Does Speed Signal Ability? The Impact of Grade Repetitions on Employment and Wages*

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Abstract

To estimate returns to education, we replace the years-of-education regressor with, (i), a variable called "education level," measuring the position on a scale of diplomas and degrees, earned by the individual, and (ii), a variable called "delay", measuring the individual's total time to degree completion. Using quarter-of-birth and distance to the nearest college at the age of junior-high-school entry as instruments, we find that a year of delay with respect to average completion times causes a significant 3% decrease of the wage, and a significant 15% decrease of the probability of employment in the first five years of career, while education level has positive effects. Results are first established with standard linear methods (3SLS). A nonlinear econometric model based on conditional expected utility maximization generates four equations determining wages, probability of employment, education level, and delay. Estimation by Maximum Likelihood confirms the results. The nonlinear model passes the likelihood-ratio test against a closely comparable "reduced form" in which education levels are endogenous dummy variables, determined by an Ordered Probit structure. Delay is interpreted as a signal in the sense of Spence. Estimation is based on a very rich sample of more than 12,000 young workers, in France.

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1 Introduction

The classic method for the estimation of returns to education uses years of schooling as a regressor. In the following, we replace the years-of-education with two variables: the first, called "education level," measures the position on a scale of diplomas and degrees, earned by the individual, and the second, called "delay", measures the individual's total time to degree completion. For a given degree, there is a substantial variability of time-to-completion, and of school-leaving age. We show that, when suitably instrumented, both education level and delay have opposite impacts on the individuals' wages, and on probabilities of employment. Delay has a significant and negative impact: a year of delay with respect to average completion times causes a 3% decrease of the wage, and a 15% decrease of the probability of employment in the first five years of career. In contrast, the education level, (when measured in years of education, marked with passed examinations), has a return of 8% per year on wages, and increases the probability of employment by 6%. In other words, two years of delay with respect to the average, if used to complete a year of study's exams, would almost completely wipe out the benefits of the additional certificate on the labor market. To obtain these results, we use a set of instruments: quarter-of-birth, distance to the nearest college and geographical location, at the age of junior-high-school entry. To these core instruments, we have added a number of family background characteristics, such as birth order and the number of siblings. We also use parental education and occupation indicators as controls for the wage equation, and show that our additional instruments pass the tests of overidentifying restrictions. These results are first established with the help of standard linear methods (i.e., 3SLS), on a system of four simultaneous equations determining respectively: wages, probability of employment, education level, and delay. We then propose a theory based on conditional expected utility maximization, which generates a nonlinear econometric model with four equations for wages, employment, education and delay. Taking direct and opportunity costs into account, we assume that individuals choose their optimal level of education, bearing risks on wages, employment, and time-to-completion simultaneously. These risks are taken behind a veil of partial uncertainty, in the following sense: students condition expectations with respect to background characteristics that the econometrician does not observe, but do affect individual education costs. Estimation of this model by Maximum Likelihood fully confirms the findings. Our nonlinear theory can be compared closely with a "reduced form" model in which education levels are endogenous dummy variables, determined by an Ordered Probit structure, as in Cameron and Heckman (1998). The constraints imposed by our theory on the Ordered Probit structure are accepted, when tested against the "reduced form" by means of a likelihood-ratio test. The finding that delay reduces wages and employment can be seen as a form of evidence for the presence of signaling in the sense of Spence (1973): delay, as defined above, would affect wages and beginning-of-career employment probabilities because it signals the presence of less productive, unobservable individual characteristics to the employers. The tests of overidentifying restrictions can be used to test for the signaling hypothesis against the traditional form of human capital theory. Our estimation results are obtained with the help of a very rich sample of young workers, in France, containing observations of education, job search, jobs, unemployment spells, and wages, during the first five years of career of each individual.

The importance of degrees (as opposed to years of education) has been discussed in the literature. "Sheepskin effects" have been identified by various authors; see e.g. Hungerford and Solon (1987), Jaeger and Page (1996). Degree holders tend to obtain higher wages than the workers with the same number of years of education, but who failed to pass the final exams. At the same time, Kane and Rouse (1995) showed that, among those who failed to earn the degree, the number of credits (i.e., partial completion of a Two-Year College's degree, for instance) does matter. Time-to-degree and other forms of schooling delays are in fact important from the empirical point of view. For instance, Brunello and Winter-Ebner (2003) have analyzed the expected completion time of college students in 10 European countries; they show that the percentage of students expecting to complete their degree at least one year later than the required time ranges from 30% in Sweden and Italy to zero in the UK. The problem seems to be important in the US, at the undergraduate as well as graduate levels (see Garibaldi *et al.* (2006), and their references). There is a literature on the time taken to complete PhDs in various countries (see Booth and Satchell (1995), Ehrenberg and Mavros (1995), Van Ours and Ridder (2003)). The recent work of Garibaldi, Giavazzi, Ichino and Ettore (2006) identifies the impact of tuition fees on the time-to-degree of students at the Bocconi University in Milan. They show that a 1000 euros increase in tuition, in the last year of the programs, would reduce the probability of late graduation by 6 percentage points (with respect to an average probability of 80%). These results bring grist to our mill, because our approach is entirely based on the identification potential of the variability in school-leaving ages, conditional on a given education level (i.e. degree). Our nonlinear model embodies the effect of expected delays on direct and opportunity costs of education, which in turn determine individual investments in human capital.

The French education data used below has several sizeable sources of delay, because grade repetitions in primary, secondary and higher education are very common. Our delay variable is the the result of an addition of these endogenous sources of variation; it is defined below as the difference between the individual's school-leaving age and the observed average completion age of the students who left school with the same level. It happens to be an important determinant of wages and employment probabilities, but its impact can be identified only with the help of instruments. Indeed, OLS estimations of log-wage regressions would yield positive coefficients on both delay and education. Instrumentation is therefore crucial. Distance to the nearest college (at the time of junior high-school entry) is one of our core instruments, and has been built with the help of detailed geographical data of the French National Geographic Institute[1]. This type of college proximity instrument, measuring a form of exogenous variation of education costs, has been used by various authors, including the pioneering work of Card (1995); see also, e.g., Duflo (2001), Carneiro *et al.* (2003). Distance to the nearest college is a very significant variable in our education equations.

Our other classic instrument is quarter-of-birth. Birth dates, months or quarters have been popularized by Angrist and Krueger[2] (1991). Date-of-birth variations have been used as a source of indentification by many authors in Education Economics; see, for instance, the recent contributions of Leuven *et al.* (2006), Bedard and Dhuey (2006), and their references). Bedard and Dhuey (2006) also serve our cause, because they explore the effect of observed age

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[2] Critics have pointed out the possibility that season of birth be correlated with family background and other potential problems (see Bound and Jaeger (2000)), but the importance of this problem can depend on the set of controls included in the equations of interest (i.e., log-wages and employment probability), and we do control for socio-economic family characteristics.

on various student outcomes, like test scores in different grades, and use “assigned relative age", i.e., the relative age that a student should have, in his (her) class, given the country’s school-entry cut-off date and his (her) birth date, as an instrument for age. Assigned relative age, which is a function of the month of birth, has long-lasting effects: children being born just before the cut-off date, and therefore the youngest in their class, have markedly smaller chances of being enrolled in a four-year college (in the US and Canada), than the others. We do find that quarter-of-birth is a significant determinant of in the “first-stage" equation for delay[3].

We now add a few comments on our structural econometric approach, and its relationship with the literature on human capital. The literature on returns to education, initiated by the work of Becker (1964), Mincer (1974) and others, has been entirely renewed in the 90s by the quest for instrumental variables, aimed at solving the problem posed by the endogeneity of education; see the surveys of Card (1999), Heckman *et al.* (2003). A small number of structural econometric approaches have tested dynamic theories of individual schooling investments in models in which schooling decisions are derived from dynamic programming, applied to expected utility maximization; see, e.g., Keane and Wolpin (1997), Eckstein and Wolpin (1999), Taber (2001), Belzil and Hansen (2002), Magnac and Thesmar (2002), Attanasio *et al.* (2005). Further impetus has been given by the increasing need to take individual heterogeneity of returns and information into account. This has led to contributions proposing a decomposition method for the cross-section variance of earnings into a component that is predictable at the time students decide to go to college, and an unforecastable component — in other words, a method of separation of individual heterogeneity from pure earnings-risk: see Carneiro *et al.* (2003b), and Cunha *et al.* (2005). These approaches are based on the identification of underlying, unobservable factor structures.

For instance, Bonhomme and Robin (2006), use two different measures of education to identify a factor structure in the residuals of a wage equation. The first measure is school-leaving age — call it ‘age’, for short. The second is a coding of the highest diploma obtained by the individual in 16 categories: this latter variable taking the median value of school-leaving age in the sample, in each diploma category — call it ‘diploma’, for short.

[3] The month of birth also works.

These two variables are close to our (education level, delay) pair, although different in principle. Bonhomme and Robin (2006) identify two factors, explaining 'age', 'diploma' and wages simultaneously. They conclude that the 'true education' variable would be a certain combination of the two factors, and that 'diploma' and 'age' measure 'true education' with error. Interestingly, their second factor is positively correlated with 'age', but negatively correlated with the residual of the wage equation. But 'age' and 'diploma' have both positive coefficients in the standard wage equation. These results have been obtained with an entirely different data set[4]; they provide a different point of view on similar phenomena, as well as an interesting indirect confirmation of the validity of our approach. In particular, they provide us with a possible interpretation of our model's error-term covariance structure. An advantage of our model is that, using a simple extension and instrumental variable estimation of the Mincer equation, it reveals a negative impact of higher school-leaving ages, conditional on diploma.

The above-quoted structural approaches have been a source of inspiration for our expected utility theory and its associated nonlinear econometric specification. As compared to the most sophisticated models à la Keane and Wolpin, our model lacks the sequential decision structure; it is essentially derived from static expected-utility maximization: as if the student would decide at the age of say, 13, his (her) highest targeted degree, bearing the risk of random completion time (with correlative random costs) and random earnings. This simplification has two sorts of advantages. First, it allows for the use of (relatively) simple estimation methods: straightforward Maximum Likelihood, without any additional computation burden due to nested algorithms, etc. Second, the model has a closely comparable "reduced-form" counterpart which is an Ordered-Probit, endogenous-dummy model à la Heckman, and the sources of identification are very clear. Yet, our model captures a dynamic element, which is the fact that individual schooling decisions are made on the basis of wage expectations, conditional on some background characteristics, observed by the student, but unobserved by the econometrician.

Finally, a by-product of our approach is a simple test for the presence of signaling. Statistical tests of signaling or sorting in the sense of Spence (1973) versus traditional human

[4] The French 1995 Labor Force Survey; 22,000 observations.

capital theories are difficult to construct; see, e.g., Wolpin (1977), Riley (1979), Lang and Kropp (1986), Bedard (2001). We remark here that the tests of overidentifying restrictions, applied to the wage (and employment) equations, happen to be a way of testing the inclusion of some individual characteristics in the employer's information sets. Some variables directly determine hiring decisions and starting wages, while some others are indirectly reflected in our delay and education variables. The latter variables therefore affect wages and employment because they are interpreted as signals of some relevant, but hidden characteristics. To perform this test, we need a core of instruments for education and delay, observed by the econometrician, but assumed unobserved by employers, and we cannot reject the fact that our delay effect is due to signaling in this sense.

In the following, Section 2 describes the data. Section 3 is devoted to the linear simultaneous-equations model, and the tests of overidentifying restrictions. Section 4 presents the nonlinear model, and Section 5 is devoted to a discussion of results.

2 Data

To perform the estimations presented below we used "Génération 92", a large scale survey conducted in France. The survey and associated data base have been produced by the CEREQ (*Centre d'Etudes et de Recherches sur les Qualifications*), a public research agency, working under the aegis of the Ministry of Education[5]. Génération 92 is a sample of 26,359 young workers of both sexes, whose education levels range from the lowest (i.e., high-school dropouts) to graduate studies, and who graduated in a large array of sectors and disciplines. Observed individuals have left the educational system between January 1rst and December[6] 31rst, 1992. They have left the educational system for the first time, and for at least one year, in 1992[7]. The labor market experience of these individuals has been observed during 5 years, until 1997. The survey provides detailed observations of individual employment and

[5] Articles and descriptive statistics, concerning various aspects of the survey, are available at www.cereq.fr.

[6] To fix ideas, the number of inhabitants of France who left school for the first time in 1992 is estimated to be of the order of 640,000.

[7] They did not return to school for more than one year after 1992, and they had not left school before 1992 except for compulsory military service, illness, or pregnancy.

unemployment spells, of wages and occupation types, as well as geographical locations of the students at the age of junior high-school entry (roughly 10), and in 1992, when they left school. The personal labor market history of each survey respondent has been literally reconstructed, month after month, during the period 1993-1997, by means of an interview. Before 1992, the individual's educational achievement is also observed.

For the purpose of estimation, we have created several variables with the help of the data. More precisely, we constructed four endogenous variables: (i) an *earnings* statistic, (ii) a probability (or rate) of *employment*, (iii) *education*, and (iv) *delay*. We also studied variants of the earnings and employment variables. We first describe the education variable, then the wages and employment variables, and finally delay.

Education levels, representing degrees, are indicator variables. But to explore the impact of degrees in a linear model, we constructed a synthetic schooling variable, dubbed *education*. By definition, it is the individual's "normal age" after a number of years of successfully concluded education. The "normal" number of years needed to reach the individual's grade, pass the exam and earn the degree, is a conventional age, associated with each individual's school-leaving degree. For each degree or certificate, the normal age is the age of those who got this degree or certificate, without any grade repetition or delay of any kind — not the average completion age. Our education variable is thus a particular construction that, albeit natural, is different from the traditional years-of-schooling used in the literature. A number of conventions have been used: (i) the high-school dropouts have a normal age of 13 years; (ii) the vocational high-school degree holders have a normal age of 16 or 18 years, depending on the category of their certificate[8]; (iii) those who passed the national high school diploma, i.e., the *baccalauréat*[9], have a normal age of 18 years; (iv) two years of college[10] correspond to a normal age of 20 years, and so on. In the linear model studied

[8] i.e., the so-called Certificats d'Aptitude and Brevet d'Etudes Professionnelles.

[9] Grade 12 students in the US correspond (roughly) to the French *classe terminale*, and the students of this grade pass an examination called *baccalauréat*. There exist vocational versions of the diploma.

[10] The corresponding exam is called DEUG (*Diplôme d'Etudes Universitaires Générales*), which is the equivalent of an Associate's degree, or DUT (*Diplôme Universitaire de Technologie*). There are exams at the end of each of the college years in French universities, and the DEUG or DUT correspond to the end of grade 14.

below, this education variable is used instead of the classic years-of-schooling measure of human capital. In the nonlinear version of the model (see below) the education variable is not useful anymore, because education levels are indicated by dummy variables.

Table 1 shows the empirical distribution of school-leaving age, conditional on the education level reached by males. As can be seen, school leaving-age is substantially dispersed, even conditional on final education level[11]. Figure 1 gives the distribution of the education variable itself, for males and females[12]. Table 2 gives further indications on the distribution of the education variable, conditional on selected family background characteristics: parental education, and birth order. Table 2 shows some well-know facts; for instance, that a student's probability of reaching the highest degrees is much higher than for any other category when his (her) father went to college. The last lines show the non-negligible impact of the student's birth order on the probabilities of reaching the different degrees[13].

We now turn to earnings. A difficulty with wages is that we do not observe the hours worked (but we know if the individual worked full-time or part-time). To solve this problem, we decided to select the individuals who experienced at least a full-time employment spell during the five-years observation period. More precisely, we first removed 717 individuals who had never worked (no employment spell recorded during 5 years). The remaining 25,642 individuals are the addition of 14,213 men and 11,429 women who worked at least once during the observation period. We then selected the individuals who experienced at least one full-time employment spell during the five years. As a consequence, we lost 11.7% of the male sub-sample, but we still had 12,538 men. The final stage was to match the sample with geographical data from the National Geographical Institute, in order to compute the *distance-to-college* instruments. Some observations of the individual's location at the age of 10 (the jurisdiction of residence's code) were missing. This left us with only 12,310 males. The possible bias introduced by this selection procedure is limited in the case of men. The same mode of selection leaves us with a sample of 8630 women, all willing to work full-time.

[11] For instance, the first line of Table 1 says 33 percent of the high-school dropouts left at the age of 18.

[12] the probabilities of 16 and 19 are zero because, due to, our conventions, nobody leaves school with an education equal to 16 or 19. There is some bunching of post-graduation diplomas such as Master's degree at level 23.

[13] For details on birth-order effects in this data set, see Gary-Bobo, Picard and Prieto (2006).

It is therefore likely that there is a sizeable selection bias in our female sub-sample. We will therefore focus on the male subsample, and use the women's subsample as a kind of robustness check.

Yet, a clear advantage of our selection procedure is that it permits us to compare earnings more precisely, given that full-time employment means a 39 hours working week for most wage-earning employees (and given the heavily regulated French labor market). More importantly, it tends to select a relatively homogeneous population of youths willing to work full-time (which has some advantages). Each individual's curriculum on the job market is an array of data including a number of jobs, with their corresponding wages and durations in months, and unemployment spells, again with a length in months. To estimate the returns to education, we rely on a single, scalar index of earnings for each worker. We constructed four different wage variables with the help of the data. The first statistic is simply the arithmetic average of the full-time wages earned during full-time employment spells, weighted by their respective spell durations. In the following, this index is called the *mean wage*. The mean wage variable ignores the length of unemployment spells, and the difficulties faced by the individual to find a stable (and well-paid) job. To capture the effect of job instability on average earnings, we employed a second index, simply called *earnings*. To compute this average, wages and unemployment benefits are weighted by the corresponding employment or unemployment spell duration[14]. We also consider a third and a fourth statistic: the wage earned by the individual in his (her) first full-time job, called the *first full-time wage*, and the *last wage*, earned in the last observed full-time job. Figure 2 presents a plot of the density of wages and earnings (in the men's subsample).

We also compute a rate of employment. Each young worker i is observed during 5 years, but depending on the exact month during which he or she left school, the number of observed months can vary a little. It varies from 60 to 72 months, to be precise. Our rate of employment, simply called *employment* in the following, is the logarithm of the ratio of the number of months spent in employment over the total number of months in the observation period. An alternative endogenous employment measure is the logarithm of the time spent

[14] A worker is eligible for unemployment benefits if he or she has worked in the recent past. Students thus get zero before their first job. The unemployment benefits are roughly a half of the lost job's wage.

searching for the first job, in months: we call this variable *search duration*, for short. We also consider the duration of search before the first full-time job is found, called search duration to full-time job. See Figure 3 for a plot of the density of employment and search-duration indices.

Finally, a substantial part of the variance of school-leaving age, conditional on education level or degrees (as shown by Table 1), happens to be due to *repeated grades.* Grade repeaters ('held back' students) are quite common, even in college[15]. Delays are thus generated by grade repetitions in primary, secondary and higher education. They are also computed with the help of some conventions. An individual's *delay* is defined as this individual's school-leaving age, minus the average school-leaving age of those for which this degree is the highest (and who thus left school with that degree)[16]. The efficiency of grade repetition in primary and secondary education is of course a hotly debated issue, but until today, the institution has survived. For instance, an individual who finished high school and passed the national examinations (i.e., the *baccalauréat*) successfully at the age of 19.33 is below par and would get a delay of approximately $-1.45 = 19.33 - 20.78$ years, because the average age of those who left school at this level is 20.78[17]. The national high-school diploma is required for admission to colleges (i.e., *Universités*) in France. Thus, a person who passed the *baccalauréat* successfully at the age of 18.5 and spent two years in college but failed to pass an Associate's or any equivalent degree has an education level of only 18 (which corresponds to that person's highest degree) and would get a delay of -0.28 years (since the average age of those who left school with the *baccalauréat* is 20.78). Employers do observe the school-leaving age, compare it to the average school-leaving age of similar students, and our hypothesis is, of course, that delay conveys information about ability. Figures 4a-4c provides various representations of the distribution of delay for males. Fig. 4a is

[15] Freshmen repeating the first and second years of college are quite common.

[16] We also studied a variant, in which delay was defined as school-leaving age minus normal age (i.e., "education"). The differences between the two approaches are small, but the chosen definition seemed to yield better results.

[17] School-leaving age is in fact measured in months, and then converted back into years. We observe that the average age at which those who went to college passed the national high-school exam is of course lower than 20.78, but the national high school exam is not their highest degree.

the plain non-parametric estimate of the density. Fig. 4b plots the densities, conditional on father education; Fig. 4c shows the density of delay, conditional on the student's education: some form of stochastic dominance is visible. But the overall impression is that, to a first approximation, the distribution of delay doesn't depend on education level.

On top of this, the survey provides information on family background: the father's and the mother's occupation in 92, the father's and the mother's education, are the most important of these variables. We also know if the parents are unemployed, inactive, retired or deceased (in 92). Are also observed, notably: the number of sisters, the number of brothers, the rank among siblings (i.e., birth order), and the month of birth, for each individual[18]. We know the geographical location of the student's family at the age of 10 and the student's location at school-leaving age (i.e. in 1992). Some of these variables can be used, either as controls, or as instruments, for education and delay. Using detailed geographical data from the National Geographical Institute, we have computed a "distance-to-college" instrument, which is the distance between the jurisdiction of residence at age 10 (i.e., the *commune*) , and the nearest college[19] (i.e., the nearest *Université*). We also used dummies indicating quartiles of the distribution of this distance-to-college variable.

3 The linear model, estimation results

We have first explored our main assumption, that delay and education, as defined above, have identifiable and different effects on labour market outcomes, with the help of standard econometric techniques. We used 3SLS on a system of four linear equations.

3.1 The four-equations system

The first equation gives $x = \ln(w)$, the log-wage (or log-earnings) as a function of delay, education, and controls; the second equation gives employment $y = \ln(\pi)$, where π is the probability of employment (or duration of search) as a function of delay, education and

[18] But we don't know the order of sexes in an individual's sibship.

[19] This distance is approximately the Euclidean distance between the two points on the map of France, in kilometers.

controls; the third equation gives education s as a function of controls and instruments; and finally, the fourth equation gives delay $d-\tau$ (where τ is the appropriate group's average school-leaving age, and d is the individual's effective school-leaving age) as a function of controls and instruments. Formally, our linear system is defined as follows,

$$\ln(w_i) = a_{00}(d_i-\tau_i)+a_{01}s_i+X_{i0}\beta_0+\nu_i, \quad (1)$$

$$y_i = a_{10}(d_i-\tau_i)+a_{11}s_i+X_{i1}\beta_1+\zeta_i, \quad (2)$$

$$d_i-\tau_i = X_{i2}\beta_2+\eta_i, \quad (3)$$

$$s_i = X_{i3}\beta_3+\epsilon_i, \quad (4)$$

where $(a_{00},a_{01},a_{10},a_{11})$ and $(\beta_0,\beta_1,\beta_2,\beta_3)$ are parameters to be estimated, $(\nu_i,\zeta_i,\eta_i,\epsilon_i)$ is vector of random disturbances, with covariance matrix Ω . In addition, $X_0,X_1,...,X_3$ are vectors of regressors. Our crucial test is whether a_{00}, a_{10} are nonzero with a negative sign[20], while a_{01}, a_{11} are positive, significant, with a reasonable order of magnitude (say, a return of 8 to 10% per certified year). The model has a particular structure, because $(s,\ln(w),y)$ do not contribute to the explanation of $d-\tau$ and $(d,\ln(w),y)$ do not contribute to the explanation of s; and finally, y is excluded from the $\ln(w)$ equation, and vice-versa. So we only need the exclusion of two variables from X_0 and X_1, the variables appearing as instruments in X_2 and X_3. We can at least use quarter-of-birth and distance-to-college to do this job. In fact we will show that it is legitimate to exclude more variables from the wage and employment equations, and use an over-identified model.

3.2 Results in the benchmark case

Table 3 reports results on a particular specification of (1-4) that we shall call the "benchmark version", although some neighboring variants could also have played this role, as will be seen below. In the benchmark version, $X_0=X_1$, and $X_2=X_3$, and the variables excluded from X_0 (i.e; hence the instruments for education and delay) are: (i) the father's employment status dummies (in employment, unemployed, retired, or deceased), (ii) the mother's employment status dummies (employed, unemployed, inactive or retired, deceased), (iii)

[20] The sign of a_{10} is expected to be positive if y is duration of search instead of log-employment.

number of brothers (indicated by dummies); (iv) number of sisters (indicated by dummies), (v) birth-order dummies, (vi) location at age 10 (indicated by dummies), (vii) quarter of birth (a dummy indicates the fourth quarter); and (viii) geographical distance to the nearest college (at age 10), with dummies indicating the quartiles of the distance distribution. So, there are several variables for which the appropriateness of exclusion can be discussed, particularly the number-of-siblings and birth-order variables. We have not excluded parental education and parental occupation from the wage and employment equations. We will show later that the excluded variables do not significantly contribute to the explanation of wages and employment, when added as controls in the log-wage and log-employment equations (1-2).

Assuming for a moment that these exclusions are legitimate, we find a number of striking results, reported on Table 3. This table shows the regression coefficients of the mean-wage and employment variables, on delay and education, expressed in percentage, for males and females. T statistics in parentheses. The left-hand side of Table 3 gives the results for the male subsample (12,310 observations), while the right-hand side gives the corresponding results for the female subsample (8,630 observations). There are OLS estimates and 3SLS estimates. In each sub-table, Column A displays the results obtained with a crude regression, in which log-mean-wage and log-employment are regressed on education, delay and a constant (and no further controls). Column B is a regression of the same variables on education, delay and the following controls: parental occupation, parental education and dummies indicating location of residence in 1992 (at the beginning of the search process).

OLS estimates yield the "wrong sign" for delay in the wage equation: it is positive in Columns A and B and in the wage equation (i.e., 'delay increases wages'), while it is negative in the men's employment equation (i.e., 'delay reduces employment'). According to OLS estimation, education increases wages and employment. But instrumentation has striking effects. In the case of males, IV estimation drastically changes the sign of the coefficient on delay in the wage equation. Now, "speed signals ability"; the effect is weaker if controls are added (weaker in column B than in column A), but it is still present and significant: in the male subsample, *a year of delay is responsible for a 3% decrease of the wage*. At the same time, the coefficient on education is still positive, with a highly significant and "classic" value of 8% per year. If we look at the bottom part of Table 3, we see that 3SLS estimates of the coefficient on delay are (negative and) higher in absolute value in the employment equation: according to these estimates, the impact of delay on employment is very strong, around 14% reduction of the probability of employment for a year of delay, while education itself still increases the probability of employment significantly. The right-hand part of Table 3 gives the corresponding figures in the female subsample, and the "signaling" effect of delay is not significant on wages, but remains significant on employment, albeit weaker than for males. The female subsample results are less striking, but still, they show a form of robustness of the result: instrumentation changes the sign of the delay coefficient from positive to zero in the wage equation, and changes the delay coefficient from zero to negative and significant in the employment equation.

3.3 Search-duration effects; last wage and first wage

We will continue our analysis with various forms of robustness checks. We first change the dependent variables, and then change the list of instruments. Table 4 displays the results obtained with the benchmark specification, but when we change the dependent variables. The first (left-hand) columns of Table 4 give the results obtained with earnings statistic: we get very significant coefficients, with the expected sign, for both delay and education, and for men and women alike. The earnings equation combines the probability of employment and the mean-wage variables, so, in a sense, it inherits their properties. This shows that the results holds for women too, if we accept to take the probability of unemployment into account in the computation of the expected wage statistic. Using the *last wage* (i.e., the last wage-rate observed in the five years period starting in 92 for each individual) instead of the mean wage (i.e., the average wage over the 5 years observation period), we find similar results, in the male subsample. The order of magnitude of the crucial coefficient on delay is 3% for males. The impact of delay on the women's last wage is however non-significant. If, on the contrary, we consider the beginning of period wage observations, results are less significant. Yet, using the first wage instead of the last wage, at the top right corner of Table 4, we see that the order of magnitude of the delay effect on wages is the same, around 3%, but is less precisely estimated.

Table 4 gives results for two other variants of the benchmark specification. When the *first full-time wage* and *duration of search to the first full-time job* are used as dependent variables instead of mean-wage and employment, we loose the significance of delay on wage for men (although we still get the correct sign), but delay very significantly increases search duration: *a year of delay increases a man's duration of search (to first full-time job) by 19%.* The last column shows that the impact of delay on *duration of search (to any job)* of men is highly significant and positive: *a year of delay causes a 22% increase of search duration (to any job).* The effect of delay on male search durations is therefore very strong and striking. These effects are still present, but much weaker, and less significant, in the case of women (see bottom right part of Table 4). Again, it is easy to check that instrumentation has drastic effects on estimated coefficients. In Table 4, the line called Fisher (p-value) gives the p-value of the Fisher test of overidentifying restrictions (as defined, for instance in Davidson and McKinnon (1993; 7.8, p 236)). A value of this p-value below 10%, say, leads one to question the appropriateness of the exclusions (i.e., of the choice of instruments). If we take these indications seriously, only the last-wage and employment model (second group of columns) passes the test with the male subsample: one cannot really reject the null assumptions that the chosen instruments do not explain wages and employment directly, and their exclusion from the wage and employment equations is therefore legitimate.

From Tables 3 and 4, we thus derive a confirmation that our delay variable matters, particularly for men, and that only instrumentation can make its true effect visible. Why does delay have more impact on last wage, mean wage, and earnings than on first wage and first full-time wage? Why does delay at the same time have a huge impact on search duration? This might be due to French labor market institutions, and more precisely to recruitment practices. It seems that most large companies adopt a kind of non-discriminatory practice, according to which starting salaries depend mostly on degrees, and not on age (and therefore also not on delay). Large firms use pay scales (or 'salary grids'). Degrees and certificates being an essential determinant of the new recruit's pay, it is however not true that all positions are equal, and some beginners have a kind of 'fast-track' evolution, while others have more limited opportunities. Discrimination would therefore take place mainly through differences in job design (and in the career opportunities attached to a starting position), and through early career promotions. Discrimination according to delay is in contrast very clear in the employment-probabilities and durations of search of individuals: high-delay students are turned down more often by employers (who could not or would not like to hire them at a discount), and therefore, these students have lower employment probabilities and higher search durations.

In spite of this, it now happens that delay effects are strong enough to be reflected in the mean-wage statistic, and all the more, in the last-wage statistic. This could point towards a classic human capital interpretation of the wage equations, — i.e., according to which wages reflect observed worker characteristics —, as opposed to a job-market signaling interpretation, because there is less discrimination according to delay in the starting wages than in the later wages (5 years later). We come back to the signaling vs 'traditional' human-capital theories debate below. It could thus very well be true that delay is correlated with unobserved talent characteristics, observed and priced by employers, explaining why it seems to command a negative premium and lower employment probabilities. It could also be true that delay is interpreted as a signal by employers, but that its consequences are not fully explicit, or fully revealed, in the starting wages, because of non-discriminatory recruitment practices, explaining why, after 5 years, wages embody the effect more accurately.

3.4 Robustness checks; overidentifying restrictions testing

We now turn to the question of the appropriate choice of exclusion restrictions and instruments. The reader might wish to question the use of some variables, or groups of variables, as intruments for education and delay. We have therefore, (i) varied the list of such intruments, and (ii), performed tests of the statisitical validity of exclusions (i.e., the usual Fisher and Chi^2 tests of overidentifying restrictions[21]), in two series of regressions. Table 5 presents 4 variants, plus the benchmark, using mean-wage as the dependent variable. Table

[21] See Davidson and MacKinnon (1993; 7.8, p 235-236). To contruct the Chi^2 test, regress the residuals of the wage (or employment) equation (estimated by 2SLS) on all the exogenous variables (all the instruments), take the R^2 of this regression and multiply it by N, the number of observations. The F-test is simply the zero-restriction test applied to the coefficients of the excluded instruments in the wage (or employment) equation.

6 presents the same 4 variants and the benchmark, using the last wage as the dependent variable. Tables 5 and 6 are therefore exactly parallel. A 'no' in the column corresponding to a variant of the model means that the corresponding variable is used as a control in X_0, X_1, X_2 and X_3; a 'yes' means that the variable, or group of variables, is excluded from the wage and employment equations. The last lines of Tables 5 and 6 give the values of a Chi^2 with the appropriate degrees of freedom, for the 2.5%, 5% and 10% thresholds, and the conclusions of the Chi^2 test for the wage and employment equations, at the bottom of each column, corresponding to a variant. The first column in Tables 5 and 6 shows that our reference version passes the test (at 10%); the Chi^2 statistic is very close to the 10% threshold. We conclude that our benchmark instrumentation system, if not perfect, cannot be rejected when the wage equation is considered. The employment equation always passes the overidentifying restrictions tests, and yields very significant effects of both delay and education, with opposite signs, and approximately the same magnitudes, accross all variants estimated with the male subsample.

The reader might then want to question the exclusion of number-of-siblings and birth-order variables from the wage equation. Family structure is important in the accumulation of human capital; there are inequalities among siblings[22] (boys and girls, first and later borns, etc.), and human capital accumulated within the family could be directly valued by the labor market. Variant 1 takes this worry into consideration by eliminating the number of brothers, the number of sisters, and the birth-order dummies from the list of instruments, and therefore by adding theses variables in the list of controls appearing in the 4 equations. Having done this, we find that our results resist quite well (looking at coefficients and Student ts). The crucial coefficient of delay in the wage equation is even higher in absolute value and more significant; the value of the wage reduction caused by a delay of a year now seems to be 4%. Variant 1, in Table 6, confirms the results too. But the overidentifying restrictions tests now reject the exclusions in the wage equation, albeit not very strongly. There are 'synergies' or interactions between particular sub-groups of instruments which explain that the value of the test statistics change from one variant to the next. In spite of the Family Economist's strong intuitions to the contrary, birth-order and number-of-siblings dummies

[22] See for instance Black, Devereux and Salvanes (2005).

are in fact excellent instruments from a statistical point of view. When we control for parental education and occupation, these variables do not explain wages in any substantial way: none of the coefficients is significant at 5% when included in the wage equation. In sharp contrast, these family-structure variables are very significant and important in the education equation. Table 7 gives the complete results of the benchmark version, and shows the 'first-stage' effect of siblings and birth-order dummies on education and delay very clearly. The typical finding is that additional brothers and sisters reduce education and increase delay, while a higher rank among siblings reduces education *and* delay. Later borns are significantly less ambitious, and at the same time more expeditious than first borns. But these variables have no impact on wages whatsoever. We can exclude birth-oder and siblings dummies safely from the wage equations (see variant 4).

The next worry comes from the father's (and mother's) so-called employment status. In essence, these variables indicate only the father's age (retired father) and if the mother stays at home (unemployed or inactive or retired mother). The father's age has a surprisingly strong influence on education and delay (see Table 7, part 2 again), but we can suspect that it could do so because the old father can devote more time to his children's education at home, with possible direct effects on wages and employment again. In fact, the retired-father dummy has a weak (and weakly significant) direct effect on wages, as well as the unemployed or inactive father, enough to perturb the tests a little, however. Variants 2 and 3, in which the mother's employment-status dummies, and the mother-and-father's employment-status dummies, respectively, are included in the wage equation, yield very significant effects of delay on wages (around -5%) and employment (around -14%), and, in spite of more demanding overidentification test thresholds, the rejection of the remaining exclusions in the wage equation is not very strong. To sum up, variant 2 can be called 'hard', and variant 3 can be called 'super-hard', because the bulk of IV estimation bears on quarter-of-birth, distance-to-college, and location at age 10 only. With the help of this limited set of instruments, we find highly significant negative effects of delay on wages and employment, with standard effects of education (around 8% per certified year on wages). Again, a look at the results of super-hard variant 3 shows that exclusions are rejected, but mildly.

Finally Variant 4 includes the mother-and-father's employment status variables in the employment and wage equations, but excludes the birth-order and siblings variables (this exclusion being empirically justified). This latter variant is reasonable, and the wage equation also passes the Chi^2, overidentifying restrictions test at the 5% threshold. Again the coefficient on delay in the wage equation is around -3%.

To sum up, we have demonstrated that there is a significant effect of delay on wages, that this effect has a negative sign, between -3% and -5% per year for males, while education has a positive effect, but that the former effect appears only when a suitable set of valid instruments is used for estimation. The impact of delay on the probability of employment is very significant and robust, between -12% and -15% per year of delay for males, and also significant, but weaker, in the case of females.

3.5 Testing signaling vs 'human capital' theories

Is the effect of delay on wages and employment a signal effect in the sense of Spence[23]? Can we test Spence's signalling hypothesis against the traditional theory of human capital, for short, can we test 'Spence' against 'Becker'[24]? In our context, the impact of delay is a signal if it is correlated with individual characteristics that do matter, but are not observable for the employer, in a consistent way: some individual characteristics determine the distribution of delay in such a way that it is possible to screen, or 'separate' students according to observed delay, and labor markets are competitive. Under the so-called human capital — hereafter 'Becker's assumption'—, the relevant individual characteristics are observed and priced by the employer, and labor markets are competitive. Under 'Becker', if delay has a negative impact, it is because it is correlated with student attributes that do matter and that the employer takes into account, but that the econometrician not necessarily observes. In contrast, under 'Spence', it might be the case that the econometrician observes relevant individual attributes that employers don't know, but that they can infer from the signals. We will show that the tests of overidentifying restrictions computed above are in a fact a way of partially

[23] See Spence (1973), Weiss (1995), Riley (2001).

[24] The thinking of Becker and Spence is certainly more subtle than the kind of pedagogical caricature used here to clarify the exposition.

testing 'Becker' (H_1) against 'Spence' (H_0). Consider for simplicity a subset of individuals with the same education s, but different delays. Suppose that the productivity of students is determined by relevant characteristics θ_0 and θ_1 that the econometrician doesn't observe. Assume in addition, that θ_0 is observed by employers, but not by the econometrician, and that the model determining log-wages is,

$$\ln(w) = \alpha E[\theta_1 | d - \tau, \theta_0, X] + X\beta_0 + \theta_0 + \varepsilon_0, \tag{5}$$

where X is a vector of exogenous variables, and ε_0 is an independent random noise. We assume that X is observed by both the econometrician and the employer. Delay is determined by the following model,

$$d - \tau = X\beta_1 + Z_0\gamma + Z_1\delta + \theta_1 + \varepsilon_1, \tag{6}$$

where Z_0 and Z_1 are vectors of instruments, and ε_1 is an independent perturbation term. Under Spence's hypothesis, the employer doesn't observe Z_0 and Z_1, but the econometrician does. There are for instance, informations in the survey that the employer doesn't find in a student's CV. Assume, in addition, that conditional expectations are linear (this could be due to normality of the variables, or simply be a reasonable approximation), that is,

$$E[\theta_1 | d - \tau, \theta_0, X] = g_0 + g_1(d - \tau) + Xg_2 + g_3\theta_0, \tag{7}$$

where the g_i are parameters. Substituting this in the wage equation, we get,

$$\ln(w) = a_0 + a_1(d - \tau) + Xb + a_2\theta_0 + \varepsilon_0, \tag{8}$$

where $a_0 = \alpha g_0$, $a_1 = \alpha g_1$, $b = \beta_0 + \alpha g_2$, etc. The econometrician doesn't observe θ_0 and therefore, $\eta_0 = a_2\theta_0 + \varepsilon_0$ is the wage equation's error term, from his (her) point of view.

Now, under Becker's hypothesis, the employer is assumed to observe Z_1, X and θ_0. The econometrician doesn't observe θ_0, but observes Z_0, Z_1, and X. Under H1, the true log-wage equation is therefore,

$$\ln(w) = \alpha E[\theta_1 | d - \tau, \theta_0, X, Z_1] + X\beta_0 + \theta_0 + \varepsilon_0, \tag{9}$$

where,

$$E[\theta_1 | d - \tau, \theta_0, X, Z_1] = f_0 + f_1(d - \tau) + Xf_2 + f_3\theta_0 + Z_1 f_4. \tag{10}$$

Substituting the expectation in the wage equation, we finally get,

$$\ln(w) = c_0 + c_1(d - \tau) + Xc_2 + Z_1c_3 + \eta_1, \qquad (11)$$

where, $c_0 = \alpha f_0$, $c_1 = \alpha f_1$, etc., and $c_3 = \alpha f_4$, and, from the econometrician's point of view, $\eta_1 = (1 + \alpha f_3)\theta_0 + \varepsilon_0$ is an error term. Now, a comparison of (8) and (11) shows that the overidentifying restrictions statistics do in fact test 'Becker' against 'Spence', as well as any test of the assumption $c_3 = 0$ in (11). To do this, both equations (8) and (11) need to be at least just identified (to be estimated by 2SLS): this is why we need the instruments Z_0. Instead of considering log-wages in the above reasoning, we could have considered the employment probability, and some model giving the probability of being hired as a function of the same variables, enabling us to test the role of delay as a signal in the recruitment process. Our reasoning can easily be extended to include two signals instead of one: education and delay instead of only delay, without any difficulty. So, the tests of Tables 5 and 6 show that, with our particular choices of Z_1 and Z_0, we cannot reject the signaling hypothesis when employment probabilities are considered, and that, for some specifications at least, we also don't reject it in the wages model. The employment probability equation reflects the uncertainty faced by the employer when deciding to hire the individual or not, based on a limited number of informations: it is thus very likely that signaling in the sense of Spence takes place. When it comes to wages, the discussion is more subtle, because we potentially observe and average different wages at different points in time for the same individual, over a period of 5 years. It is therefore likely that, during these 5 years, some hidden talent characteristics of the individual are disclosed at work, and included in the (subsequent) employers' information sets. This might be the reason why, with the wage model, the overidentifying restrictions tests are ambiguous, and we do not find a clearcut answer to the question of signaling.

4 The nonlinear model

Until now, the analysis has been based on a number of conventions concerning the notion of education, measured by "levels," and the reader might wonder if delay effects are an artificial result of the construction of our education variable. The nonlinear model described below replaces the education variable with a set of endogenous dummies indicating education levels (i.e. degrees): this is much more flexible. The nonlinear model also proposes a theoretical rationalization for the type of model studied so far, and more precisely, it provides a positive answer to the following question: does there exist a theoretical human-capital investment model, based on individual rationality (expected utility maximization) which underpins the observed joint distribution of durations and degrees?

4.1 Basic Assumptions

Individuals are indexed by $i = 1, ..., N$. Let $s = 0, 1, ..., S$, denote the certified schooling level, and let w denote the wage. Let $x = \ln(w)$. Let s_i be the education level chosen by individual i. Let m_i be the number of months during which individual i is observed; our data set is such that $60 \leq m_i \leq 72$. Let π_i denote the probability of employment, that is, the number of months in employment divided by m_i, and let $y_i = \ln(\pi_i)$. Utility is logarithmic, and defined as follows,

$$u(w, \pi) = \ln(w\pi), \tag{12}$$

Let d_{is} denote the individual's age while leaving school at level s, and let τ_{is_i} denote the "usual age" of i at level $s = s_i$. In the following, the "usual age" will be taken to be the average age at which individuals leave school with a level s certificate, in the sample. We assume.that individuals form expectations about their future wages as a function of education level s, of delay $(d_{is} - \tau_{is})$, and of exogenous variables X_{i0}, by means of an extended Mincer equation,

$$x_i = \ln(w_i) = \sum_{s=1}^{S} \chi_{is} f_s + \alpha_0(d_{is_i} - \tau_{is_i}) + X_{i0}\beta_0 + \nu_i, \tag{13}$$

where, $\chi_{is} = 1$ if $s = s_i$ and 0 otherwise, and ν_i is a Gaussian error term. To simplify notation, we drop index i and define,

$$x_s = \ln(w_s) = f_s + \alpha_0(d_s - \tau_s) + X_0\beta_0 + \nu. \tag{14}$$

We assume that individual i predicts her (his) employment probability as the conditional expected value of π_i, using the model,

$$y_i = \ln(\pi_i) = \sum_{s=1}^{S} \chi_{is} g_s + X_{i1}\beta_1 + \alpha_1(d_{is_i} - \tau_{is_i}) + \zeta_i, \tag{15}$$

where X_{i1} is a vector of exogenous variables and ζ_i is a Gaussian error term. To simplify notation, we again drop index i and denote,

$$y_s = \ln(\pi_s) = g_s + X_1\beta_1 + \alpha_1(d_s - \tau_s) + \zeta. \tag{16}$$

Then, define the individual's instantaneous utility as

$$u_s = \ln(\pi_s w_s) = x_s + y_s. \tag{17}$$

We use 8 different education levels, i.e., $S = 7$.

Delay is assumed to be given (predicted) by the equation,

$$d_{is_i} - \tau_{is_i} = X_{i2}\beta_2 + \eta_i. \tag{18}$$

where η_i is a Gaussian error term, and where X_{i2} is a vector of exogenous variables.

Finally, we specify the education costs of a year spent preparing for the exams of level s, as a fraction $1 - h_s$ of the expected wage $\pi_{s-1}w_{s-1}$, where $0 \leq h_s \leq 1$. The costs are thus a fraction of the wage that could have been earned if the individual did go to work with education level $s - 1$, instead of studying to reach level s. We thus assume that the opportunity and direct costs of education, incurred by an individual per period, are of the form $(1 - h_s)\pi_{s-1}w_{s-1}$. We adopt the following specification for h_s,

$$h_{si} = \exp(-X_{i3}\beta_3 - c_s + \epsilon_i), \tag{19}$$

where X_{i3} is a vector of exogenous variables, related to environment and family background, β_3 and c_s are parameters, and ϵ is an error term with a normal distribution, interpreted as unobserved resources, or "help" from the family. In contrast, the error term $-\eta$ can be viewed as unobserved "talent" at school.

We have introduced 4 error terms, $(\nu, \zeta, \eta, \epsilon)$, respectively: "ability" at work, "ability" in job search, handicap at school (the opposite of talent at school), and unobserved "family help". This vector is assumed multivariate-normal with a zero mean and covariance matrix

$$\Omega = \begin{pmatrix} & & & \sigma_{\epsilon\nu} \\ & \Omega_0 & & \sigma_{\epsilon\zeta} \\ & & & \sigma_{\epsilon\eta} \\ \sigma_{\epsilon\nu} & \sigma_{\epsilon\zeta} & \sigma_{\epsilon\eta} & 1 \end{pmatrix}, \tag{20}$$

and the sub-matrix,

$$\Omega_0 = \begin{pmatrix} \sigma_\nu^2 & \sigma_{\nu\zeta} & \sigma_{\nu\eta} \\ \sigma_{\nu\zeta} & \sigma_\zeta^2 & \sigma_{\zeta\eta} \\ \sigma_{\nu\eta} & \sigma_{\zeta\eta} & \sigma_\eta^2 \end{pmatrix}, \tag{21}$$

Note that $E(\epsilon^2) = 1$, for the sake of identification.

4.2 Expected utility maximization

Assuming that each individual lives for T periods (i.e., years) and has a zero rate of time preference (or a discount rate equal to one), we can express the individual's expected utility, conditional on ϵ, as follows,

$$\begin{aligned} V(s \mid \epsilon) &= E\left[\sum_{t=1+d_s}^{T} u_s + \sum_{z=1}^{s} \sum_{t=1+d_{z-1}}^{t=d_z} \ln(h_z \pi_{z-1} w_{z-1}) \mid \epsilon\right] \\ &= E\left[(T-d_s)u_s + \sum_{z=1}^{s} (\Delta d_z)(\ln(h_z) + u_{z-1}) \mid \epsilon\right], \end{aligned} \tag{22}$$

where $\Delta d_z = d_z - d_{z-1}$. Each individual is then assumed to choose level s so as to maximize V, the expected utility over the life-cycle, knowing the unobserved family factors ϵ, but bearing several kinds of risk, affecting employment, wages, and the costs of education (the duration of studies being random). Remark that $(T-d_s) + \sum_{z=1}^{s} (\Delta d_z) = T - d_0$. We assume that d_0 is exogenously given, for instance, $d_0 = 0$. Define then

$$\Delta V(s \mid \epsilon) = V(s \mid \epsilon) - V(s-1 \mid \epsilon). \tag{23}$$

We easily get,

$$\begin{aligned} \Delta V(s \mid \epsilon) &= E\left[(T-d_s)u_s - (T-d_{s-1})u_{s-1} + \Delta d_s(\ln(h_s) + u_{s-1}) \mid \epsilon\right] \\ &= E\left[(T-d_s)\Delta u_s + \Delta d_s \ln(h_s) \mid \epsilon\right]. \end{aligned} \tag{24}$$

Denoting $\Delta f_s = f_s - f_{s-1}$, and $\Delta g_s = g_s - g_{s-1}$, and using (14)-(18), we find

$$\Delta u_s = \Delta f_s + \Delta g_s. \tag{25}$$

and $\Delta d_s = \Delta \tau_s$. It then follows that,

$$\Delta V(s \,|\, \epsilon) = \Delta u_s[T - E(d_s \,|\, \epsilon)] + \Delta d_s[-X_3\beta_3 - c_s + \epsilon]. \tag{26}$$

But

$$E(d_s \,|\, \epsilon) = \tau_s + X_2\beta_2 + E(\eta \,|\, \epsilon) = E(d_s) + E(\eta \,|\, \epsilon). \tag{27}$$

Because of normality, $E(\eta \,|\, \epsilon) = (\sigma_{\epsilon\eta}/\sigma_\epsilon^2)\epsilon = \epsilon\sigma_{\epsilon\eta}$. Hence,

$$\begin{aligned} \Delta V(s \,|\, \epsilon) &= \Delta u_s[T - E(d_s) - \epsilon\sigma_{\epsilon\eta}] + \Delta d_s[-X_3\beta_3 - c_s + \epsilon] \\ &= \Delta u_s[T - E(d_s)] - \Delta d_s[X_3\beta_3 + c_s] + \epsilon[\Delta d_s - \sigma_{\epsilon\eta}\Delta u_s]. \end{aligned} \tag{28}$$

4.3 Necessary conditions for optimal choice of education

We can now state the necessary conditions for an individually optimal choice of s as: $\Delta V(s \mid \epsilon) \geq 0$ *and* $\Delta V(s+1 \mid \epsilon) \leq 0$. Assume that $\Delta d_s - \sigma_{\epsilon\eta}\Delta u_s \geq 0$. This property holds if $\Delta u_s \geq 0$, and $\sigma_{\epsilon\eta} \leq 0$, which, given that ϵ represents help, and $-\eta$ represents unobservable academic talent, is a reasonable assumption. It is then easy to see that $\Delta V(s \mid \epsilon) \geq 0$ is equivalent to,

$$\epsilon \geq -\frac{\Delta u_s(T - E(d_s))}{(\Delta d_s - \sigma_{\epsilon\eta}\Delta u_s)} + \frac{\Delta d_s}{(\Delta d_s - \sigma_{\epsilon\eta}\Delta u_s)}(X_3\beta_3 + c_s) \equiv k_s, \tag{29}$$

where Δu_s, Δd_s, and $E(d_s)$ are given by expression (25) and $E(d_s) = \tau_s + X_2\beta_2$. Family help ϵ must be greater than a threshold denoted k_s (the right-hand side of the above inequality). Then, s is an individually optimal level of education, knowing ϵ, only if

$$k_s \leq \epsilon \leq k_{s+1}. \tag{30}$$

Thus, education is determined by an ordered discrete choice (Ordered Probit) model with cuts k_s. Remark that if $\sigma_{\epsilon\eta} = 0$, the necessary condition (29)-(30) boils down to the following easily interpretable expression,

$$\frac{\Delta u_s(T - E(d_s))}{\Delta d_s} \geq X_3\beta_3 + c_s - \epsilon, \tag{31}$$

i.e., marginal utility $\Delta u_s/\Delta d_s$, multiplied by the expected number of years at work, $T-E(d_s)$, must be greater or equal than marginal costs $X_3\beta_3 + c_s$ minus family help ϵ.

The model has a meaning only if it is true that $k_s < k_{s+1}$, for all s, which is equivalent to say that second-order conditions hold. This discrete concavity condition can be written,

$$\frac{\Delta d_{s+1}}{A_{s+1}}(X_3\beta_3 + c_{s+1}) - \frac{\Delta d_s}{A_s}(X_3\beta_3 + c_s) > \frac{\Delta u_{s+1}(T - E(d_{s+1}))}{A_{s+1}} - \frac{\Delta u_s(T - E(d_s))}{A_s},$$

where by definition, $A_s = \Delta d_s - \sigma_{\epsilon\eta}\Delta u_s$. Assume that $\sigma_{\epsilon\eta} \simeq 0$, so that $A_s \simeq \Delta d_s$; then, the above inequality is approximately equivalent to

$$\Delta c_{s+1} > \left(\frac{\Delta u_{s+1}}{\Delta d_{s+1}} - \frac{\Delta u_s}{\Delta d_s}\right)(T - E(d_s)) - \frac{\Delta u_{s+1}}{\Delta d_{s+1}}(E(d_{s+1} - d_s)).$$

Given that $E(d_{s+1}) - E(d_s) = E(\Delta d_{s+1}) = \Delta d_{s+1}$, we get the equivalent condition,

$$\Delta c_{s+1} + \Delta u_{s+1} > \left(\frac{\Delta u_{s+1}}{\Delta d_{s+1}} - \frac{\Delta u_s}{\Delta d_s}\right)(T - E(d_s)).$$

This latter condition is sufficient for $k_s < k_{s+1}$, provided that $\sigma_{\epsilon\eta}$ is sufficiently small. It is easy to see that the condition holds under the stronger conditions of “increasing cost”, i.e., $\Delta c_{s+1} \geq 0$, increasing utility $\Delta u_{s+1} \geq 0$, and concave utility, i.e., if $\Delta u_s/\Delta d_s$ is decreasing with s. But the model can easily accomodate moderately increasing returns, i.e., $\Delta u_s/\Delta d_s$ increasing with s, provided that $\Delta c_s + \Delta u_s$ is high enough, and T is not too large.

4.4 Estimation and identification

The parameters to be estimated are α_0, α_1, β_0, β_1, β_2, β_3, f_s, g_s, c_s and Ω. We can write,

$$\epsilon = E(\epsilon|\nu, \zeta, \eta) + \xi, \tag{32}$$

where ξ is an independent error term, orthogonal to (ν, ζ, η). Due to normality, we get,

$$E(\epsilon|\nu, \zeta, \eta) = \gamma_0\nu + \gamma_1\zeta + \gamma_2\eta, \tag{33}$$

where $\gamma = (\gamma_0, \gamma_1, \gamma_2)$ are theoretical regression coefficients, given by the formula,

$$\gamma = (\gamma_0, \gamma_1, \gamma_2) = (\sigma_{\epsilon\nu}, \sigma_{\epsilon\zeta}, \sigma_{\epsilon\eta})\Omega_0^{-1} \tag{34}$$

Using the constraint $Var(\epsilon) = 1$,we see that the variance of ξ satisfies,

$$\begin{aligned} Var(\xi) &= 1 - Var(\gamma_0 \nu + \gamma_1 \zeta + \gamma_2 \eta) \\ &= 1 - \rho^2 \end{aligned} \tag{35}$$

where by definition,

$$\rho^2 = \gamma' \Omega_0 \gamma = \begin{pmatrix} \sigma_{\epsilon\nu} & \sigma_{\epsilon\zeta} & \sigma_{\epsilon\eta} \end{pmatrix} \Omega_0^{-1} \begin{pmatrix} \sigma_{\epsilon\nu} \\ \sigma_{\epsilon\zeta} \\ \sigma_{\epsilon\eta} \end{pmatrix}. \tag{36}$$

We can now derive individual contributions to likelihood, denoted, L_i. We have,

$$L_i = \Pr(s_i | x_i, y_i, d_{si}, X_i) \Pr(x_i, y_i, d_{si} | X_i). \tag{37}$$

Remark then that, using the decomposition of ϵ, inequalities $k_{i,s} \leq \epsilon_i \leq k_{i,s+1}$, are equivalent to

$$k_{i,s} - \gamma_0 \widehat{\nu}_i - \gamma_1 \widehat{\zeta}_i - \gamma_2 \widehat{\eta}_i \leq \xi_i \leq k_{i,s+1} - \gamma_0 \widehat{\nu}_i - \gamma_1 \widehat{\zeta}_i - \gamma_2 \widehat{\eta}_i, \tag{38}$$

where by definition,

$$\widehat{\nu}_i = x_{is_i} - f_{s_i} - X_{i0} \beta_0 - \alpha_0 (d_{is_i} - \tau_{is_i}), \tag{39}$$

$$\widehat{\zeta}_i = y_{is_i} - g_{s_i} - X_{i1} \beta_1 - \alpha_1 (d_{is_i} - \tau_{is_i}), \tag{40}$$

$$\widehat{\eta}_i = d_{is_i} - \tau_{is_i} - X_{i2} \beta_2. \tag{41}$$

Let $\Phi(x) = \int_{-\infty}^{x} \phi(v) dv$, be the normal c.d.f., and $\phi(x) = (\sqrt{2\pi})^{-1} \exp(-x^2/2)$ be the normal density function. We can then write, using the definitions stated above,

$$\Pr(s_i | x_i, y_i, d_{si}, X_i) = \Phi_{s_i+1,i} - \Phi_{s_i,i}, \tag{42}$$

where by definition,

$$\Phi_{s,i} = \Phi \left[\frac{k_{i,s} - \gamma_0 \widehat{\nu}_i - \gamma_1 \widehat{\zeta}_i - \gamma_2 \widehat{\eta}_i}{\sqrt{1 - \rho^2}} \right]. \tag{43}$$

The transformation $(x, y, d) \mapsto (\nu, \zeta, \eta)$ is linear, one-to-one and upper triangular, that is,

$$\begin{pmatrix} \nu \\ \zeta \\ \eta \end{pmatrix} = \begin{pmatrix} 1 & 0 & -\alpha_0 \\ 0 & 1 & -\alpha_1 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ d \end{pmatrix} + C. \tag{44}$$

It follows that the Jacobian determinant J of this transformation is equal to the product of its diagonal terms, i.e., $J = 1$. Now, (x_i, y_i, d_{is}) has a multivariate normal distribution, and we finally get,

$$\Pr(x_i, y_i, d_{s_i i} \mid X_i) = \frac{1}{(\sqrt{2\pi})^3 \sqrt{\det \Omega_0}} \exp\{-\frac{1}{2} \begin{pmatrix} \widehat{\nu}_i & \widehat{\zeta}_i & \widehat{\eta}_i \end{pmatrix} \Omega_0^{-1} \begin{pmatrix} \widehat{\nu}_i \\ \widehat{\zeta}_i \\ \widehat{\eta}_i \end{pmatrix} \}. \quad (45)$$

4.5 Variants of the model: Model A and Model B

The complete model, called Model A, can be estimated by straightforward ML. It is fully identified. The three-dimensional system (13)-(15)-(18) can be estimated separately by ML, or 3SLS, to provide preliminary estimates[25] of all parameters except β_3, c_s, and $(\sigma_{\epsilon\nu}, \sigma_{\epsilon\zeta}, \sigma_{\epsilon\eta})$. In the course of estimating the full model, we can also estimate a simplified version, hereafter called Model B, in which the particular functional form of the thresholds $k_1, ..., k_s, ...$, as defined by (29), is not imposed. In this simplified version, the Ordered Probit part can be simply specified as

$$b_s + X_3\delta_3 \leq \epsilon \leq b_{s+1} + X_3\delta_3, \quad (46)$$

(meaning that the individual chooses level s if and only if his (her) realization of ϵ falls in the above interval). With Model B, the estimated values of δ_3 and the cuts b_s are not the same as β_3 and c_s. We report estimations of Model B below; it can be viewed as a standard, endogenous-dummy variable system of equations à la Heckman (see Heckman (1978)), or as an extension of Cameron and Heckman (1998), because of its reliance on the Ordered Probit to describe educational choices.

The advantage of our specification is now that we have two models, Model A and Model B, a "structural" and a "reduced-form" model, respectively, that are closely comparable. An immediate term-by-term comparison of Models A and B is possible for almost all

[25] Preliminary estimates for β_3 and $(\sigma_{\epsilon\nu}, \sigma_{\epsilon\zeta}, \sigma_{\epsilon\eta})$ can be obtained as follows. Compute the residuals $(\widehat{\nu}_i, \widehat{\zeta}_i, \widehat{\eta}_i)$ of (13)-(15)-(18), and use them as regressors, in addition to X_3, to estimate a standard ordered Probit on s separately. This provides preliminary estimates of β_3, and $(\gamma_0, \gamma_1, \gamma_2)$, and thus, of the corresponding covariances $(\sigma_{\epsilon\nu}, \sigma_{\epsilon\zeta}, \sigma_{\epsilon\eta})$ (using the one-to-one mapping (34)). The model can then be estimated fully by ML, using all the preliminary estimates as initial values for the maximization routine.

parameters, except the cuts and β_3. We will of course compare the likelihoods of the two models.

Model A embodies more structure, because it imposes a particular functional form of the cuts k_s. This form is not simply a nonlinear function of other structural parameters, because it involves individual variations of expected durations, through the terms $E(d_s) = \tau_s + X_2\beta_2$, and of education costs, through $X_3\beta_3$, which all depend on observations. But, as suggested by the preliminary explorations of this model by means of standard linear methods, identification does not hinge upon functional forms: the variability of school-leaving ages is an essential source of identification, and two instruments would in principle be enough. Intuitively, we need only one instrument for education, and one for delay, to identify the crucial parameters α_0 and α_1. Distance to college and quarter of birth constitute a minimal set of such instruments, in the following application.

To obtain a fully specified model, we must finally choose the variables appearing in $X_0, ..., X_3$. In addition to delay and education dummies, we will typically use the same controls in log-employment and log-wage equations, i.e., $X_1 = X_0$. The variables included in X_1 and X_0 are (i) parental occupation (father and mother separately), (ii) parental education (father and mother separately), and (iii), the individual's geographical location at school-leaving age (1992), indicated by a list of dummies: Paris and suburbs, jurisdictions surrounding major provincial towns, and foreign countries. Other variables are supposed to explain mainly delay $d_s - \tau_s$ and education levels s. These variables, excluded from the wage and employment equations, are: (i) the father's employment status (if the father is retired, unemployed or inactive, or deceased — father in employment being the reference), (ii) the mother's employment status (if the mother is unemployed, inactive or retired, or deceased — the employed mother being the reference), (iii) the number of brothers, (iv) the number of sisters (indicated by dummies), (v) birth-order dummies (only children being the reference), (vi) quarter of birth (with a dummy indicating birth during the fourth quarter), (vii) location of residence at age 10 (indicated by dummies), and (viii) distance to college (again captured by dummies indicating quartiles of the distance distribution). For lack of good reasons of doing otherwise, X_2 is just X_3 plus a constant[26]. The specification is thus

[26] Location-in-1992 variables are not included in X_2 and X_3.

the same as in Section 3 above. At this point, it is clear that economic theory suggest that a number of family background variables can have a direct and independent effect on wages. But as shown in the preliminary analysis of the linear model, in Section 3, these overidentifying restrictions are not rejected.

5 Results and discussion

The estimation of Model B and Model A produce remarkably similar results, confirming the results of Section 3, especially with the subsample of males. Table 8a shows the complete results for Model B with the male subsample, while Table 8b shows the corresponding results for Model B and the female subsample. The qualitative features of the men's and women's results are also very close. Table 8a shows significant coefficients on delay in both the wage and employment equations. The 'signalling effect' of delay on the males' wages is stronger than in the linear model: a year of delay causes a 6.6% reduction of the wage, and an 18.8% reduction of the employment probability, *ceteris paribus*. It is easy to see that returns to education are precisely estimated (the reported coefficients are the Δf_s and the Δg_s). The father's and mother's occupations do not play an important role in the wage and employment equation, but are very significant and important in the education model (i.e., coefficients β_3). The location dummies are essentially separating Paris (and its suburbs) from the rest (there are some local variations of the labor markets explaining the differences between locations in the wage and employment equations). The final education level is also significantly and positively influenced by residence in the Paris region at age 10. Again, the father's and the mother's educations do not play an important part in explaining wages and employment directly, as can be seen from the fact that none of the parental education dummies are significant (except the "father-went-to-college" dummy, in some regressions). But we find the classic result that parental education is a very important and significant determinant of the children's education. The father's education increases the son's education *and* delay, while the mother's education very distinctly increases the son's education and *reduces* the son's delay.

We now turn to the impact of excluded variables. The retired-father effect is strong and highly significant, as in the linear model. To a lesser extent, there is also an impact of the retired-or-inactive mother. Retired parents increase education *and* delay very substantially. The numbers of brothers and sisters are also quite significant. Additional brothers and sisters *reduce* education and *increase* delay. Given this, birth-order effects are also very significant: a higher rank among siblings *reduces* education *and* delay. Quarter-of-birth has a very significant negative impact on delay, as expected. Finally, distance-to-college has a strong and significant negative impact on education and delay. The estimated correlation matrix shows that $\sigma_{\epsilon\eta}$ is negative, as expected, given that ϵ represents an unobservable positive push from family background, while η is the negative of personal talent at school (or an unobservable personal handicap).

The other correlations also deserve a comment. The correlation of ν and ζ (i.e., of the residuals of the wage and employment equations) is positive, as expected: unobserved factors that push up wages also tend to push up employment. The fact that the residuals of the education (i.e., ϵ) and delay (i.e., η) equations have respectively negative and positive correlations with both ν and ζ is more surprising. Those who are above par in terms of delay for unobservable reasons tend to find jobs with higher wages, and to find them more often. This could be the result of a 'maturity effect': arriving with a delay means being older, and in a sense maybe more mature, and maturity is a form of experience valued by the job market. Those who have received an unobservable push from family background (i.e., a high ϵ) tend to get a lower wage, *ceteris paribus*. The traditional *ability bias* of Mincerian econometrics is then negative, implying that OLS estimates of the returns to education are in fact biased downwards. We know that these supposedly paradoxical results depend in fact very much on the number and choice of controls in the regressions. Given our specification, we find that, *all other observables being equal*, the students with a higher latent score ϵ, and who thus potentially reached higher education levels, tend to earn less money on the job market. Table 8b shows that the Model B results obtained with men and women are qualitatively very similar. To sum up, in essence, Model B results confirm those obtained with the linear model.

We now turn to estimations of Model A. Results are given by Table 9a for men, and Table 9b for women. First of all, Model A yields a stronger effect of delay on the men's wages than Model B and the linear models: a year of delay costs a 7% reduction of wages and an 18% reduction of the employment probability. In the case of women, the effect of delay on wages is weaker and non-significant, but the impact on women's employment survives, with a significant 10% reduction in employment for a year of delay. Model A and Model B are very close, and exhibit the same qualitative and quantitative properties. The estimated parameters are numerically close, with the exception of some of the β_3 coefficients and of the Ordered Probit cuts, as expected. Detailed comments of Table 9 are therefore not necessary.

However, can we say that Model A dominates Model B as a description of the data? We use Vuong's test of non-nested hypotheses to compare Model A and Model B rigorously. The test is based on the difference of the log-likelihoods. In the case of men, Model A has a sufficiently higher likelihood, and we therefore conlude that it is significantly better than Model B. In the case of women, Model A cannot be rejected (its likelihood is not sufficiently smaller in this case, to conclude in favor of Model B). This is surprising, because we could have expected rejection of the constraints imposed by our theory on the education part of the model. On the contrary, according to Vuong's conceptions, our theory is closer to the 'unknown true model', (see Vuong (1989)); it leads to a richer and more accurate description of individual education decisions. We can safely conclude that, at least in the case of men, our signalling through delay theory is not rejected by the data. The structural analysis shows that these effects do exist even if rationally anticipated by individuals; the negative effect of delay is compatible with educational decisions made under risk by individuals, the risk affecting education costs as well as wages and employment probabilities.

6 Conclusion

Using standard linear, but also nonlinear econometric methods based on human capital theory, we have separated the effect of degrees from that of time-to-degree, i.e., of education levels and delays, in the analysis of wages, and of employment probabilities. Delay (or total time-to-degree) has a robust negative impact on wages and employment, while degrees continue to exhibit a standard positive impact. These effects appear only if education and delay are suitably instrumented. We interpret delay as a signal in the sense of Spence, used by employers to sort potential candidates on the labour market, showing that overidentifying-restrictions tests can be used to test for the presence of signaling. The nonlinear approach gives a synthethic view of the interplay of observable and unobservable family background factors, of wage and time-to-degree expectations, in the determination of individual schooling investment choices, under the assumption of rational student behavior.

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Table 1: Empirical Distribution of School-Leaving Age, Conditional on Education Level / Males

Age while leaving school	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
High school dropouts	1	**17**	**24**	**33**	**16**	7	1	1	0	0	0	0	0	0	0	0	0	0
Vocational degree	0	0	3	**30**	**37**	**21**	**6**	2	1	0	0	0	0	0	0	0	0	0
High school graduates (grade 12)	0	0	0	2	**12**	**31**	**32**	**15**	6	2	1	0	0	0	0	0	0	0
Two years of college (grade 14)	0	0	0	0	0	**13**	**27**	**28**	**19**	8	2	1	1	0	0	0	0	0
Four years of college (grade 16)	0	0	0	0	0	0	4	**17**	**20**	**27**	**13**	9	4	3	1	1	1	1
Graduate studies	0	0	0	0	0	0	0	4	**24**	**29**	**15**	**11**	7	4	2	2	1	0

Table 2: Distribution of Education Variable, Conditional on Parental Education and Birth Order

Education	**13**	**14**	**15**	**17**	**18**	**20**	**21**	**22**	**23**	**Total**
Father's education										
Observation Missing	6.5	22.5	24.5	24.2	10.7	8.3	0.9	0.9	1.5	9.5
Without Qualification	4.7	18.4	16.2	24.1	12.7	13.3	2.2	2.8	5.6	16.9
Elementary Certificate	1.6	9.3	13.0	24.7	17.7	19.8	2.3	3.1	8.6	33.7
Vocational Degree	1.9	11.7	17.7	22.8	15.7	18.0	1.6	2.8	7.8	22.6
High School Degree	0.8	5.0	7.6	15.7	18.7	22.4	4.5	7.0	18.3	7.0
College	0.5	3.3	4.9	11.2	12.8	16.7	3.0	8.1	39.4	10.3
Mother's education										
Without Qualification	4.5	17.7	16.9	23.0	14.0	13.8	1.7	2.3	6.0	22.1
Elementary Certificate	1.4	9.4	13.4	24.3	17.0	19.4	2.4	3.3	9.4	38.6
Vocational Degree	2.1	9.7	15.7	22.4	15.8	19.2	2.5	4.0	8.7	14.1
High School Degree	0.9	5.7	8.8	16.7	15.8	19.9	3.9	6.6	21.6	9.2
College	0.2	3.7	4.6	10.6	14.4	17.8	2.1	8.0	38.6	6.9
Observation Missing	6.3	22.2	24.4	24.5	10.2	8.5	0.5	0.8	2.7	9.1
Birth Order										
Only child	2.0	10.5	12.6	21.8	16.8	17.2	2.3	4.0	12.8	41.6
First	2.2	10.9	15.6	21.9	14.7	18.1	2.0	3.5	11.1	29.5
2nd	2.5	11.3	14.8	22.7	14.7	17.2	2.2	3.7	10.8	15.2
3rd	2.6	15.7	15.6	23.7	13.7	17.2	2.0	2.3	7.3	6.7
4th	6.1	15.0	17.4	21.8	12.9	14.0	3.2	2.9	6.8	3.1
5th and higher	6.4	22.8	20.5	22.4	10.7	10.1	2.3	1.4	3.5	4.0
Total	2.5	11.7	14.5	22.1	15.3	17.1	2.2	3.6	11.1	100.0

Figure 1: Duration of Schooling

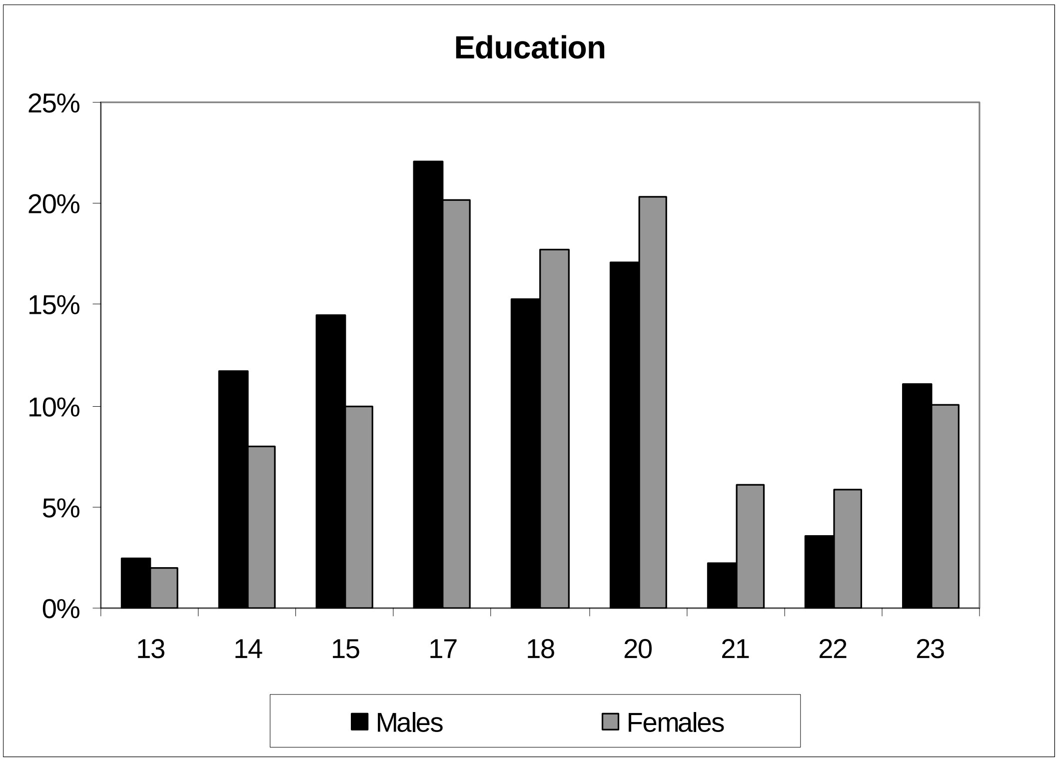

Figure 2: Wage Distributions (in euros) / Males

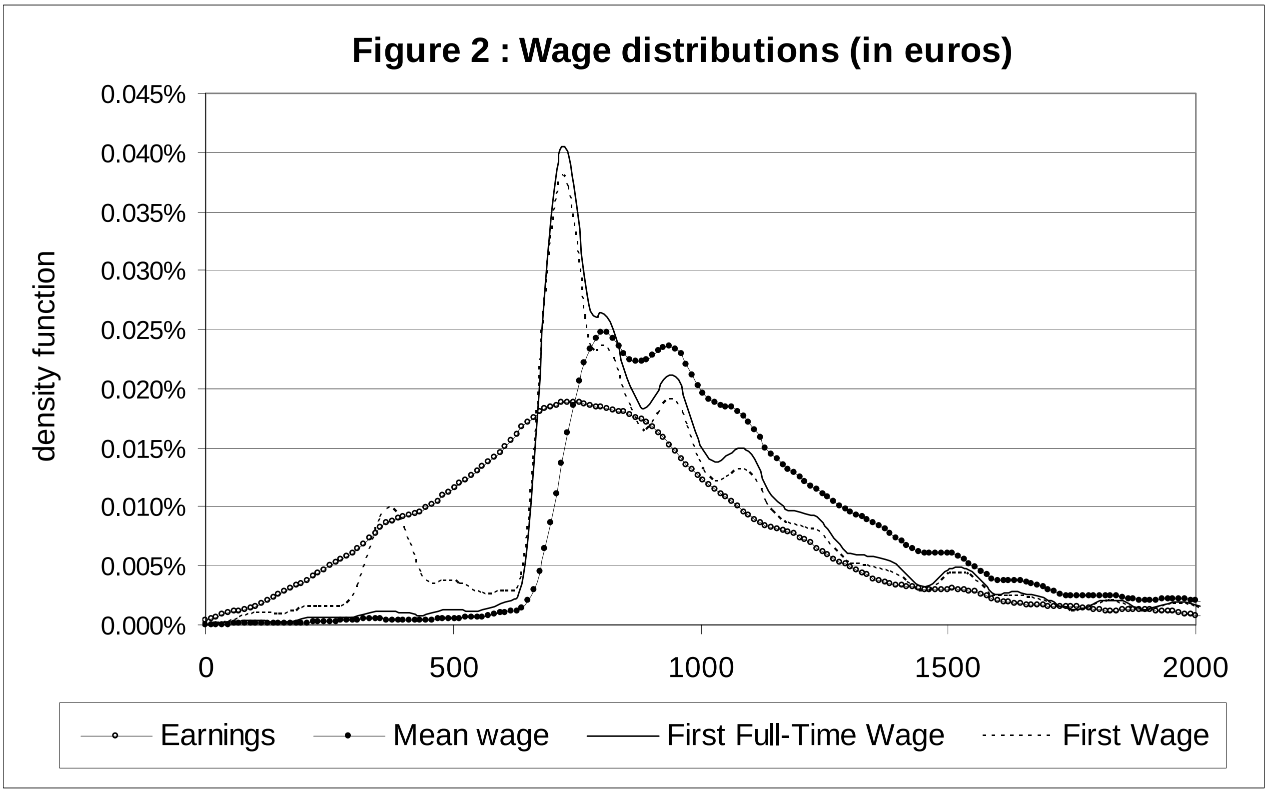

Figure 3: Employment Rate Distributions / Males

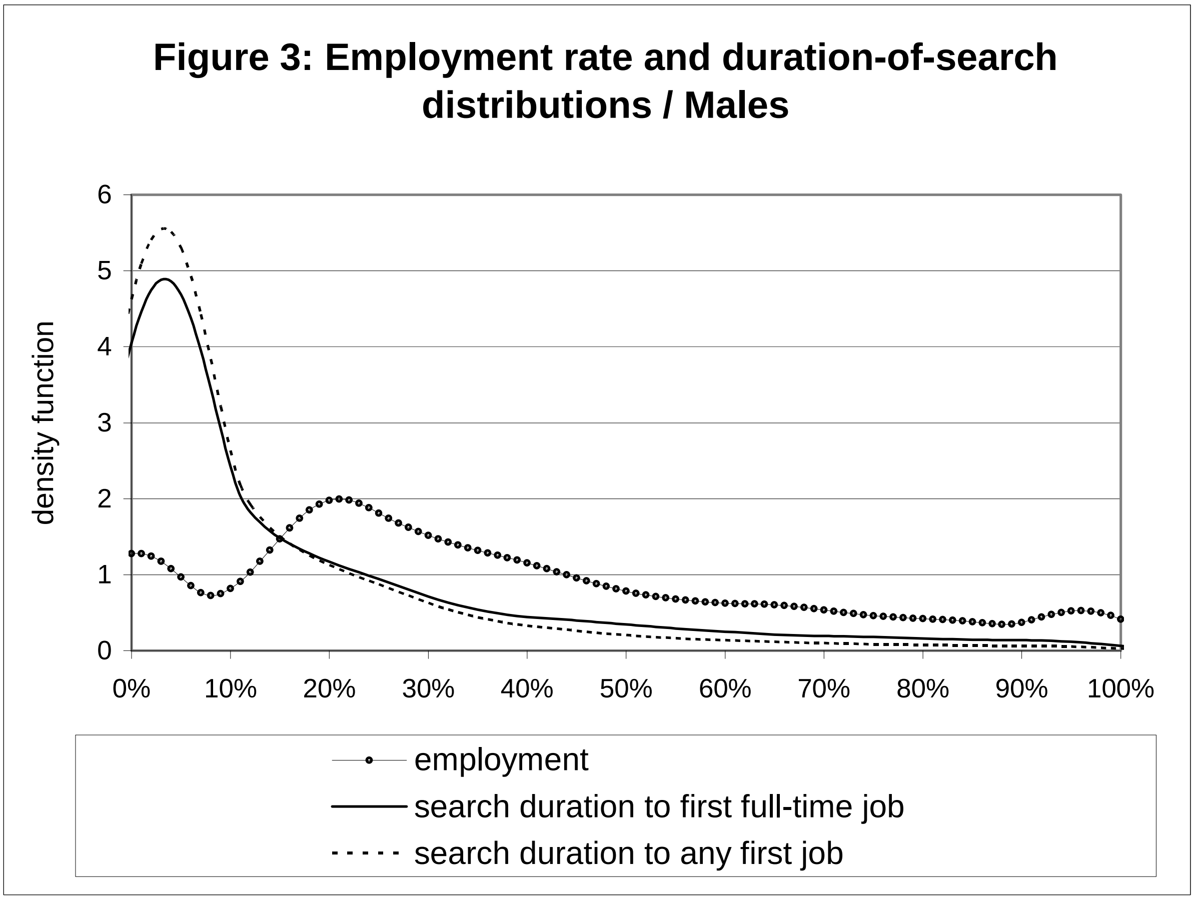

Figure 4: Distribution of Delays / Males

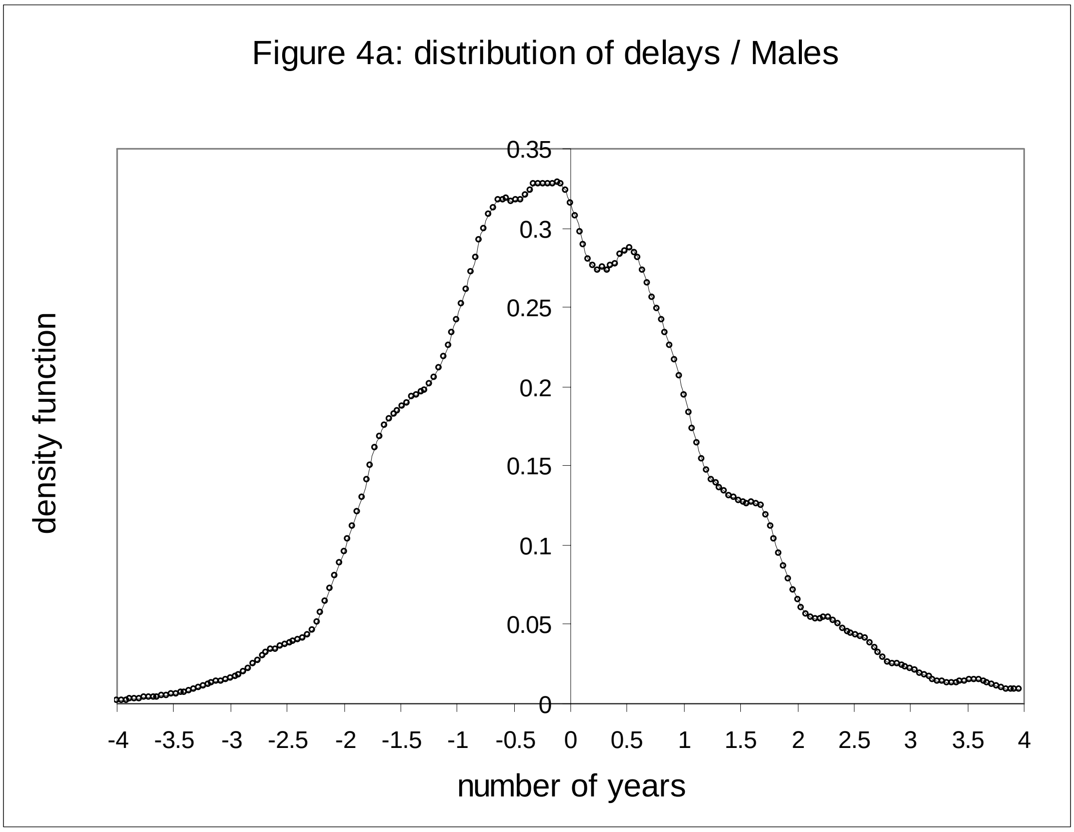

Figure 4b: distribution of delays according to father's education / Males

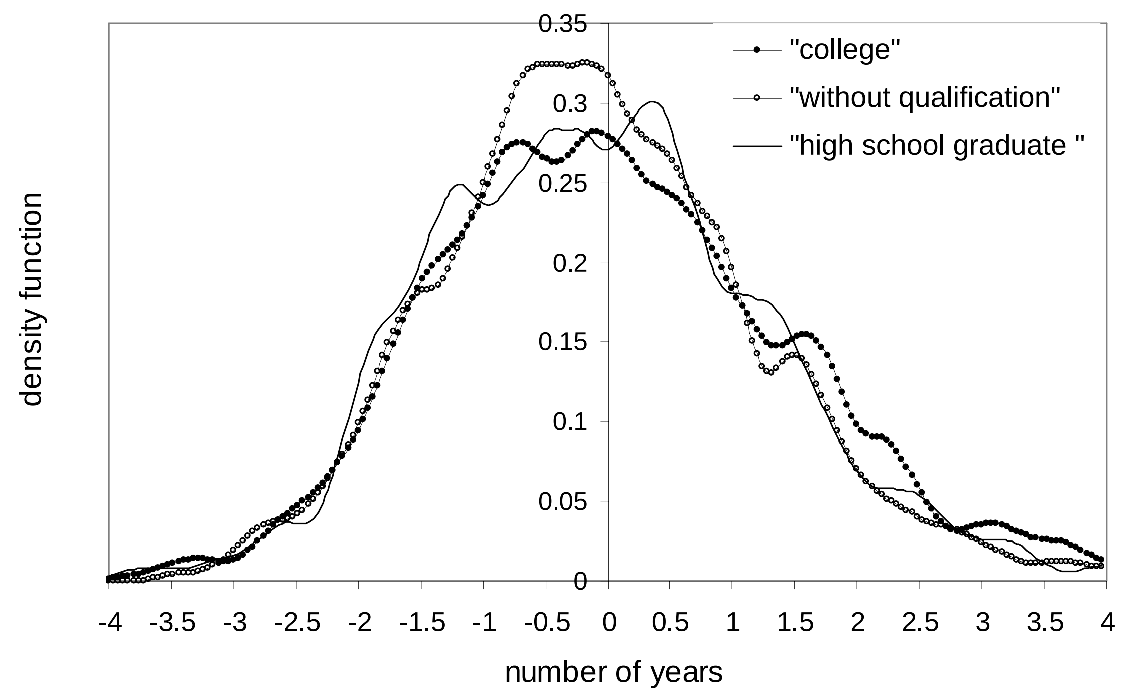

Figure 4c: distribution of delays according to student's education / Males

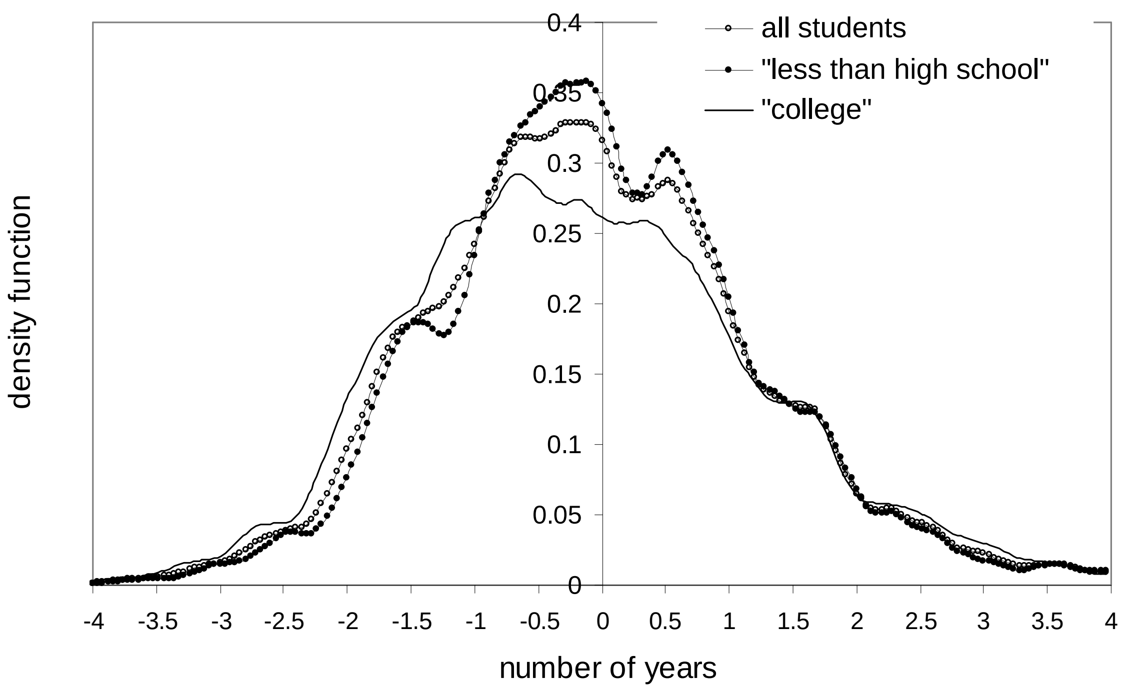

Table 3: Mean Wage / Benchmark Version

	MALES (12,310)				**FEMALES (8,630)**			
	Mean Wage				**Mean Wage**			
	OLS		3SLS		OLS		3SLS	
	A	B	A	**B**	A	B	A	**B**
Delay	0.95%	0.81%	-3.93%	**-3.07%**	0.62%	0.47%	0.45%	**-0.60%**
	(5.56)	(4.79)	(-3.81)	**(-2.23)**	(3.29)	(2.55)	(0.48)	**(-0.57)**
Education	7.12%	6.47%	10.97%	**7.83%**	7.54%	6.87%	11.06%	**8.11%**
	(84.01)	(69.09)	60.08	**(17.07)**	(71.50)	(58.69)	(52.12)	**(15.77)**
R-Square	0.3655	0.3911	0.1847	**0.2116**	0.3725	0.3989	0.1955	**0.22438**
	Employment				**Employment**			
	OLS		3SLS		OLS		3SLS	
	A	B	A	**B**	A	B	A	B
Delay	-2.07%	-1.88%	-21.49%	**-14.65%**	0.28%	0.44%	-10.25%	**-7.76%**
	(-3.87)	(-3.49)	(-6.64)	**(-3.33)**	(0.75)	(1.16)	(-5.32)	**(-3.55)**
Education	5.64%	5.46%	7.84%	**6.56%**	4.66%	4.58%	6.09%	**6.87%**
	(21.17)	(18.26)	(13.66)	**(4.48)**	(22.00)	(19.17)	(14.18)	**(6.42)**
R-Square	0.0363	0.0442	0.0116	**0.0184**	0.0532	0.0650	0.0186	**0.02915**

Controls: Father's occupation, Mother's occupation, Location in 1992 and Parental education.
Instruments: Father's employment status, Mother's employment status, Number of brothers, Number of sisters, Birth order, Location at age 10, Quarter of birth and Distance to college

Table 4 : Other Wage Statistics / Benchmark Version

MALES (12,310)								
	Earnings		**Last Wage**		**First Full-Time Wage**		**First Wage**	
	OLS	3SLS	OLS	3SLS	OLS	3SLS	OLS	3SLS
Delay	0.20%	-11.67%	0.63%	-2.93%	1.28%	-0.78%	1.61%	-2.82%
	(0.64)	(-4.41)	(3.51)	(-1.99)	(6.14)	(-0.46)	(6.03)	(-1.30)
Education	8.30%	10.30%	6.80%	8.26%	5.20%	6.76%	6.10%	7.56%
	(47.36)	(11.70)	(67.74)	(16.88)	(44.96)	(12.09)	(41.05)	(10.48)
R-Square	0.2229	0.0946	0.3808	0.2058	0.2302	0.1264	0.1859	0.0885
Fisher (p-value)	-	0.0029	-	0.1018	-	0.0406	-	0.0391
			Employment		**Duration of Search Full Time**		**Duration of Search**	
			OLS	3SLS	OLS	3SLS	OLS	3SLS
Delay			-1.88%	-14.65%	-0.75%	21.72%	-0.04%	22.12%
			(-3.49)	(-3.33)	(-0.90)	(3.15)	(-0.05)	(3.48)
Education			5.46%	6.55%	-2.21%	-1.09%	0.79%	-0.14%
			(18.26)	(4.48)	(-4.76)	(-0.47)	(1.84)	(-0.07)
R-Square			0.0442	0.0184	0.0118	0.0103	0.0100	0.0104
Fisher (p-value)			-	0.1596	-	0.0032	-	0.0001
FEMALES (8,630)								
	Earnings		**Last Wage**		**First Full-Time Wage**		**First Wage**	
	OLS	3SLS	OLS	3SLS	OLS	3SLS	OLS	3SLS
Delay	1.09%	-5.40%	0.32%	-0.39%	0.96%	-0.70%	1.37%	-1.28%
	(3.28)	(-2.82)	(1.64)	(-0.36)	(4.30)	(-0.55)	(4.38)	(-0.72)
Education	10.38%	11.48%	7.21%	8.44%	5.76%	7.33%	7.36%	8.01%
	(49.35)	(12.26)	(58.77)	(15.67)	(40.83)	(11.80)	(37.32)	(9.26)
R-Square	0.3074	0.1458	0.4011	0.2279	0.2455	0.1262	0.2043	0.0931
Fisher (p-value)	-	0.0067	-	0.1043	-	0.3790	-	0.8422
			Employment		**Duration of Search Full Time**		**Duration of Search**	
			OLS	3SLS	OLS	3SLS	OLS	3SLS
Delay			0.44%	-7.76%	-7.15%	10.00%	-6.86%	4.94%
			(1.16)	(-3.55)	(-7.36)	(1.79)	(-8.27)	(1.04)
Education			4.58%	6.86%	-4.99%	-0.05%	0.28%	3.36%
			(19.17)	(6.41)	(-8.13)	(-0.02)	(0.53)	(1.45)
R-Square			0.0650	0.0292	0.0198	0.0066	0.0179	0.0103
Fisher (p-value)				0.0001	-	0.2268	-	0.0028

Table 5: Tests of Overidentifying Restrictions on Mean Wage

		MALES (12,310)					FEMALES (8,630)
		Benchmark	**Variant 1**	**Variant 2**	**Variant 3**	**Variant 4**	**Benchmark**
Mean Wage	Delay	-3.07%	-4.65%	-4.73%	-5.50%	-3.34%	-0.60%
		(-2.23)	(-2.58)	(-2.58)	(-2.53)	(-2.06)	(-0.57)
	Education	7.83%	8.29%	8.29%	7.24%	7.57%	8.11%
		(17.07)	(14.35)	(13.58)	(8.72)	(12.89)	(15.77)
	R-Square	0.2116	0.2085	0.20839	0.20374	0.21081	0.22438
	Chi² overident. restr. test	**36.93**	**27.08**	**27.08**	**19.70**	**30.78**	**40.56**
	Fisher (p-value)	0.09110	0.01510	0.00600	0.01220	0.07290	0.03860
Employment	Delay	-14.65%	-14.68%	-13.76%	-14.51%	-12.12%	-7.76%
		(-3.33)	(-2.58)	(-2.38)	(-2.15)	(-2.37)	(-3.55)
	Education	6.56%	6.17%	6.65%	5.18%	7.27%	6.87%
		(4.48)	(3.38)	(3.45)	(1.98)	(3.91)	(6.42)
	R-Square	0.0184	0.01967	0.0200	0.0203	0.0192	0.02915
	Chi² overident. restr. test	**33.24**	**17.23**	**14.77**	**9.85**	**25.85**	**66.45**
	Fisher (p-value)	0.15960	0.19750	0.19540	0.30210	0.21640	0.00010
Instruments	Father's occupation	No	No	No	No	No	No
	Mother's occupation	No	No	No	No	No	No
	Location in 1992	No	No	No	No	No	No
	Parental education	No	No	No	No	No	No
	Father's employment status (3)	Yes	Yes	Yes	No	No	Yes
	Mother's employment status (2)	Yes	Yes	No	No	No	Yes
	Number of brothers (4)	Yes	No	No	No	Yes	Yes
	Number of sisters (4)	Yes	No	No	No	Yes	Yes
	Birth Order (5)	Yes	No	No	No	Yes	Yes
	Location at age 10 (6)	Yes	Yes	Yes	Yes	Yes	Yes
	Quarter of birth (1)	Yes	Yes	Yes	Yes	Yes	Yes
	Distance to college (3)	Yes	Yes	Yes	Yes	Yes	Yes
Chi2 at 2.5%		Chi2(26)=41.92	Chi2(13)=24.74	Chi2(11)=21.92	Chi2(8)=17.53	Chi2(21)=35.48	Chi2(26)=41.92
Chi2 at 5%		**Chi2(26)=38.88**	**Chi2(13)=22.36**	**Chi2(11)=19.67**	**Chi2(8)=15.51**	**Chi2(21)=32.67**	**Chi2(26)=38.88**
Chi2 at 10%		Chi2(26)=35.56	Chi2(13)=19.81	Chi2(11)=17.27	Chi2(8)=13.36	Chi2(21)=29.61	Chi2(26)=35.56
Mean Wage		**OK at 5%**	**Not OK at 2.5%**	**Not OK at 2.5%**	**Not OK at 2.5%**	**OK at 5%**	**OK at 2.5%**
Employment		**OK at 10%**	**OK at 10%**	**OK at 10%**	**OK at 10%**	**OK at 10%**	**Not OK at 2.5%**

Table 6 : Tests of Overidentifying Restrictions on Last Wage

		MALES (12,310)					FEMALES (8,630)
		Benchmark	**Variant 1**	**Variant 2**	**Variant 3**	**Variant 4**	**Benchmark**
Last Wage	Delay	-2.93%	-3.68%	-3.86%	-4.72%	-3.63%	-0.39%
		(-1.99)	(-1.93)	(-1.99)	(-2.06)	(-2.09)	(-0.36)
	Education	8.26%	8.52%	8.53%	7.59%	7.85%	8.44%
		(16.88)	(13.90)	(13.16)	(8.61)	(12.48)	(15.67)
	R-Square	0.2058	0.2058	0.2055	0.2022	0.2043	0.2279
	Chi² overident. restr. test	**35.70**	**27.08**	**27.08**	**19.70**	**28.31**	**35.38**
	Fisher (p-value)	0.10180	0.01340	0.00570	0.01440	0.12040	0.10430
Employment	Delay	-14.65%	-14.67%	-13.75%	-14.52%	-12.13%	-7.76%
		(-3.33)	(-2.58)	(-2.38)	(-2.15)	(-2.37)	(-3.55)
	Education	6.55%	6.16%	6.64%	5.16%	7.27%	6.86%
		(4.48)	(3.37)	(3.44)	(1.98)	(3.91)	(6.41)
	R-Square	0.0184	0.0197	0.0200	0.0203	0.0192	0.0292
	Chi² overident. restr. test	**33.24**	**17.23**	**14.77**	**9.85**	**25.85**	**66.45**
	Fisher (p-value)	0.15960	0.19750	0.19540	0.30200	0.21650	0.00010
Instruments	Father's occupation	No	No	No	No	No	No
	Mother's occupation	No	No	No	No	No	No
	Location in 1992	No	No	No	No	No	No
	Parental education	No	No	No	No	No	No
	Father's employment status (3)	Yes	Yes	Yes	No	No	Yes
	Mother's employment status (2)	Yes	Yes	No	No	No	Yes
	Number of brothers (4)	Yes	No	No	No	Yes	Yes
	Number of sisters (4)	Yes	No	No	No	Yes	Yes
	Birth Order (5)	Yes	No	No	No	Yes	Yes
	Location at age 10 (6)	Yes	Yes	Yes	Yes	Yes	Yes
	Quarter of birth (1)	Yes	Yes	Yes	Yes	Yes	Yes
	Distance to college (3)	Yes	Yes	Yes	Yes	Yes	Yes
Chi2 at 2.5%		Chi2(26)=41.92	Chi2(13)=24.74	Chi2(11)=21.92	Chi2(8)=17.53	Chi2(21)=35.48	Chi2(26)=41.92
Chi2 at 5%		**Chi2(26)=38.88**	**Chi2(13)=22.36**	**Chi2(11)=19.67**	**Chi2(8)=15.51**	**Chi2(21)=32.67**	**Chi2(26)=38.88**
Chi2 at 10%		Chi2(26)=35.56	Chi2(13)=19.81	Chi2(11)=17.27	Chi2(8)=13.36	Chi2(21)=29.61	Chi2(26)=35.56
Last Wage		**OK at 10%**	**Not OK at 2.5%**	**Not OK at 2.5%**	**Not OK at 2.5%**	**OK at 10%**	**OK at 10%**
Employment		**OK at 10%**	**OK at 10%**	**OK at 10%**	**OK at 10%**	**OK at 10%**	**Not OK at 2.5%**

Table 7: 3SLS on Mean Wages / Males / Benchmark Version (Part 1)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Constant	7.4493	98.36	-1.8597	-7.69	16.7098	160.52	0.0276	0.48
Delay	-0.0307	-2.23	-0.1465	-3.33	-	-	-	-
Education	0.0783	17.07	0.0656	4.48	-	-	-	-
Father's occupation								
Farmer	-0.0505	-2.96	0.0738	1.36	0.6341	4.11	-0.1060	-1.23
Craftsman	0.0147	1.53	0.0814	2.65	0.1193	1.34	0.0282	0.56
Executive	0.0205	1.92	-0.0259	-0.76	1.1313	12.63	0.0930	1.85
Middle Manager	0.0243	2.45	0.0026	0.08	0.6471	7.31	0.0686	1.38
White Collar. **Reference group**								
Blue Collar	0.0134	1.80	-0.0283	-1.19	-0.2733	-4.00	-0.0041	-0.11
Missing or Deceased	-0.0134	-1.26	-0.1037	-3.07	-0.2866	-1.26	0.0886	0.71
Mother's occupation								
Farmer	-0.0325	-1.77	0.0592	1.01	0.0842	0.50	-0.1324	-1.39
Craftsman	0.0277	2.05	0.0514	1.19	0.1075	0.86	0.0550	0.78
Executive	0.0195	1.63	0.0401	1.05	0.5014	4.58	0.1146	1.87
Middle Manager	0.0074	0.60	0.0708	1.79	0.2945	2.60	0.2094	3.30
White Collar. **Reference group**								
Blue Collar	0.0144	1.78	0.0093	0.36	-0.4990	-6.74	-0.0703	-1.69
Missing or Deceased	-0.0038	-0.58	0.0113	0.54	-0.0604	-0.81	-0.0315	-0.76
Location in 1992 (region)								
Reference (rest of France)								
Paris (75)	0.0896	10.34	0.0876	3.17	-	-	-	-
Marseilles (13)	-0.0133	-0.72	0.0210	0.36	-	-	-	-
Toulouse (31)	0.0141	0.79	0.0430	0.75	-	-	-	-
Lyons (69)	0.0503	3.23	0.0150	0.30	-	-	-	-
Nice (06)	0.0237	1.12	0.0651	0.96	-	-	-	-
Lille (59)	-0.0039	-0.35	-0.0217	-0.61	-	-	-	-
Foreign Countries	0.1614	2.53	-0.0410	-0.20	-	-	-	-
Father's education								
High school dropouts. **Reference group**								
Vocational degree	-0.0001	-0.01	0.0072	0.28	0.6139	8.73	0.0348	0.88
Advanced vocational degree	0.0102	1.23	-0.0056	-0.21	0.4642	6.29	-0.0199	-0.48
High school graduates	0.0136	1.06	-0.0272	-0.67	1.2205	11.33	0.0351	0.58
Father went to College	0.0463	3.40	-0.0435	-1.00	1.5937	14.20	0.1989	3.16
Mother's education								
High school dropouts. **Reference group**								
Vocational degree	-0.0151	-1.94	0.0326	1.32	0.6258	9.59	-0.0012	-0.03
Advanced vocational degree	-0.0088	-0.95	0.0463	1.56	0.4848	5.90	-0.0445	-0.97
High school graduates	-0.0145	-1.22	0.0147	0.39	0.9296	9.45	-0.1184	-2.15
Mother went to College	0.0111	0.69	-0.0769	-1.50	1.2106	9.38	-0.2780	-3.84

Table 7: 3SLS on Mean Wages / Males / Benchmark Version (Part 2, end of table)

	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
Father's employment status								
Employed. **Reference group**								
Unemployed or Inactive	-	-	-	-	0.0890	0.75	0.0528	0.81
Retired	-	-	-	-	1.6451	19.73	0.4857	10.49
Deceased (or Missing observ).	-	-	-	-	0.6300	2.62	0.0308	0.23
Mother's employment status								
Employed. **Reference group**								
Unemployed, inactive or retired	-	-	-	-	0.3159	5.30	0.0947	2.90
Deceased (or Missing observ).	-	-	-	-	-0.5233	-3.09	0.0524	0.57
Number of brothers								
0. **Reference group**								
1	-	-	-	-	-0.0370	-0.66	0.0230	0.75
2	-	-	-	-	-0.1535	-2.03	0.0874	2.11
3	-	-	-	-	-0.3199	-2.65	0.1721	2.61
4, or more	-	-	-	-	-0.5560	-3.73	0.3479	4.24
Number of sisters								
0. **Reference group**								
1	-	-	-	-	-0.1390	-2.52	0.0497	1.64
2	-	-	-	-	-0.1915	-2.46	0.1755	4.10
3	-	-	-	-	-0.1704	-1.38	0.2529	3.73
4, or more	-	-	-	-	-0.5321	-3.28	0.2395	2.69
Birth Order								
Only child. **Reference group**								
First	-	-	-	-	-0.1429	-2.56	-0.0567	-1.86
2nd	-	-	-	-	-0.1059	-1.40	-0.2378	-5.73
3rd	-	-	-	-	-0.3585	-3.27	-0.2255	-3.75
4th	-	-	-	-	-0.3183	-2.05	-0.3579	-4.20
5th and higher	-	-	-	-	-0.8581	-4.92	-0.4358	-4.56
Location at age 10								
Reference (rest of France)								
Paris (75)	-	-	-	-	0.5397	6.98	0.0321	0.75
Marseilles (13)	-	-	-	-	0.4180	2.35	0.1954	1.98
Toulouse (31)	-	-	-	-	-0.4049	-2.04	0.0476	0.43
Lyons (69)	-	-	-	-	-0.1046	-0.72	-0.3203	-3.97
Nice (06)	-	-	-	-	-0.1866	-0.93	-0.0898	-0.80
Lille (59)	-	-	-	-	0.1065	1.02	0.2493	4.29
Quarter of birth								
Fourth Quarter	-	-	-	-	0.0965	2.00	-0.1961	-7.37
Distance to college								
First quartile. **Reference group**	-	-	-	-				
Second quartile	-	-	-	-	-0.2696	-4.16	-0.1171	-3.30
Third quartile	-	-	-	-	-0.3467	-5.04	-0.1990	-5.28
Fourth quartile	-	-	-	-	-0.0469	-0.67	-0.0871	-2.26

Number of observations	12,310			
System Weighted R-Square	0.2116	0.0184	0.2393	0.0321
Cross Model Correlation	Mean Wage	Employment	Education	Delay
Mean Wage	1	0.2438	-0.1085	0.1814
Unemployment	0.2438	1	-0.0314	0.2046
Education	-0.1085	-0.0314	1	-0.0389
Delay	0.1814	0.2046	-0.0389	1

Table 8a: Model B / Maximum Likelihood Estimation for Men (Part 1)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Constant	8.5588	245.29	-1.0766	-12.40	-	-	0.012	0.19
Delay	-0.0663	-2.91	-0.1881	-3.14				
Education (Reference group: High school dropouts)								
Vocational degree	0.1045	4.86	0.3146	5.66	-	-	-	-
Advanced vocational degree	0.0621	3.92	0.0621	1.47	-	-	-	-
High school graduates (grade 12)	0.1046	7.20	0.0257	0.65	-	-	-	-
Two years of college (grade 14)	0.1696	11.54	0.1906	4.79	-	-	-	-
Four years of college (grade 16)	0.1396	8.86	0.1042	2.29	-	-	-	-
Graduate studies (grade 17 or more)	0.2760	13.20	0.0899	1.58	-	-	-	-
Father's occupation (Reference group: White collars)								
Farmer	-0.0568	-3.03	0.0632	1.12	0.2408	3.78	-0.0963	-1.10
Craftsman	0.0056	0.55	0.0783	2.49	0.0563	1.52	0.0196	0.39
Executive	0.0044	0.32	-0.0299	-0.78	0.4746	12.72	0.0947	1.86
Middle Manager	0.0205	1.82	-0.0012	-0.04	0.2607	7.13	0.0654	1.30
Blue Collar	0.0119	1.38	-0.0268	-1.05	-0.1370	-4.82	0.0063	0.16
Missing or Deceased	-0.0172	-1.53	-0.1013	-2.92	-0.1335	-1.42	0.0132	0.11
Mother's occupation (Reference group: White collars)								
Farmer	-0.0363	-1.86	0.0588	0.98	0.0487	0.69	-0.1241	-1.29
Craftsman	0.0325	2.27	0.0515	1.17	0.0554	1.07	0.0563	0.79
Executive	0.0103	0.81	0.0430	1.10	0.2112	4.58	0.1005	1.62
Middle Manager	0.0106	0.81	0.0773	1.91	0.1237	2.62	0.2039	3.16
Blue Collar	0.0098	1.10	0.0075	0.28	-0.1983	-6.45	-0.0834	-1.98
Missing or Deceased	-0.0045	-0.64	0.0154	0.72	-0.0275	-0.89	-0.0474	-1.15
Location (Reference group: Rest of France)*								
Paris (75)	0.0829	9.99	0.0957	3.72	0.2047	6.35	0.0504	1.17
Marseilles (13)	-0.0311	-1.68	0.0254	0.43	0.1657	2.23	0.1764	1.82
Toulouse (31)	-0.0032	-0.18	0.0466	0.82	-0.1356	-1.64	0.0154	0.14
Lyons (69)	0.0350	2.31	0.0186	0.39	-0.0774	-1.28	-0.2720	-3.38
Nice (06)	0.0052	0.24	0.0640	0.94	-0.1077	-1.28	-0.1039	-0.92
Lille (59)	0.0040	0.33	-0.0100	-0.27	0.0474	1.10	0.2303	3.97
Foreign Countries	0.0972	1.59	-0.0157	-0.08	-	-	-	-
Father's education (Reference group: High school dropouts)								
Vocational degree	0.0046	0.49	-0.0020	-0.07	0.1395	4.23	0.0556	1.22
Advanced vocational degree	0.0105	1.10	-0.0152	-0.52	0.0752	2.18	0.0131	0.27
High school graduates	0.0112	0.75	-0.0388	-0.88	0.3638	7.59	0.0624	0.95
Father went to College	0.0274	1.73	-0.0505	-1.08	0.5324	10.57	0.2218	3.23
Deceased (or Missing observ).	0.0007	0.04	0.0111	0.24	-0.3358	-6.71	0.0628	0.91
Mother's education (Reference group: High school dropouts)								
Vocational degree	-0.0121	-1.24	0.0056	0.20	0.2085	7.03	-0.0200	-0.50
Advanced vocational degree	-0.0066	-0.58	0.0147	0.44	0.1540	4.24	-0.0786	-1.58
High school graduates	-0.0219	-1.38	-0.0209	-0.47	0.3273	7.57	-0.1416	-2.41
Mother went to College	-0.0083	-0.38	-0.1171	-1.93	0.4534	8.08	-0.2886	-3.81
Deceased (or Missing observ).	0.0024	0.18	-0.0713	-1.75	-0.1629	-3.37	-0.1217	-1.85
Father's employment status (Reference group: Employed)								
Unemployed or Inactive	-	-	-	-	-0.0133	-0.27	0.0644	1.03
Retired	-	-	-	-	0.6626	18.82	0.4986	10.66
Deceased (or Missing observ).	-	-	-	-	0.3126	3.14	0.0964	0.75
Mother's employment status (Reference group: Employed)								
Unemployed, inactive or retired	-	-	-	-	0.1130	4.58	0.1006	3.22
Deceased (or Missing observ).	-	-	-	-	-0.1391	-1.98	0.0428	0.48

(To be continued)

*Location indicates residence in 1992 in employment and wage equations, and residence at age 10 for education and delay equations.

Table 8a: Model B / Maximum Likelihood Estimation for Men (Part 2, end of table)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Number of brothers (Reference group: 0)								
1	-	-	-	-	-0.0232	-1.01	0.0288	1.00
2	-	-	-	-	-0.0787	-2.51	0.0732	1.82
3	-	-	-	-	-0.1528	-3.02	0.1471	2.24
4 or more	-	-	-	-	-0.2794	-4.44	0.2907	3.51
Number of sisters (Reference group: 0)								
1	-	-	-	-	-0.0644	-2.82	0.0377	1.27
2	-	-	-	-	-0.0856	-2.63	0.1534	3.59
3	-	-	-	-	-0.1198	-2.32	0.2004	3.04
4 or more	-	-	-	-	-0.2819	-4.13	0.2038	2.37
Birth order (Reference group: Only child)								
First	-	-	-	-	-0.0572	-2.48	-0.0408	-1.38
2nd	-	-	-	-	-0.0412	-1.31	-0.2168	-5.21
3rd	-	-	-	-	-0.1427	-3.14	-0.1824	-3.13
4th	-	-	-	-	-0.1054	-1.63	-0.3375	-4.06
5th and higher	-	-	-	-	-0.3297	-4.55	-0.3968	-4.33
Quarter of birth								
Fourth Quarter	-	-	-	-	0.0327	1.48	-0.1678	-5.51
Distance to college (Reference group: First quartile)								
Second quartile	-	-	-	-	-0.0964	-3.62	-0.1276	-3.79
Third quartile	-	-	-	-	-0.1399	-4.94	-0.2105	-5.87
Fourth quartile	-	-	-	-	-0.0175	-0.60	-0.0799	-2.06
Ordered Probit Cuts								
b1	-	-	-	-	-0.9620	-20.40	-	-
b2	-	-	-	-	-0.3920	-8.41	-	-
b3	-	-	-	-	0.2799	6.01	-	-
b4	-	-	-	-	0.7396	15.81	-	-
b5	-	-	-	-	1.3869	29.10	-	-
b6	-	-	-	-	1.7085	35.23	-	-
Covariance parameters								
v1	-1.2514	-21.48						
v2	-0.1275	-4.01						
v3	0.3551	55.68						
v4	0.5411	5.40						
v5	0.7108	3.18						
v6	0.4814	2.75						
v7	-0.3410	-2.59						
v8	-0.1244	-1.18						
v9	-0.0693	-4.66						
Estimated Standard Deviations								
s.d.	0.286	16.63	0.880	30.15	1	-	1.426	156.74

Estimated Correlation Matrix*	Mean Wage	Employment	Education	Delay
Mean Wage	1.000	-	-	-
Employment	0.315 (6.07)	1.000	-	-
Education	-0.209 (-2.68)	-0.078 (-1.13)	1.000	-
Delay	0.393 (4.04)	0.285 (3.03)	-0.044 (-4.69)	1.000

Number of observations	12,310
Mean Log-Likelihood	-4.80668

* standard errors are computed using the Delta Method

Table 8b: Model B / Maximum Likelihood Estimation for Women (Part 1)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Constant	8.4232	303.45	-0.8514	-14.36	-	-	-0.098	-1.24
Delay	-0.0195	-1.56	-0.1079	-3.85	-	-	-	-
Education (Reference group: High school dropouts)								
Vocational degree	0.0863	4.85	0.3141	8.39	-	-	-	-
Advanced vocational degree	0.0730	5.07	0.0689	2.28	-	-	-	-
High school graduates (grade 12)	0.0734	5.62	0.0787	2.87	-	-	-	-
Two years of college (grade 14)	0.1906	14.72	0.2028	7.45	-	-	-	-
Four years of college (grade 16)	0.1911	13.17	0.0767	2.52	-	-	-	-
Graduate studies (grade 17 or more)	0.1726	9.09	0.0466	1.16	-	-	-	-
Father's occupation (Reference group: White collars)								
Farmer	-0.0569	-2.99	-0.0023	-0.06	0.3423	4.79	-0.1709	-1.62
Craftsman	0.0095	0.85	0.0222	0.92	0.1311	3.02	0.0822	1.28
Executive	0.0049	0.35	-0.0456	-1.51	0.5421	12.11	0.0865	1.31
Middle Manager	0.0065	0.56	-0.0046	-0.18	0.1974	4.54	-0.0149	-0.23
Blue Collar	-0.0001	-0.01	-0.0173	-0.91	-0.0812	-2.40	-0.0834	-1.66
Missing or Deceased	-0.0046	-0.36	-0.0218	-0.78	0.0894	0.82	0.0404	0.26
Mother's occupation (Reference group: White collars)								
Farmer	0.0222	1.12	0.0345	0.82	0.1304	1.68	0.0688	0.60
Craftsman	0.0073	0.49	0.0190	0.59	0.0077	0.13	0.1305	1.52
Executive	-0.0005	-0.03	-0.0519	-1.71	0.2847	5.32	0.0394	0.50
Middle Manager	0.0084	0.59	-0.0629	-2.04	0.1484	2.67	-0.0456	-0.56
Blue Collar	-0.0041	-0.42	-0.0283	-1.35	-0.1604	-4.30	-0.0780	-1.41
Missing or Deceased	-0.0222	-2.81	-0.0720	-4.21	0.0934	2.50	-0.0459	-0.84
Location (Reference group: Rest of France)*								
Paris (75)	0.1087	12.64	0.0754	4.13	0.1812	5.07	0.0804	1.55
Marseilles (13)	-0.0216	-1.08	-0.0092	-0.22	0.2094	2.49	0.2506	2.07
Toulouse (31)	-0.0040	-0.19	0.0012	0.03	0.4761	4.60	0.5067	3.45
Lyons (69)	0.0627	3.30	0.0902	2.24	-0.1968	-2.32	0.1215	0.99
Nice (06)	-0.0197	-0.83	0.0801	1.59	-0.0066	-0.07	0.0620	0.44
Lille (59)	0.0025	0.19	-0.0075	-0.25	0.0741	1.29	-0.0791	-0.94
Foreign Countries	-0.0314	-0.51	-0.1273	-1.01	-	-	-	-
Father's education (Reference group: High school dropouts)								
Vocational degree	-0.0010	-0.10	-0.0199	-0.94	0.0993	2.63	0.0383	0.68
Advanced vocational degree	0.0014	0.13	-0.0157	-0.69	0.1048	2.54	0.0750	1.23
High school graduates	0.0065	0.42	-0.0427	-1.28	0.3060	5.29	0.0940	1.10
Father went to College	-0.0062	-0.38	-0.0890	-2.55	0.3870	6.53	0.0378	0.44
Deceased (or Missing observ).	0.0097	0.64	0.0170	0.52	-0.3990	-7.14	-0.0577	-0.70
Mother's education (Reference group: High school dropouts)								
Vocational degree	-0.0006	-0.06	-0.0124	-0.56	0.2726	7.73	-0.0262	-0.50
Advanced vocational degree	-0.0119	-0.98	-0.0133	-0.51	0.2767	6.39	-0.0222	-0.35
High school graduates	0.0085	0.53	-0.0123	-0.35	0.5151	9.69	-0.0118	-0.15
Mother went to College	0.0173	0.90	-0.0141	-0.34	0.5917	8.75	0.0301	0.30
Deceased (or Missing observ).	-0.0014	-0.09	0.0257	0.80	-0.0349	-0.59	0.0757	0.87
Father's employment status (Reference group: Employed)								
Unemployed or Inactive	-	-	-	-	-0.0219	-0.40	0.0690	0.87
Retired	-	-	-	-	0.6582	15.68	0.6227	10.46
Deceased (or Missing observ).	-	-	-	-	0.1322	1.15	0.3290	2.01
Mother's employment status (Reference group: Employed)								
Unemployed, inactive or retired	-	-	-	-	0.0659	2.25	0.1221	2.94
Deceased (or Missing observ).	-	-	-	-	-0.2716	-3.21	0.2984	2.50

(To be continued)

*Location indicates residence in 1992 in employment and wage equations, and residence at age 10 for education and delay equations.

Table 8b: Model B / Maximum Likelihood Estimation for Women (Part 2, end of table)

	Mean Wage		Employment		Education		Delay	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
Number of brothers (Reference group: 0)								
1	-	-	-	-	-0.0964	-3.52	0.0648	1.65
2	-	-	-	-	-0.1911	-5.01	0.2575	4.69
3	-	-	-	-	-0.3880	-6.63	0.5546	6.60
4 or more	-	-	-	-	-0.4451	-5.61	0.6271	5.56
Number of sisters (Reference group: 0)								
1	-	-	-	-	-0.0680	-2.50	0.0104	0.26
2	-	-	-	-	-0.0989	-2.65	0.1772	3.30
3	-	-	-	-	-0.1483	-2.54	0.4236	5.07
4 or more	-	-	-	-	-0.3877	-4.93	0.5090	4.51
Birth order (Reference group: Only child)								
First	-	-	-	-	-0.0743	-2.72	-0.0221	-0.56
2nd	-	-	-	-	-0.1315	-3.58	-0.2203	-4.18
3rd	-	-	-	-	-0.1410	-2.63	-0.4047	-5.25
4th	-	-	-	-	-0.1509	-1.93	-0.5180	-4.66
5th and higher	-	-	-	-	-0.1418	-1.62	-0.8299	-6.70
Quarter of birth								
Fourth Quarter	-	-	-	-	-0.0212	-0.80	-0.2236	-5.62
Distance to college (Reference group: First quartile)								
Second quartile	-	-	-	-	-0.1666	-5.33	-0.1715	-3.83
Third quartile	-	-	-	-	-0.1368	-4.04	-0.1279	-2.61
Fourth quartile	-	-	-	-	-0.1079	-3.11	-0.0827	-1.64
Ordered Probit cuts								
b1	-	-	-	-	-1.2276	-21.94	-	-
b2	-	-	-	-	-0.7304	-13.30	-	-
b3	-	-	-	-	-0.0466	-0.86	-	-
b4	-	-	-	-	0.4797	8.80	-	-
b5	-	-	-	-	1.1715	21.15	-	-
b6	-	-	-	-	1.7839	31.17	-	-
Covariance parameters								
v1	-1.3322	-69.64						
v2	-0.5614	-17.93						
v3	0.4259	55.91						
v4	0.5782	9.46						
v5	0.2554	2.12						
v6	0.5595	4.00						
v7	-0.2454	-2.33						
v8	-0.2779	-2.70						
v9	-0.0587	-3.32						
Estimated Standard Deviations								
s.d.	0.264	52.78	0.570	32.04	-	-	1.531	130.85

Estimated Correlation Matrix*	Mean Wage	Employment	Education	Delay
Mean Wage	1.000	-	-	-
Employment	0.333 (11.54)	1.000	-	-
Education	-0.153 (-2.40)	-0.172 (-2.83)	1.000	-
Delay	0.159 (2.25)	0.324 (4.80)	-0.037 (-3.33)	1.000

Number of observations	8,630
Mean Log-Likelihood	-4.39811

* standard errors are computed using the Delta Method

Table 9a: Model A / Maximum Likelihood Estimation for Men (Part 1)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Constant	8.5874	336.76	-0.9605	-20.18	-	-	0.0857	1.65
Delay	-0.0705	-3.01	-0.1814	-3.13	-	-	-	-
Education (Reference group: High school dropouts)								
Vocational degree	0.0808	4.99	0.1909	7.89	-	-	-	-
Advanced vocational degree	0.0619	4.69	0.0788	2.71	-	-	-	-
High school graduates (grade 12)	0.1011	8.57	0.0228	0.94	-	-	-	-
Two years of college (grade 14)	0.1561	13.12	0.1206	4.77	-	-	-	-
Four years of college (grade 16)	0.1373	10.02	0.1091	3.34	-	-	-	-
Graduate studies (grade 17 or more)	0.2531	15.25	-0.0354	-1.18	-	-	-	-
Father's occupation (Reference group: White collars)								
Farmer	-0.0507	-2.86	0.0828	1.54	0.2313	3.46	-0.0533	-0.72
Craftsman	0.0033	0.33	0.0776	2.50	0.0500	1.28	-0.0270	-0.62
Executive	0.0120	1.00	0.0011	0.03	0.5038	12.92	0.0920	2.12
Middle Manager	0.0232	2.19	0.0123	0.39	0.2780	7.28	0.0457	1.09
Blue Collar	0.0061	0.77	-0.0422	-1.76	-0.1519	-5.08	-0.0445	-1.37
Missing or Deceased	-0.0143	-1.30	-0.0954	-2.79	-0.0879	-0.88	0.1343	1.35
Mother's occupation (Reference group: White collars)								
Farmer	-0.0363	-1.89	0.0617	1.05	0.0265	0.36	-0.1120	-1.35
Craftsman	0.0313	2.25	0.0490	1.13	0.0658	1.22	0.0324	0.54
Executive	0.0165	1.33	0.0607	1.58	0.2510	5.20	0.1348	2.49
Middle Manager	0.0104	0.81	0.0773	1.94	0.1668	3.38	0.1666	3.02
Blue Collar	0.0071	0.85	-0.0016	-0.06	-0.2297	-7.05	-0.0825	-2.36
Missing or Deceased	-0.0022	-0.32	0.0183	0.86	-0.0279	-0.86	0.0035	0.10
Location (Reference group: Rest of France)*								
Paris (75)	0.0879	10.85	0.1117	4.42	0.2337	6.87	0.0907	2.46
Marseilles (13)	-0.0286	-1.56	0.0371	0.64	0.2107	2.68	0.1525	1.89
Toulouse (31)	-0.0031	-0.17	0.0471	0.83	-0.1426	-1.63	0.0162	0.18
Lyons (69)	0.0355	2.37	0.0241	0.51	-0.1471	-2.27	-0.2413	-3.47
Nice (06)	0.0088	0.41	0.0759	1.12	-0.1135	-1.27	-0.0419	-0.45
Lille (59)	0.0044	0.38	-0.0134	-0.37	0.1115	2.46	0.2350	4.97
Foreign Countries	0.1026	1.67	0.0106	0.05	-	-	-	-
Father's education (Reference group: High school dropouts)								
Vocational degree	0.0026	0.28	-0.0019	-0.07	0.1435	4.12	-0.0007	-0.02
Advanced vocational degree	0.0060	0.63	-0.0205	-0.70	0.0593	1.62	-0.0661	-1.70
High school graduates	0.0136	0.96	-0.0233	-0.57	0.3781	7.55	0.0216	0.39
Father went to College	0.0267	1.76	-0.0338	-0.78	0.5662	10.72	0.0959	1.64
Deceased (or Missing observ).	-0.0120	-0.86	-0.0242	-0.57	-0.3538	-6.65	-0.0423	-0.78
Mother's education (Reference group: High school dropouts)								
Vocational degree	-0.0097	-1.07	0.0184	0.70	0.2020	6.47	-0.0304	-0.90
Advanced vocational degree	-0.0035	-0.33	0.0277	0.88	0.1359	3.55	-0.0686	-1.65
High school graduates	-0.0138	-0.99	0.0096	0.25	0.3031	6.69	-0.1008	-1.99
Mother went to College	0.0027	0.14	-0.0738	-1.44	0.4022	6.83	-0.2227	-3.35
Deceased (or Missing observ).	-0.0011	-0.08	-0.0800	-1.99	-0.2163	-4.19	-0.1331	-2.50
Father's employment status (Reference group: Employed)								
Unemployed or Inactive	-	-	-	-	0.0320	0.61	0.1128	2.18
Retired	-	-	-	-	0.7667	20.23	0.3692	8.49
Deceased (or Missing observ).	-	-	-	-	0.3014	2.84	-0.0213	-0.20
Mother's employment status (Reference group: Employed)								
Unemployed, inactive or retired	-	-	-	-	0.1432	5.47	0.0894	3.36
Deceased (or Missing observ).	-	-	-	-	-0.1380	-1.82	0.0006	0.01

(To be continued)

*Location indicates residence in 1992 in employment and wage equations, and residence at age 10 for education and delay equations.

Table 9a: Model A / Maximum Likelihood Estimation for Men (Part 2, end of table)

	Mean Wage		Employment		Education		Delay	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
Number of brothers (Reference group: 0)								
1	-	-	-	-	-0.0189	-0.77	0.0118	0.48
2	-	-	-	-	-0.0701	-2.10	0.0409	1.20
3	-	-	-	-	-0.1304	-2.43	0.1050	1.94
4 or more	-	-	-	-	-0.2290	-3.44	0.2037	3.14
Number of sisters (Reference group: 0)								
1	-	-	-	-	-0.0631	-2.61	0.0217	0.85
2	-	-	-	-	-0.0545	-1.58	0.1236	3.46
3	-	-	-	-	-0.0545	-0.99	0.2085	3.80
4 or more	-	-	-	-	-0.2118	-2.89	0.2042	2.90
Birth order (Reference group: Only child)								
First	-	-	-	-	-0.0755	-3.07	-0.0678	-2.63
2^{nd}	-	-	-	-	-0.0983	-2.93	-0.1967	-5.46
3^{rd}	-	-	-	-	-0.1985	-4.07	-0.1797	-3.61
4^{th}	-	-	-	-	-0.1907	-2.75	-0.2869	-4.07
5th and higher	-	-	-	-	-0.4520	-5.77	-0.3840	-5.01
Quarter of birth								
Fourth Quarter	-	-	-	-	-0.0050	-0.21	-0.1468	-5.65
Distance to college (Reference group: First quartile)								
Second quartile	-	-	-	-	-0.1266	-4.46	-0.0994	-3.43
Third quartile	-	-	-	-	-0.1919	-6.33	-0.1668	-5.33
Fourth quartile	-	-	-	-	-0.0276	-0.89	-0.0452	-1.40
Ordered Probit 'cuts'								
c1	-	-	-	-	32.1863	11.14	-	-
c2	-	-	-	-	5.8891	4.02	-	-
c3	-	-	-	-	5.2521	4.88	-	-
c4	-	-	-	-	11.5499	10.78	-	-
c5	-	-	-	-	6.3363	8.64	-	-
c6	-	-	-	-	14.6235	8.02	-	-
Covariance parameters								
v1	-1.2516	-22.72						
v2	-0.1327	-4.97						
v3	0.3566	55.72						
v4	0.5195	6.46						
v5	0.7581	3.16						
v6	0.4584	2.72						
v7	-0.2519	-2.56						
v8	-0.0052	-0.09						
v9	-0.0753	-5.27						
Estimated Standard Deviations								
s.d.	0.286	18.22	0.876	36.19	-	-	1.428	156.97

Estimated Correlation Matrix*	Mean Wage	Employment	Education	Delay
Mean Wage	1.000	-	-	-
Employment	0.305 (7.33)	1.000	-	-
Education	-0.157 (-2.66)	-0.003 (-0.08)	1.000	-
Delay	0.413 (4.27)	0.273 (2.97)	-0.047 (-5.25)	1.000

Number of observations	12,310
Mean Log-Likelihood	-4.80412
Quong Vuong's test (against reduced form)	2.255

* standard errors are computed using the Delta Method

Table 9b: Model A / Maximum Likelihood Estimation for Women (Part 1)

	Mean Wage		Employment		Education		Delay	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
							-0.0752	-1.03
Constant	8.4627	348.37	-0.7379	-16.39	-	-		
Delay	-0.0137	-1.03	-0.1028	-3.51	-	-	-	-
Education (Reference group: High school dropouts)								
Vocational degree	0.0346	2.41	0.1604	7.82	-	-	-	-
Advanced vocational degree	0.0882	6.61	0.1184	4.67	-	-	-	-
High school graduates (grade 12)	0.0714	6.06	0.0758	3.50	-	-	-	-
Two years of college (grade 14)	0.1704	14.57	0.1440	6.56	-	-	-	-
Four years of college (grade 16)	0.1797	13.32	0.0458	1.72	-	-	-	-
Graduate studies (grade 17 or more)	0.1551	9.06	-0.0016	-0.05	-	-	-	-
Father's occupation (Reference group: White collars)								
Farmer	-0.0506	-2.71	0.0159	0.40	0.3232	4.30	-0.1142	-1.15
Craftsman	0.0113	1.03	0.0290	1.23	0.1576	3.44	0.0980	1.66
Executive	0.0142	1.06	-0.0183	-0.66	0.5738	12.26	0.1027	1.66
Middle Manager	0.0106	0.93	0.0074	0.31	0.2049	4.48	0.0057	0.10
Blue Collar	-0.0013	-0.15	-0.0185	-1.00	-0.0944	-2.63	-0.0334	-0.72
Missing or Deceased	-0.0046	-0.36	-0.0157	-0.56	0.1003	0.87	0.0046	0.04
Mother's occupation (Reference group: White collars)								
Farmer	0.0217	1.11	0.0314	0.75	0.1410	1.72	0.0327	0.30
Craftsman	0.0063	0.43	0.0170	0.54	0.0376	0.62	0.1259	1.59
Executive	0.0047	0.34	-0.0375	-1.29	0.2971	5.36	0.0398	0.54
Middle Manager	0.0122	0.87	-0.0507	-1.67	0.1465	2.51	-0.0098	-0.12
Blue Collar	-0.0065	-0.68	-0.0375	-1.82	-0.1976	-4.96	-0.1109	-2.20
Missing or Deceased	-0.0222	-2.83	-0.0702	-4.17	0.0842	2.13	-0.0370	-0.74
Location (Reference group: Rest of France)*								
Paris (75)	0.1108	13.03	0.0846	4.68	0.2185	5.79	0.1398	2.84
Marseilles (13)	-0.0187	-0.94	0.0029	0.07	0.2788	3.13	0.3001	2.64
Toulouse (31)	-0.0007	-0.03	0.0115	0.26	0.5717	5.24	0.4270	3.15
Lyons (69)	0.0608	3.21	0.0857	2.15	-0.1660	-1.84	0.1184	1.05
Nice (06)	-0.0179	-0.77	0.0881	1.77	0.0242	0.23	0.1131	0.86
Lille (59)	0.0035	0.26	-0.0063	-0.22	0.0604	0.99	-0.1058	-1.37
Foreign Countries	-0.0313	-0.51	-0.1254	-0.99	-	-	-	-
Father's education (Reference group: High school dropouts)								
Vocational degree	0.0007	0.08	-0.0183	-0.88	0.0942	2.36	-0.0189	-0.37
Advanced vocational degree	0.0032	0.31	-0.0126	-0.56	0.1093	2.50	0.0263	0.47
High school graduates	0.0120	0.79	-0.0286	-0.89	0.3167	5.23	0.0612	0.77
Father went to College	0.0012	0.08	-0.0709	-2.12	0.3782	6.11	-0.0207	-0.25
Deceased (or Missing observ).	0.0037	0.25	-0.0046	-0.15	-0.4498	-7.50	-0.1388	-1.81
Mother's education (Reference group: High school dropouts)								
Vocational degree	0.0049	0.49	0.0014	0.07	0.2645	7.08	-0.0433	-0.90
Advanced vocational degree	-0.0061	-0.52	0.0023	0.09	0.2742	5.99	-0.0228	-0.39
High school graduates	0.0180	1.16	0.0116	0.36	0.5100	9.17	-0.0422	-0.58
Mother went to College	0.0271	1.46	0.0118	0.30	0.5955	8.48	0.0068	0.08
Deceased (or Missing observ).	-0.0030	-0.21	0.0187	0.59	-0.0328	-0.52	0.0183	0.22
Father's employment status (Reference group: Employed)								
Unemployed or Inactive	-	-	-	-	0.0082	0.14	0.1078	1.47
Retired	-	-	-	-	0.7865	17.66	0.5092	8.80
Deceased (or Missing observ).	-	-	-	-	0.2437	1.98	0.4283	3.25
Mother's employment status (Reference group: Employed)								
Unemployed, inactive or retired	-	-	-	-	0.1045	3.34	0.1343	3.46
Deceased (or Missing observ).	-	-	-	-	-0.1770	-1.93	0.3299	3.04

(To be continued)

*Location indicates residence in 1992 in employment and wage equations, and residence at age 10 for education and delay equations.

Table 9b: Model A / Maximum Likelihood Estimation for Women (Part 2, end of table)

	Mean Wage		Employment		Education		Delay	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Number of brothers (Reference group: 0)								
1	-	-	-	-	-0.0793	-2.70	0.0693	1.87
2	-	-	-	-	-0.1315	-3.21	0.2551	4.96
3	-	-	-	-	-0.2474	-3.92	0.5322	6.80
4 or more	-	-	-	-	-0.2860	-3.31	0.5639	5.41
Number of sisters (Reference group: 0)								
1	-	-	-	-	-0.0648	-2.23	0.0272	0.75
2	-	-	-	-	-0.0569	-1.42	0.1716	3.45
3	-	-	-	-	-0.0431	-0.69	0.4058	5.26
4 or more	-	-	-	-	-0.2775	-3.25	0.4009	3.81
Birth Order (Reference group: Only child)								
First	-	-	-	-	-0.0837	-2.86	-0.0247	-0.68
2^{nd}	-	-	-	-	-0.1918	-4.81	-0.2067	-4.18
3^{rd}	-	-	-	-	-0.2488	-4.22	-0.3985	-5.51
4^{th}	-	-	-	-	-0.2671	-3.14	-0.4252	-4.07
5th and higher	-	-	-	-	-0.3701	-3.85	-0.7418	-6.36
Quarter of birth								
Fourth Quarter	-	-	-	-	-0.0622	-2.15	-0.1983	-5.24
Distance to college (Reference group: First quartile)								
Second quartile	-	-	-	-	-0.2078	-6.11	-0.1676	-3.95
Third quartile	-	-	-	-	-0.1655	-4.50	-0.1358	-2.95
Fourth quartile	-	-	-	-	-0.1219	-3.26	-0.0962	-2.03
Ordered Probit 'cuts'								
c1	-	-	-	-	25.0975	8.93	-	-
c2	-	-	-	-	10.9293	6.38	-	-
c3	-	-	-	-	7.1215	5.68	-	-
c4	-	-	-	-	12.7140	12.55	-	-
c5	-	-	-	-	6.0967	8.71	-	-
c6	-	-	-	-	7.1178	5.53	-	-
Covariance parameters								
v1	-1.3439	-93.94						
v2	-0.5748	-20.79						
v3	0.4267	55.93						
v4	0.5361	10.29						
v5	0.1977	1.54						
v6	0.5340	3.61						
v7	-0.1307	-1.41						
v8	-0.1334	-1.65						
v9	-0.0605	-3.49						
Estimated Standard Deviations								
s.d.	0.261	70.49	0.563	35.85	-	-	1.532	130.96

Estimated Correlation Matrix*	Mean Wage	Employment	Education	Delay
Mean Wage	1.000	-	-	-
Employment	0.313 (12.19)	1.000	-	-
Education	-0.082 (-1.40)	-0.084 (-1.63)	1.000	-
Delay	0.124 (1.58)	0.312 (4.23)	-0.038 (-3.50)	1.000

Number of observations	8,630
Mean Log-Likelihood	-4.39827
Quong Vuong's test (against reduced form)	-0.127

* standard errors are computed using the Delta Method