	0.0923	0.132
higher secondary degree	0.0628	0.0531	0.0587	0.0671	0.0674	0.0639	0.0576	0.0614	0.0534	0.0848
lower sec. voc. degree	0.127	0.0361	0.0552	0.0852	0.116	0.134	0.160	0.203	0.242	0.304
lower sec. gen. degree	0.0393	0.0350	0.0396	0.0467	0.0456	0.0393	0.0278	0.0271	0.0535	0.0314
primary degree	0.351	0.336	0.351	0.360	0.370	0.372	0.360	0.344	0.331	0.246
no degree	0.349	0.497	0.441	0.371	0.340	0.321	0.316	0.280	0.228	0.201

Notes : standard deviations in parenthesis. Computations are based on the main sample, as described on page 12.

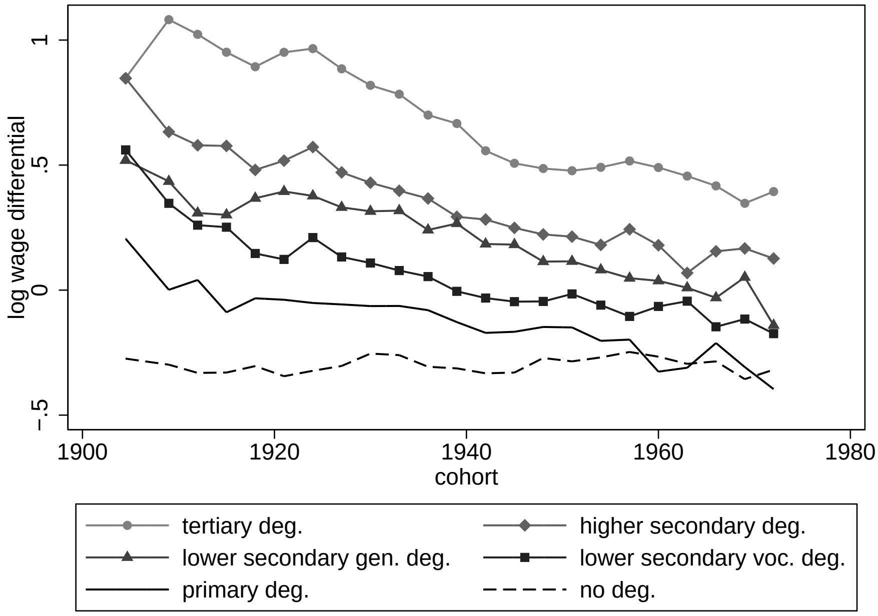
Figure 1: Distribution of education by cohort



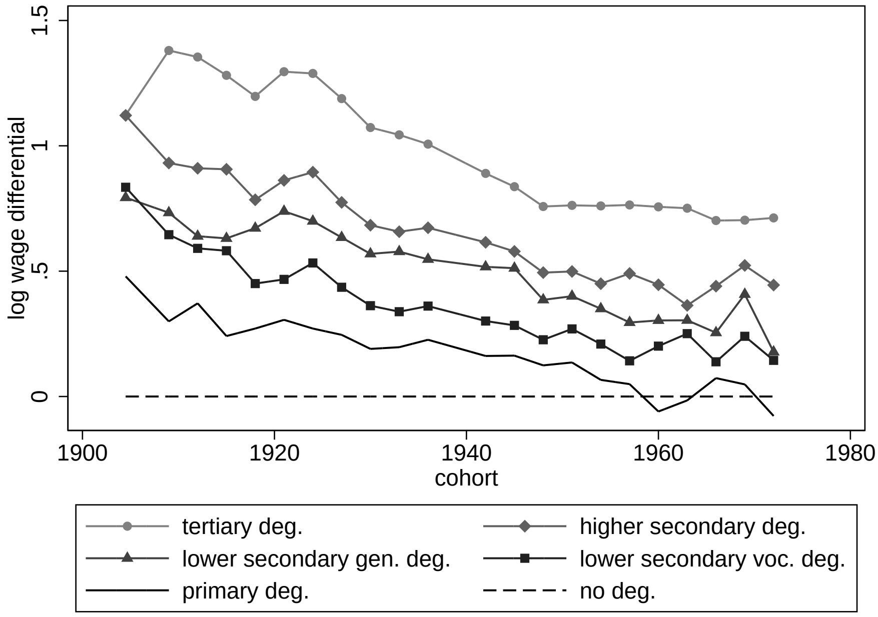
Notes : The figure gives the distribution of highest degree obtained, by cohort for three-year cohorts.

Figure 2: Education earnings differentials by cohort - predicted at age 40

A- Earnings differentials relative to mean earnings

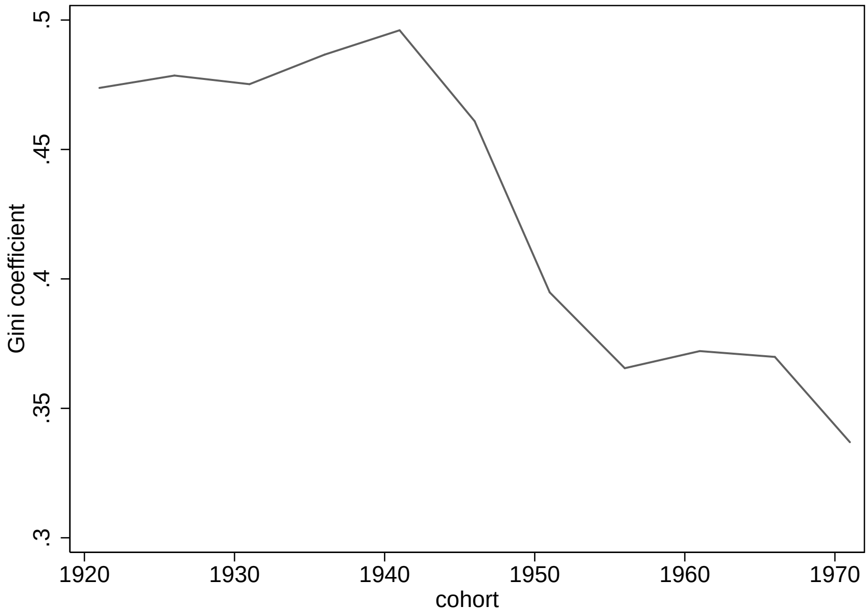


B- Earnings differentials relative to individuals without degree



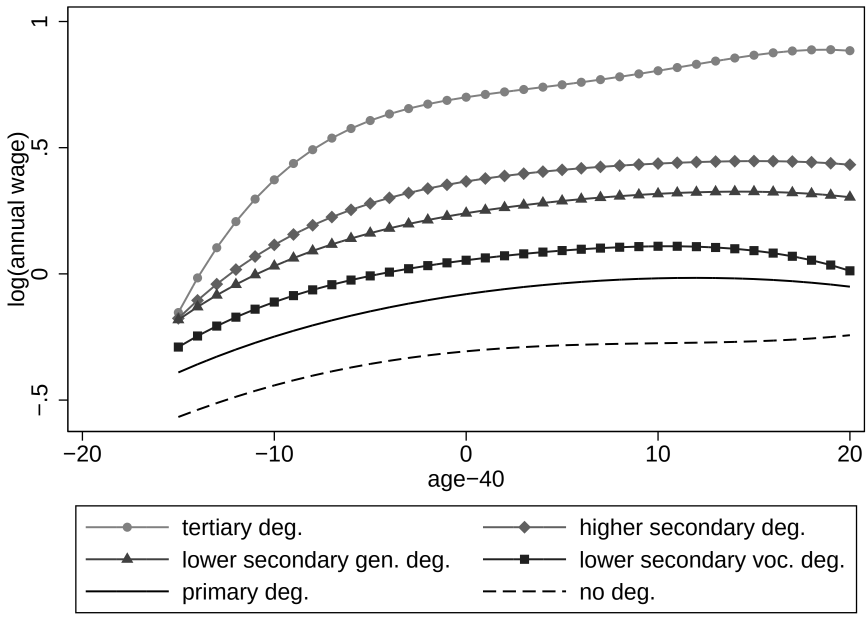
Notes : The figure gives the log annual earnings differential between each educational group and the mean annual earnings (panel A) or the earnings of individuals without any degree (panel B), for each three-years cohorts, based on the estimates of equation 5, reported in table A1. Earnings differentials are predicted at age 40.

Figure 3: Labor earnings inequality by cohort



Notes : to account for life-cycle effects, age-effects are subtracted so as to predict earnings at age 40 for each cohort. This is done using an earnings equation that allows for education- and cohort-specific age-effects.

Figure 4: Age-earnings profile by education



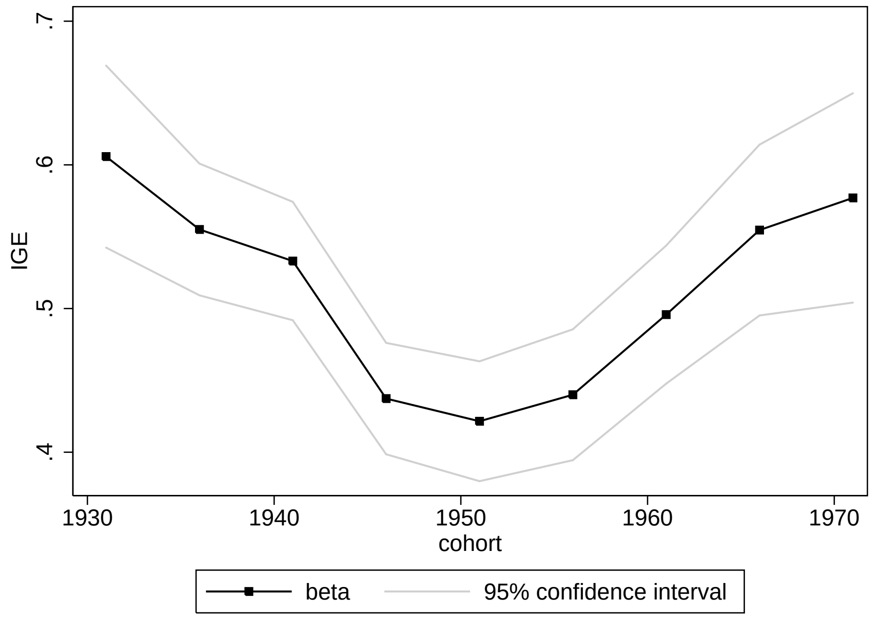
Notes : The figure gives the age-earnings profile for each educational group based on the estimates of equation 5, reported in table A1. The earnings variable on the y-axis is the log of annual earnings.

Table 2: Intergenerational earnings elasticity, by cohort

	(1)	(2)	(3)	(4)
father's earnings	.511			
	(.0159)			
father's earnings ×cohort				
1931-1935		.605	.594	.631
		(.0323)	(.0314)	(.0309)
1936-1940		.555	.529	.562
		(.0233)	(.0216)	(.0216)
1941-1945		.533	.495	.546
		(.0210)	(.0190)	(.0192)
1946-1950		.437	.390	.436
		(.0197)	(.0171)	(.0178)
1951-1955		.421	.378	.438
		(.0212)	(.0186)	(.0192)
1956-1960		.440	.403	.429
		(.0232)	(.0208)	(.0209)
1961-1965		.495	.462	.511
		(.0245)	(.0235)	(.0222)
1966-1970		.554	.515	.551
		(.0303)	(.0294)	(.0282)
1971-1975		.577	.499	.580
		(.0371)	(.0338)	(.0338)
father's earnings×(age-40)	.00446	.00416		.004823
	(.00136)	(.00142)		(.001242)
father's earnings×(age-40)^2	-.000735	-.000525		-.000461
	(.000197)	(.000205)		(.000178)
Joint test of equality of IGEs across cohorts				
Wald statistic		54.25	65.56	69.86
p-value		.026	.002	.0006
Observations	19699	19699	19699	26986

Notes : Standard errors in parentheses are corrected following Murphy & Topel (1985). The dependent variable is the log of annual earnings. Reported estimates are based on equation 4. Columns 1-3 exclude self-employed children and the children of self-employed fathers. Column 4 includes the children of self-employed fathers. All equations include year and age effects.

Figure 5: IGE by cohort



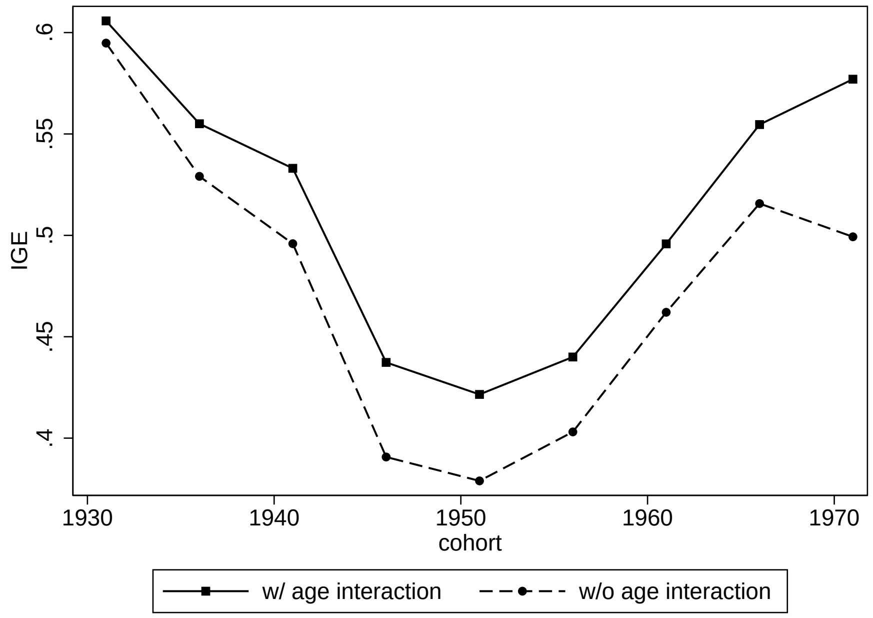
Notes : reported IGEs are based on the estimates in table 2, column 2.

Table 3: Statistical significance of IGE differences between cohorts (p-values for pair-wise equality tests)

cohorts	1931-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960	1961-1965	1966-1970
1936-1940	.1057	.						
1941-1945	.0289	.3793	.					
1946-1950	<.0001	<.0001	.0001	.				
1951-1955	<.0001	<.0001	<.0001	.5238	.			
1956-1960	<.0001	.0002	.0011	.9212	.4839	.		
1961-1965	.0057	.0662	.218	.0433	.0135	.0647	.	
1966-1970	.2423	.9911	.5396	.0007	.0002	.0014	.0836	.
1971-1975	.55	.5966	.2683	.0003	.0001	.0007	.034	.5707

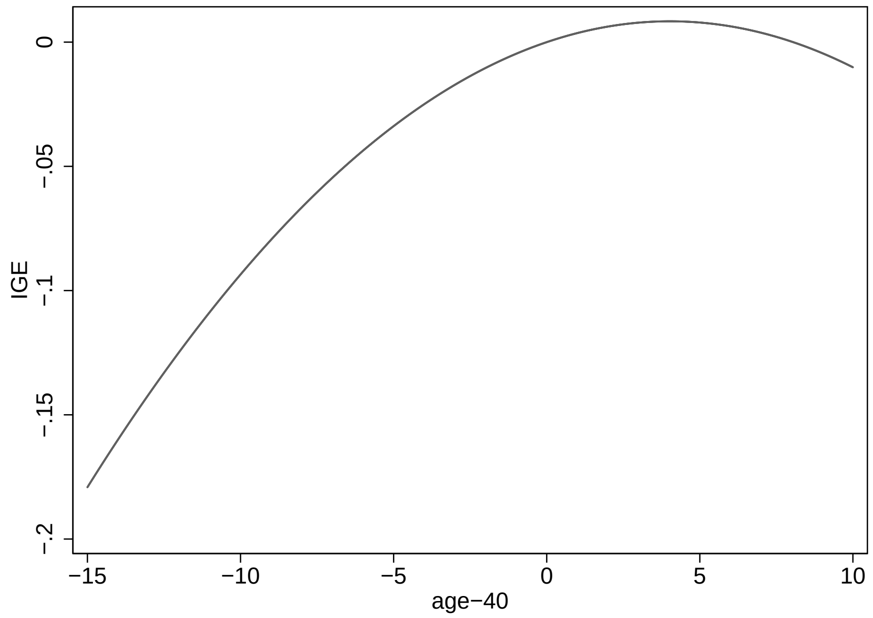
Notes : tests are based on IGE estimates reported in table 2 column2.

Figure 6: IGE by cohort - Influence of age× father's earnings interactions



Notes : reported IGEs are based on the estimates in table 2, columns 2 and 3.

Figure 7: IGE - age× father's earnings profile



Notes : age profiles are based on the estimates in table 2, columns 2

Figure 8: IGE by cohort - Influence of the inclusion the children of self-employed

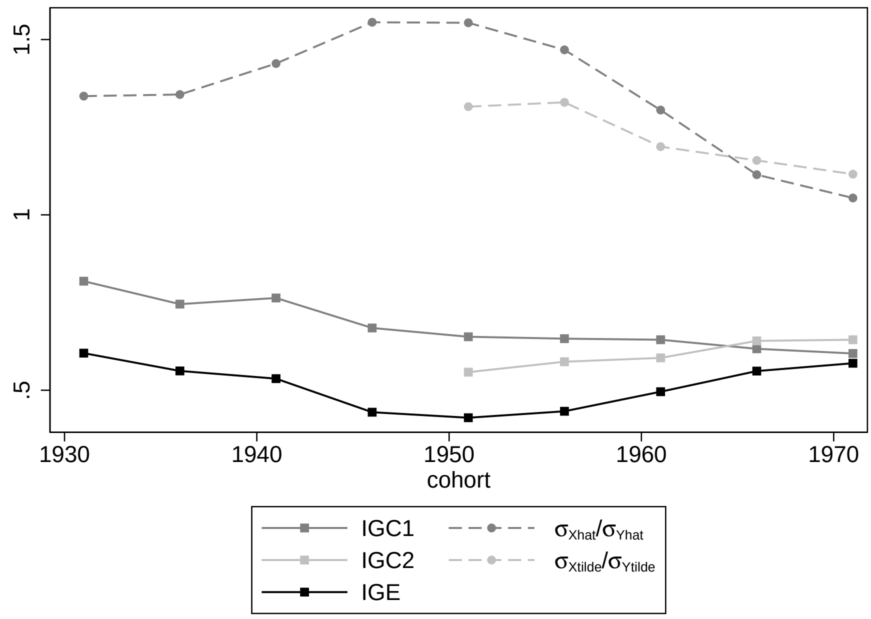
Notes : reported IGEs are based on the estimates in table 2, columns 2 and 4.

Table 4: Intergenerational earnings correlation, by cohort

	(1) IGE	(2) IGC1	(3) $\sigma_{\hat{X}}/\sigma_{\hat{Y}}$	(4) IGC2	(5) $\sigma_{\tilde{X}}/\sigma_{\tilde{Y}}$
1931-1935	.605	.81	1.338		
	(.0323)	(.0516)			
1936-1940	.555	.745	1.343		
	(.0233)	(.0388)			
1941-1945	.533	.763	1.431		
	(.021)	(.037)			
1946-1950	.437	.677	1.549		
	(.0197)	(.0353)			
1951-1955	.421	.652	1.547	.551	1.308
	(.0212)	(.0372)		(.0298)	
1956-1960	.44	.647	1.47	.581	1.32
	(.0232)	(.0397)		(.0336)	
1961-1965	.495	.644	1.298	.592	1.194
	(.0245)	(.0408)		(.0343)	
1966-1970	.554	.618	1.114	.64	1.155
	(.0303)	(.0423)		(.0408)	
1971-1975	.577	.604	1.048	.644	1.116
	(.0371)	(.0479)		(.0478)	
Joint test of equality of IGEs across cohorts					
Wald statistic		15.97		4.75	
degrees of freedom		36		10	
p-value		0.998		0.907	

Notes : IGEs are based on the estimates in table 2, column 2. IGC1 and IGC2 are estimated using equations 6 and 7.

Figure 9: IGE and IGC by cohort



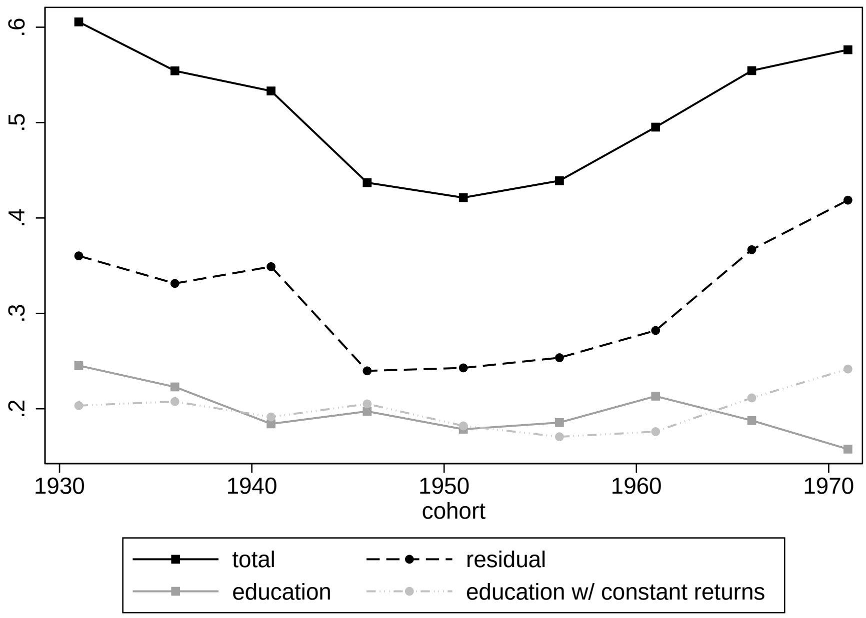
Notes : see details on page 20. The ratio $\frac{\sigma_X}{\sigma_Y}$ is computed using earnings net of age effects for children and predicted earnings for fathers. The estimated IGC is derived from estimates of $\frac{\sigma_X}{\sigma_Y}$ and the IGE

Table 5: Decomposition of the intergenerational earnings elasticity and analysis of the contribution of education, by cohort

		(1)	(2)	(3)
Dependent variable		log annual earnings		years of education
father's earnings				
×cohort	1931-1935	.605	.360	4.263
		(.0323)	(.0333)	(.193)
	1936-1940	.554	.331	4.352
		(.0233)	(.0241)	(.146)
	1941-1945	.533	.348	4.014
		(.021)	(.0215)	(.143)
	1946-1950	.437	.239	4.301
		(.0197)	(.0204)	(.145)
	1951-1955	.421	.242	3.817
		(.0212)	(.0215)	(.160)
	1956-1960	.439	.253	3.579
		(.0232)	(.0237)	(.175)
	1961-1965	.495	.282	3.691
		(.0245)	(.026)	(.184)
	1966-1970	.554	.366	4.432
		(.0303)	(.0325)	(.228)
	1971-1975	.576	.418	5.068
		(.0371)	(.0399)	(.279)
years of education				
×cohort	1931-1935		.0577	
			(.00292)	
	1936-1940		.0513	
			(.00217)	
	1941-1945		.0459	
			(.00216)	
	1946-1950		.0463	
			(.00204)	
	1951-1955		.0471	
			(.00238)	
	1956-1960		.0524	
			(.00296)	
	1961-1965		.0556	
			(.00316)	
	1966-1970		.0404	
			(.00340)	
	1971-1975		.0320	
			(.00352)	
Observations		19689	19689	19689

Notes : Standard errors in parentheses are corrected following Murphy & Topel (1985). Column 1 reports IGE estimates based on equation 4. Column 2 reports estimates of equation 9. Column 3 reports estimates of equation 8.

Figure 10: Contributions to changes in the IGE by cohort



Notes : total denotes the overall IGE (β_c); residual denotes the residual elasticity of child's earnings w.r.t. father's earnings, conditional on child's education(β_c^2); education denotes the gap between total and residual and represents the component of the intergenerational transmission that occurs through education acquisition ($\beta_c^1\gamma_c$); education w/ constant returns assumes that the earnings returns are constant ($\beta_c^1\overline{\gamma}$). See page 23 for details.

Figure 11: Effect of parental earnings on child's education

Notes : see table 5, column 3.

A Appendix

A.1 First-step estimation results

Table A1: First-step equation estimation- Dependant variable : log(annual earning)

		Coefficient	Standard error
Intercept		11.07849	0.02317
Survey wave 1964		-2.02079	0.05239
Survey wave 1970		-1.54555	0.03763
Survey wave 1977		-0.77385	0.02083
Survey wave 1985		REF	REF
Survey wave 1993		0.195	0.02162
Survey wave 2003		0.36777	0.0452
Higher education ×	cohort 1903-1908	0.81475	0.12866
	cohort 1909-1911	1.16551	0.10197
	cohort 1912-1914	1.10396	0.08439
	cohort 1915-1917	1.08556	0.08202
	cohort 1918-1920	1.06448	0.06438
	cohort 1921-1923	1.15622	0.05626
	cohort 1924-1926	1.1459	0.04904
	cohort 1927-1929	1.13798	0.04263
	cohort 1930-1932	1.06117	0.03787
	cohort 1933-1935	1.02424	0.03331
	cohort 1936-1938	0.97107	0.03055
	cohort 1939-1941	0.9793	0.03024
	cohort 1942-1944	0.93336	0.02902
	cohort 1945-1947	0.88995	0.03228
	cohort 1948-1950	0.83229	0.03663
	cohort 1951-1953	0.79944	0.0432
	cohort 1954-1956	0.82623	0.04941
	cohort 1957-1959	0.85314	0.05731
	cohort 1960-1962	0.81899	0.06513
	cohort 1963-1965	0.78852	0.07122
	cohort 1966-1968	0.76642	0.07735
	cohort 1969-1971	0.68211	0.08634
	cohort 1972-1974	0.79002	0.09634
	cohort 1975-1977	0.89199	0.12369
Upper secondary education ×	cohort 1903-1908	0.81341	0.11635
	cohort 1909-1911	0.71667	0.09527
	cohort 1912-1914	0.66017	0.08053
	cohort 1915-1917	0.71072	0.07883
	cohort 1918-1920	0.65198	0.06351
	cohort 1921-1923	0.72269	0.05454
	cohort 1924-1926	0.75209	0.04972
	cohort 1927-1929	0.72382	0.04221
	cohort 1930-1932	0.67149	0.03715
	cohort 1933-1935	0.63794	0.03384
	cohort 1936-1938	0.63742	0.03057
	cohort 1939-1941	0.60632	0.03114
	cohort 1942-1944	0.65838	0.03028
	cohort 1945-1947	0.63164	0.03356

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		Coefficient	Standard error
	cohort 1948-1950	0.56864	0.03854
	cohort 1951-1953	0.53562	0.04506
	cohort 1954-1956	0.51598	0.05174
	cohort 1957-1959	0.5798	0.05963
	cohort 1960-1962	0.50812	0.06751
	cohort 1963-1965	0.40081	0.07498
	cohort 1966-1968	0.50465	0.08356
	cohort 1969-1971	0.50156	0.09001
	cohort 1972-1974	0.52222	0.10059
	cohort 1975-1977	0.52277	0.12804
Vocational lower secondary education ×	cohort 1903-1908	0.52683	0.10706
	cohort 1909-1911	0.43077	0.08902
	cohort 1912-1914	0.34072	0.07847
	cohort 1915-1917	0.38576	0.07435
	cohort 1918-1920	0.31771	0.06465
	cohort 1921-1923	0.32774	0.0567
	cohort 1924-1926	0.39001	0.04807
	cohort 1927-1929	0.38538	0.04041
	cohort 1930-1932	0.35044	0.03377
	cohort 1933-1935	0.31888	0.02919
	cohort 1936-1938	0.32502	0.02602
	cohort 1939-1941	0.30817	0.02576
	cohort 1942-1944	0.34435	0.02664
	cohort 1945-1947	0.33661	0.0295
	cohort 1948-1950	0.30067	0.03372
	cohort 1951-1953	0.30649	0.03925
	cohort 1954-1956	0.27512	0.04615
	cohort 1957-1959	0.23128	0.05271
	cohort 1960-1962	0.26338	0.06003
	cohort 1963-1965	0.28808	0.06708
	cohort 1966-1968	0.20279	0.07467
	cohort 1969-1971	0.21897	0.08381
	cohort 1972-1974	0.2218	0.0964
	cohort 1975-1977	0.13839	0.11209
General lower secondary education ×	cohort 1903-1908	0.48551	0.16436
	cohort 1909-1911	0.51844	0.113
	cohort 1912-1914	0.38922	0.09497
	cohort 1915-1917	0.43514	0.09527
	cohort 1918-1920	0.53869	0.06946
	cohort 1921-1923	0.59943	0.05973
	cohort 1924-1926	0.55672	0.05514
	cohort 1927-1929	0.58391	0.04942
	cohort 1930-1932	0.55715	0.04569
	cohort 1933-1935	0.55848	0.04114
	cohort 1936-1938	0.51152	0.03915
	cohort 1939-1941	0.57927	0.03974
	cohort 1942-1944	0.56049	0.03729
	cohort 1945-1947	0.56478	0.03746
	cohort 1948-1950	0.45991	0.04103
	cohort 1951-1953	0.43696	0.04703

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		Coefficient	Standard error
	cohort 1954-1956	0.41605	0.05376
	cohort 1957-1959	0.38419	0.05995
	cohort 1960-1962	0.36589	0.06886
	cohort 1963-1965	0.34144	0.07735
	cohort 1966-1968	0.31887	0.09141
	cohort 1969-1971	0.3862	0.1149
	cohort 1972-1974	0.25528	0.12127
	cohort 1975-1977	0.18722	0.14538
Primary education ×	cohort 1903-1908	0.17138	0.09765
	cohort 1909-1911	0.08483	0.08412
	cohort 1912-1914	0.12143	0.07472
	cohort 1915-1917	0.04544	0.07036
	cohort 1918-1920	0.13836	0.05796
	cohort 1921-1923	0.16632	0.0505
	cohort 1924-1926	0.1284	0.0437
	cohort 1927-1929	0.1956	0.03771
	cohort 1930-1932	0.17811	0.03275
	cohort 1933-1935	0.17726	0.02868
	cohort 1936-1938	0.19038	0.02618
	cohort 1939-1941	0.18506	0.02556
	cohort 1942-1944	0.20507	0.02746
	cohort 1945-1947	0.21596	0.03033
	cohort 1948-1950	0.1985	0.03508
	cohort 1951-1953	0.17256	0.04162
	cohort 1954-1956	0.13222	0.04978
	cohort 1957-1959	0.13845	0.06296
	cohort 1960-1962	0.002561	0.09492
	cohort 1963-1965	0.02179	0.12145
	cohort 1966-1968	0.13773	0.12587
	cohort 1969-1971	0.027	0.15483
	cohort 1972-1974	REF	REF
	cohort 1975-1977	0.25003	0.27188
No degree ×	cohort 1903-1908	-0.30789	0.09562
	cohort 1909-1911	-0.21478	0.082
	cohort 1912-1914	-0.25026	0.07362
	cohort 1915-1917	-0.1957	0.06831
	cohort 1918-1920	-0.1328	0.05839
	cohort 1921-1923	-0.13952	0.05116
	cohort 1924-1926	-0.14278	0.04413
	cohort 1927-1929	-0.05048	0.03753
	cohort 1930-1932	-0.01186	0.03143
	cohort 1933-1935	-0.0195	0.02644
	cohort 1936-1938	-0.03573	0.02393
	cohort 1942-1944	0.04328	0.02649
	cohort 1945-1947	0.05283	0.03011
	cohort 1948-1950	0.07432	0.03414
	cohort 1951-1953	0.03682	0.04068
	cohort 1954-1956	0.06587	0.04801
	cohort 1957-1959	0.08896	0.05413
	cohort 1960-1962	0.06238	0.06132

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		Coefficient	Standard error
	cohort 1963-1965	0.03734	0.0688
	cohort 1966-1968	0.06437	0.0777
	cohort 1969-1971	-0.02133	0.0863
	cohort 1972-1974	0.0776	0.09626
	cohort 1975-1977	-0.06945	0.11295
Higher education ×	age	0.01171	0.0030438
	age^2	-0.0007823	0.0002258
	age^3	0.00009903	0.00001326
	age^4	-3.31E-06	1.01E-06
Upper secondary education×	age	0.01238	0.0030364
	age^2	-0.0008048	0.0002229
	age^3	0.0000373	0.00001137
	age^4	-9.86E-07	9.17E-07
Vocational lower secondary education×	age	0.0096945	0.0027407
	age^2	-0.000448	0.000169
	age^3	0.00001352	7.71E-06
	age^4	-1.03E-06	6.80E-07
General lower secondary education×	age	0.01222	0.0033687
	age^2	-0.0005944	0.0002856
	age^3	0.00002086	0.00001465
	age^4	-6.88E-07	1.18E-06
Primary education×	age	0.01091	0.0027908
	age^2	-0.0005035	0.0001539
	age^3	6.33E-06	8.46E-06
	age^4	-2.36E-07	6.35E-07
No degree ×	age	0.0070362	0.002777
	age^2	-0.0005369	0.0001511
	age^3	0.00001314	8.43E-06
	age^4	2.04E-07	6.25E-07
σ	Normal	0.4423	0.0014413
Number of Observations		48245	
Noncensored Values		41394	
Log Likelihood		-36966.33378	

A.2 Father's birth year assignment in case of missing information

In waves 1970 and 1977, respondents do not report their father's birth year although it needs to be taken into account to impute father's earnings. To perform this imputation, I use information is available in subsequent survey waves. It allows computing, for each child's birth cohort, the distribution of father's birth cohorts. This distribution is used in the imputation of father's earnings.

For an individual in waves 1970 and 1977, from cohort c, reporting father's level of education s, imputed father's earnings is computed as

$$\hat{X}_{cs} = \sum_b p_{bc}\gamma_b^s$$

where b is an index of father's cohorts, γ_b^s is the earnings premium attached to education s for cohort b, as defined in equation 5; p_{bc}=P(father's birth cohort=b|child's cohort=c) is the relative frequency of father's birth cohort b, among child's cohort c.

In other words, conditional on reported father's education, when father's birth cohort is missing, imputed earnings are equal to the weighted average of father's earnings taken over father's birth cohorts, where weights p_{bc} are computed using non-missing information. The values of p_{bc} are given in table A2.

Table A2: Distribution of father's triennial birth cohort, by cohort

	children's cohort								
	1931-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960	1961-1965	1966-1970	1971-1975
father's birth cohort :									
median	1903	1906	1909	1918	1921	1927	1933	1939	1945
distribution									
$\geq$ median +3	0.030	0.091	0.220	0.049	0.126	0.072	0.064	0.045	0.023
median+2	0.108	0.160	0.094	0.119	0.168	0.132	0.113	0.133	0.097
median+1	0.176	0.201	0.165	0.182	0.190	0.207	0.176	0.182	0.214
median	0.200	0.168	0.153	0.154	0.168	0.184	0.198	0.175	0.218
median-1	0.179	0.141	0.123	0.098	0.117	0.141	0.157	0.143	0.145
median-2	0.098	0.111	0.102	0.140	0.062	0.111	0.110	0.111	0.103
$\leq$ median-3	0.209	0.129	0.143	0.259	0.169	0.153	0.181	0.211	0.199

Notes : Fathers' birth cohorts are grouped in three-year cohorts: 1903 denotes the birth cohorts 1903-1905, 1906 denotes the birth cohorts 1906-1908, etc. The distribution of triennial cohorts are given relative to the median cohort. In the first column, the median cohort is 1903-1905; median+1 denotes the cohort 1906-1908; median+2 denotes the cohort 1909-1911, etc.

A.3 Earnings variance decomposition model

In section 5, the estimator IGC2 rests on the assumption that the standard deviation of permanent earnings is a constant fraction of the standard deviation of current earnings across cohorts. To assess the validity of this assumption, I rely on external data set providing longitudinal information on individual earnings to estimate a variance decomposition model for France.

The data set used come from the DADS (*Déclarations Annuelles de Données Sociales*) files which provides yearly information on annual wages for a 1/25th sample of French salaried population working with private sector employers. Information is reported for the period 1976-2010.

I estimate a simple earnings variance decomposition model of the form:

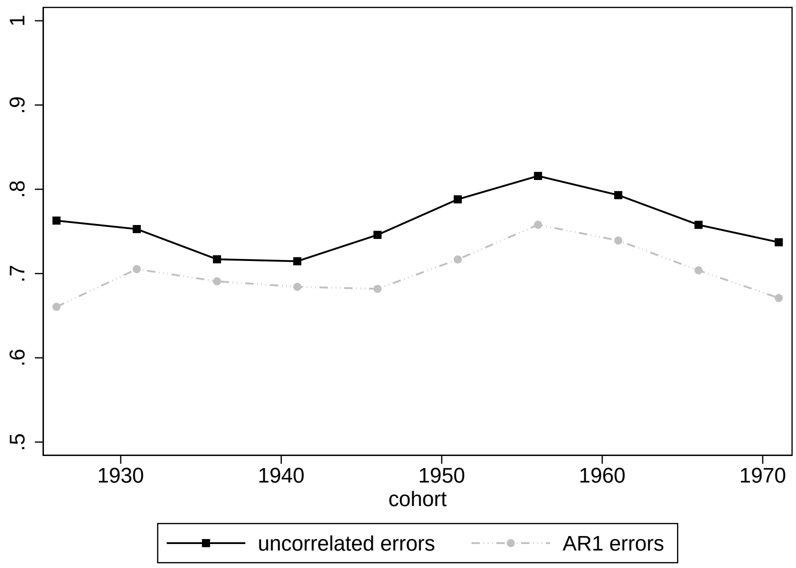
$$w_{it} = e_i + u_{it}$$

where: w denotes individual log-earnings net of cohort- and year-effects[31]; e_i is an individual random effect; u_{it} is a time-varying component. I estimate the above random-effect model under two assumptions on the time-series properties of u_{it}. First, I assume no intra-individual time-correlation. Second, I assume that u_{it} follows an AR(1) process.

The variance decomposition model is estimated separately on each of the 5-years birth cohorts 1926-1930 to 1971-1975. I restrict individual observations to years where the individuals was aged 30 to 50 years old.

Results are presented in figure A1. The figure displays the variance of the individual component e_i as a fraction of the variance of w_{it}, for both models. The share of the individual component in cross-section variance of earnings is between .7 and .8. It is of course larger under the assumption of no serial correlation. The variation in this share across cohorts is small and displays no clear trend. Equality of this share across cohorts cannot be rejected at conventional levels. This may be seen as supportive of the assumption that the standard deviation of permanent earnings is a constant fraction of the standard deviation of current earnings across cohorts.

Figure A1: Earnings variance decomposition: share of individual component in yearly variance



Notes : author's computation on DADS data.

[31] In a first-stage, I regress earnings on cohort×year dummies.