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Estimating the Intergenerational Education Correlation from a Dynamic Programming Model*

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Résumé / Abstract

À l'aide d'un modèle de programmation dynamique, nous analysons l'importance relative des antécédents familiaux et de l'habilité non-observée dans la détermination du niveau de scolarité et des salaires. Nous évaluons aussi la corrélation intergénérationelle au niveau de l'éducation et déterminons l'effet d'une augmentation exogène du niveau de scolarité de la génération présente sur le niveau d'éducation de la génération future.

Using a structural dynamic programming model, we investigate the relative importance of initial household human capital endowments and unobserved individual abilities in explaining cross-sectional differences in schooling attainments and wages. We evaluate the true intergenerational education correlation and the effect of an exogenous increase in human capital of the current generation on schooling attainments of the next generation. We find that the variation in schooling attainments explained by differences in household human capital is twice as large as the variation explained by unobserved abilities. However, the variation in labor market wages explained by differences in unobserved abilities is 3 times larger than the variation explained by household human capital endowments. We also find that the true partial correlations between son and father's schooling and between son and mother's education are respectively 17% and 40% lower than the sample correlations. Increasing the level of schooling of the current generation by one year raises schooling attainments of the next generation by 0.4 year.

Mots Clés : Corrélation intergénérationelle de l'éducation, rendements en éducation, capital humain du foyer, croissance, décision d'études

Keywords: Intergenerational education correlation, returns to education, household human capital, growth, schooling decision

JEL: J2, J3

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1 Introduction

Individual schooling attainments are one of the key components of the level of human capital in an economy. They are an important determinant of income distribution and are often thought to be one of the key factors explaining the wealth of nations as well as cross-nation differences in economic growth. Indeed, the recent revival of neo-classical growth models is largely based on human capital theory (Lucas, 1988, Barro and Sala-i-Martin, 1995).[1]

At the micro level, it is customary to assume a strong correlation between one's schooling attainment and parents' (or household) education. The effects of household background variables on individual schooling attainments can take various forms. While enrolled in school, young individuals typically receive parental support. Although parental support is usually unobservable to the econometrician, it is expected to be highly correlated with household human capital and income. At the same time, innate ability, also correlated with household human capital, should have an impact on the decision to attend school and on labor market wages.

The net effects of household human capital on individual schooling attainments are far from obvious. On the one hand, households who have higher income may transfer more resources to their children and reduce substantially the opportunity cost of school attendance. On the other hand, wealthier households also face a higher opportunity cost of spending time with children and may reduce their investment in children. The effect of innate ability on school attendance is also unclear. If skill endowments are strongly correlated with household human capital (especially father's and mother's education), those young individuals raised in households endowed with a high level of human capital will have a high level of school ability but will also have a high level of market ability (absolute advantage in the labor market).

Whether individual schooling attainments are more affected by household human capital or by innate ability remains an open question. Nevertheless, labor economists should be skeptical of drawing strong conclusions on the causal effect of parents' human capital from the empirical correlations between various household background variables and individual schooling attainments, which are obtained from OLS regressions. For instance, reduced-form OLS estimates of the effects of household human capital on schooling attainments ignore dynamic dimensions and cannot distinguish between the utility of attending school and labor market outcomes. They are also incapable of identifying the relative importance of individual ability and pure stochastic shocks.

The effect of parental background on educational achievements has been well documented in a reduced-form framework (Kane, 1994 and Lazear, 1980), as well

[1]Although the links between schooling and private wages is well established at the micro level, the relationship between economic growth and education is substantially weaker. This paradox is currently the object of a large amount of work (see Topel, 1999, for a survey).

as in a semi-structural framework (Cameron and Heckman, 1998 and Magnac and Thesmar, 1998). As of now, the effects of household background on schooling attainments have only rarely been investigated within a full structural framework. Eckstein and Wolpin (1999) have estimated a finite mixture model of school attendance and work behavior. While their model does not allow them to estimate the direct effect of household background variables, they can merge actual data on schooling attainments with data on household characteristics and use Bayes' rule to relate those data to unobserved type probabilities. Belzil and Hansen (2001) use a dynamic programming model of schooling decisions in order to estimate the returns to schooling. In this model, the utility of attending school depends explicitly on household background variables. In both of these papers there is evidence that school attendance increases with household human capital although the relative importance of household characteristics and unobserved abilities are difficult to evaluate.

Although the notion of a "true" intergenerational education correlation has not raised much interest amongst empirical labor economists, it naturally arises in the dynamic macroeconomic literature concerned with economic growth, overlapping generations and intergenerational transfers. If the true intergenerational education correlation can be inferred from micro data, it can allow economists to simulate the effect of an exogenous increase in human capital (accompanied by the resulting growth in income) of the current generation on schooling attainments and labor market productivity of the next generation. This may help determine if education is a consequence as well as a cause of economic growth.

The main objective of the present paper is to estimate a structural model of schooling decisions in which the separate effects of unobserved abilities and household human capital endowments on the key determinants of schooling attainments (the instantaneous utility of attending school and labor market outcomes) can be identified. We pay particular attention to the following 4 questions.

1. How much of individual differences in schooling attainments is explained by individual heterogeneity in unobserved school and market abilities as opposed to differences in household human capital endowments (father's education, mother's education, household income and the like)?

2. How much of predicted wages is explained by individual heterogeneity in school and market abilities as opposed to differences in household human capital endowments?

3. Does the intergenerational education correlation, predicted by the structural dynamic programming model, differ substantially from the sample correlation?

4. What is the effect of an exogenous increase in the level of education and income of the current generation on schooling attainments of the next generation?

As far as we know, none of these questions have been answered to date. Following Belzil and Hansen (2001), we estimate a finite horizon dynamic programming model which is solved using recursive methods. In our model, schooling decisions affect future wages and lifetime employment rates. Individuals are endowed with exogenous household characteristics and innate abilities. Both of these affect the utility of attending school and labor market outcomes. Individuals share a common rate of time preference. Labor market ability affects both wages and employment rates. We assume that individual ability is the sum of a deterministic (observable) component capturing the effect of household human capital and a stochastic (unobserved) component representing idiosyncratic ability which is orthogonal to household human capital. Given their endowments, individuals decide on the optimal allocation of time between school attendance and the labor market.

The estimation of our model is computer intensive. In order to estimate a model where the degree of flexibility is high enough to capture the importance of both unobserved ability and observed initial endowments in household human capital, we assume that population unobserved abilities can be described by 6 discrete types of individuals. The model must therefore be solved recursively 6 times for each individual. For this reason, we concentrate on a model specification which can be solved in closed-form. The model is implemented on a panel of white males taken from the National Longitudinal Survey of Youth (NLSY). The panel covers the period from 1979 until 1990.

The results show that there is overwhelming evidence that household human capital variables affect both the utility of attending school and labor market outcomes. Our estimates indicate that the differences in predicted schooling attainments explained by household human capital are generally twice as large as the differences explained by unobserved abilities. On the other hand, the differences in predicted wages explained by unobserved abilities are three times as large as the differences explained by household human capital. These results are easily explained. First, household human capital has a much larger effect on the utility of attending school than on labor market outcomes. Second, the wage return to schooling is found to be quite low so that individual differences in schooling do not explain differences in wages accurately. Third, labor market ability appears to be the prime factor explaining predicted wages.

We find that the true intergenerational education correlation predicted by the dynamic programming model is much lower than the correlation obtained by standard OLS regressions of observed schooling on household human capital variables. The true partial correlation between son and father's schooling (around 0.17) is 17% lower than the correlation found in the data (around 0.21). The true partial correlation between son and mother's education (around 0.11) is 40% lower than correlation disclosed by the data (0.17). The structural model also predicts that the true correlation between schooling attainments and household income and the correlation between schooling attainments and the number of siblings are lower than the sample correlation.

Finally, these estimates imply that an exogenous increase of 1 year in the level of schooling of the current generation will increase schooling attainments of the next generation by 0.4 year.

The main features of the paper are the following. Section 2 is devoted to the presentation of the dynamic programming model. Section 3 contains a brief description of the sample used in this paper (NLSY). The main empirical results are discussed in Section 4. The conclusion is in Section 5.

2 The Model

Individuals are initially endowed with household human capital, innate ability and a rate of time preference (denoted ρ). Given their endowments, young individuals decide sequentially whether it is optimal or not to enter the labor market or continue accumulate human capital. Individuals maximize discounted expected lifetime utility. The control variable, d_t, summarizes the stopping rule. When $d_t = 1$, an individual invests in an additional year of schooling at the beginning of period t. When $d_t = 0$, an individual leaves school at the beginning of period t (to enter the labor market). Every decision is made at the beginning the period and the amount of schooling acquired by the beginning of date t is denoted S_t. As it is difficult to write down a full structural model which would include all the effects that household human capital variables may have on the probability of transiting from one grade level to the next, we specify a reduced-form function for the utility of attending school. The function is allowed to depend on various household background variables as well as individual unobserved ability.

The instantaneous utility of attending school is

$$U^{school}(.) = X_i'\delta + \psi(S_{it}) + \upsilon_i^{\xi} + \varepsilon_{it}^{\xi} \tag{1}$$

where X_i contains the following variables: father's education, mother's education, household income, number of siblings, household composition at age 14 and regional controls. The number of siblings is used to control for the fact that, other things equal, the amount of parental resources spent per child decreases with the number of siblings. The household composition variable (Nuclear Family) is equal to 1 for those who lived with both their biological parents (at age 14) and is likely to be correlated with the psychic costs of attending school. The geographical variables are introduced in order to control for the possibility that direct (as well as psychic) costs of schooling may differ between those raised in urban areas and those raised in rural areas, and between those raised in the south and those raised in the north. Yearly household income is measured in units of \$1,000. The term υ_i^{ξ} represents individual heterogeneity (ability) affecting the utility of attending school. It is discussed in more details below. The utility of attending school is allowed to depend on the level of schooling in a flexible fashion. This is done using a spline function approximation of $\psi(S_t)$. Finally, ε_t^{ξ} represents a stochastic utility shock and is assumed to be *i.i.d* Normal with mean 0 and variance σ_{ξ}^2.

We assume that individuals interrupt schooling with exogenous probability $\zeta(S_t)$ and, as a consequence, the possibility to take a decision depends on a state variable I_t. When $\mathrm{I}_t = 1$, the decision problem is frozen for one period. If $\mathrm{I}_t = 0$, the decision can be made. The interruption state is meant to capture events such as illness, injury, travel, temporary work, incarceration or academic failure. When an interruption occurs, the stock of human capital remains constant over the period. The NLSY does not contain data on parental transfers and, in particular, does not allow a distinction in income received according to the interruption status. As a consequence, we ignore the distinction between income support at school and income support when school is interrupted.[2]

Once the individual has entered the labor market, he receives monetary income $\tilde{w}_t$, which is the product of the yearly employment rate, e_t, and the wage rate, w_t. The instantaneous utility of work

$$U^{work}(.) = \log(\tilde{w}_t) = \log(e_t \cdot w_t)$$

The log wage received by individual i, at time t, is given by

$$\log w_{it} = \varphi_1(S_{it}) + \varphi_2.Exper_{it} + \varphi_3.Exper_{it}^2 + \upsilon_i^w + \varepsilon_{it}^w \tag{2}$$

where $\varphi_1(S_t)$ is the function representing the wage return to schooling. Both φ_2 and φ_3 are parameters to be estimated and υ_i^w is unobserved labor market ability affecting wages.

To characterize the stochastic process of the employment security variable, e_t, we assume that

$$\log(e_{it}^*) = \mu_{it} + \varepsilon_{it}^e$$

where $e_{it}^* = \log(\frac{1}{e_{ti}})$ and where ε_{it}^e is a random shock normally distributed with mean 0 and variance σ_e^2.[3] The employment rate is also allowed to depend on accumulated human capital (S_{it} and $Exper_{it}$) so that

$$\mu_{it} = \kappa_1 \cdot S_{it} + \kappa_2 \cdot Exper_{it} + \kappa_3 \cdot Exper_{it}^2 + \upsilon_i^e \tag{3}$$

where υ_i^e is an individual specific intercept term, κ_1 represents the employment security return to schooling, both κ_2 and κ_3 represent the employment security

[2]When faced with a high failure probability, some individuals may spend a portion of the year in school and a residual portion out of school. As a result, identifying a real interruption from a true academic failure is tenuous. In the NLSY, we find that more than 85% of the sample has never experienced school interruption.

[3]It follows that $E \log e_t = -\exp(\mu_t + \frac{1}{2}\sigma_e^2)$ and that $Var(\log e_t) = \exp(2\mu_t + \sigma_e^2) \cdot (\exp(\sigma_e^2) - 1)$.

return to experience. All random shocks $(\varepsilon^{\xi}_{it}, \varepsilon^{w}_{it}, \varepsilon^{e}_{it})$ are assumed to be independent.

In order to express the solution to the dynamic programming problem in a compact fashion, it is convenient to summarize the state variables in a vector (S_t, η_t) where η_t is itself a vector containing the interruption status (I_t), the utility shock (ε^{ξ}_t), the wage shock (ε^{w}_t), accumulated experience $(Exper_t)$ and a set of individual characteristics. As it is done often in dynamic optimization problems, the solution to the stochastic dynamic problem can be characterized using recursive methods (backward induction). The decision to remain in school, given state variables S_t and η_t, denoted $V^s_t(S_t, \eta_t)$, can be expressed as

$$V^s_t(S_t, \eta_t) = E\log(\xi_t) + \varepsilon^{\xi}_t + \beta\{\zeta \cdot EV^I_{t+1}(S_{t+1}, \eta_{t+1})$$

$$+(1-\zeta) \cdot EMax[V^s_{t+1}(S_{t+1}, \eta_{t+1}), V^w_{t+1}(S_{t+1}, \eta_{t+1})]\}$$

or, more compactly, as

$$V^s_t(S_t, \eta_t) = \log(\xi_t) + \beta E(V_{t+1} \mid d_t = 1) \tag{4}$$

where $V^I_t(S_t, \eta_t)$ denotes the value of interrupting schooling acquisition and where $E(V_{t+1} \mid d_t = 1)$ denotes the value of following the optimal policy next period (either remain at school or start working). As we do not distinguish between income support while in school and income support during an interruption, the value of entering the interruption status, $V^I_{t+1}(S_t, \eta_t)$, can be expressed in a similar fashion.

The value of stopping school (that is entering the labor market) at the beginning of period t, at wage w_t and with S_t years of schooling, while taking into account the distribution of e_t (because e_t is unknown when w_t is drawn), $V^w_t(S_t, \eta_t)$, is given by

$$V^w_t(S_t, \eta_t) = \log(w_t \cdot e_t) + \beta E(V_{t+1} \mid d_t = 0) \tag{5}$$

where $E(V_{t+1} \mid d_t = 0)$ is simply

$$E(V_{t+1} \mid d_t = 0) = \sum_{j=t+1}^{T} \beta^{j-(t+1)}(-\exp(\mu_j + \frac{1}{2}\sigma^2_e) + \varphi_1(S_j) + \varphi_2.Exper_j + \varphi_3.Exper^2_j)$$

Using the terminal value as well as the distributional assumptions about the stochastic shocks, the probability of choosing a particular sequence of discrete choice can readily be expressed in closed-form.

2.1 Unobserved Ability in School and in the Market

Ability heterogeneity has 3 dimensions: school ability (υ_i^{ξ}), market ability affecting wages (υ_i^{w}) and market ability affecting employment rates (υ_i^{e}). We assume that individual ability is the sum of a deterministic component capturing the effect of household human capital and a stochastic component representing idiosyncratic unobserved ability which is orthogonal to household human capital. The unobserved ability regression function is given by the following expression;

$$\upsilon_i^s = \upsilon_1^s \cdot father's\ educ + \upsilon_2^s \cdot mother's\ educ + \upsilon_3^s \cdot household\ income + \upsilon_4^s \cdot siblings + \tilde{\upsilon}_i^s$$

for $s = \xi, w$ and e.

We assume that there are K types of individuals and that each type is endowed with a vector $(\tilde{\upsilon}_k^w, \tilde{\upsilon}_k^{\xi}, \tilde{\upsilon}_k^e)$. We set $K = 6$.[4] The probabilities of belonging to type k, p_k, are estimated using logistic transforms

$$p_k = \frac{\exp(q_k)}{\sum_{j=1}^{6} \exp(q_j)}$$

and with the restriction normalize q_6 to 0.

2.2 Identification

Identification of the wage and employment returns to human capital (schooling and experience) is straightforward with data on labor market wages. Given knowledge of the intercept term of the wage function and the employment rate function, data on schooling attainments can be used to identify the utility of attending school and, especially, the importance of heterogeneity in the intercept term of the utility of attending school.

However, estimation of our model will require normalization. Given the absence of data on the utility of attending school, it will be impossible to separate the direct effects of household human capital on the utility of attending school (the $\delta' s$) from the effect of household human capital on individual school ability. As a consequence, we set $\upsilon_1^{\xi} = \upsilon_2^{\xi} = \upsilon_3^{\xi} = \upsilon_4^{\xi} = 0$. In practice, this means that our estimates of the effect of parents' background are a the sum of a direct effect on the utility of attending school and an indirect effect capturing the transmission of ability across generations.

2.3 The Likelihood Function

In order to implement the model empirically, we must make some additional assumptions. First, we only model the decision to acquire schooling beyond 6

[4] We initially started with 4 types but we were finally able to get up to 6 types.

years (as virtually every individual has completed at least six years of schooling). Second, we set T (the finite horizon) to 65 years. Finally, we set the maximum number of years of schooling ($\tilde{\mathrm{t}}$) to 22.Constructing the likelihood function is relatively straightforward. Using the definitions of d_t and I_t, it is easy to specify all transition probabilities needed to derive the likelihood function. These transition probabilities characterize the decision to leave school permanently or to continue in school. Altogether, they represent all possible destinations.

The transition probabilities that define the choice between interrupting school permanently (start working) and obtaining an additional year of schooling, are given by

$$\Pr(d_{t+1} = 0 \mid d_t = 1) = (1 - \zeta) \cdot \Pr(V_t^w(S_t) \geq V_t^s(S_t)) \tag{6}$$

$$\Pr(d_{t+1} = 1 \mid d_t = 1) = (1 - \zeta) \cdot \Pr(V_t^w(S_t) < V_t^s(S_t)) \tag{7}$$

$$\Pr(I_{t+1} = 1 \mid d_t = 1) = \zeta \tag{8}$$

where $\Pr(V_t^w(S_t) \geq V_t^s(S_t))$ is easily evaluated using (4) and (5). Equation (6) represents the probability of exercising the right to leave school permanently in $t+1$ (implicitly assuming $I_{t+1} = 0$) while equation (7) represents the probability of staying in school to acquire an additional year of human capital (also implicitly assuming $I_{t+1} = 0$) . Equation (8) represents the exogenous probability of entering the interruption state. The likelihood function is constructed from data on the allocation of time between years spent in school $(I_t = 0, d_t = 1)$ and years during which school was interrupted $(I_{t+1} = 1, d_t = 1)$, and on employment histories (wage/unemployment) observed when schooling acquisition is terminated (until 1990).

Ignoring the individual identification subscript, the construction of the likelihood function requires the evaluation of the following probabilities;

- the probability of having spent at most τ years in school (including years of interruption), which can be easily derived from (6), (7) and (8).

$$L_1 = Pr[(d_0 = 1, I_0), (d_1 = 1, I_1)....(d_\tau = 1, I_\tau)]$$

- the probability of entering the labor market in year $\tau + 1$, at observed wage $w_{\tau+1}$, which can be factored as the product of a normal conditional probability times a marginal.

$$L_2 = \Pr(d_{\tau+1} = 0, w_{\tau+1}) = \Pr(d_{\tau+1} = 0 \mid w_{\tau+1}) \cdot \Pr(w_{\tau+1})$$

- the density of observed wages and employment rates from $\tau+2$ until 1990. Using the fact that the random shocks affecting the employment process and the wage process are mutually independent and are both *i.i.d.*, the contribution to the likelihood for labor market histories observed from $\tau+2$ until 1990 is given by

$$L_3 = Pr\left(\{\tilde{w}_{\tau+2}\}..\{\tilde{w}_{1990}\}\right) = Pr\left(\{w_{\tau+2}\cdot e_{\tau+2}\}\cdot....\Pr\{w_{1990}\cdot e_{1990}\}\right)$$

The likelihood function, for a given individual and conditional on a vector of unobserved heterogeneity components $\vartheta_j = \left(\upsilon^{\xi}, \upsilon^{w}, \upsilon^{e}\right)_j$, is given by $L_i(\vartheta_j) = L_{1i}(\vartheta_j)\cdot L_{2i}(\vartheta_j)\cdot L_{3i}(\vartheta_j)$. The unconditional contribution to the log likelihood, for individual i, is therefore given by

$$\log L_i = \log \sum_{j=1}^{K=6} p_j \cdot L_i(. \mid \vartheta_j) \tag{9}$$

where each p_j represents the population proportion of type ϑ_j.

3 The Data

The sample used in the analysis is extracted from 1979 youth cohort of the *The National Longitudinal Survey of Youth* (NLSY). The NLSY is a nationally representative sample of 12,686 Americans who were 14-21 years old as of January 1, 1979. After the initial survey, re-interviews have been conducted in each subsequent year until 1996. In this paper, we restrict our sample to white males who were age 20 or less as of January 1, 1979. We record information on education, wages and on employment rates for each individual from the time the individual is age 16 up to December 31, 1990.[5]

The original sample contained 3,790 white males. However, we lacked information on household background variables (such as household income as of 1978 and parents' education).[6] The age limit and missing information regarding actual work experience further reduced the sample to 1,710. Descriptive statistics are found in Table 1.

Before discussing descriptive statistics, it is important to describe the construction of some important variables. In particular, both the schooling attainment variable and the experience variable deserve some discussions. First, the education length variable is the reported highest grade completed as of May 1 of the survey year. Individuals are also asked if they are currently enrolled in

[5] The reason for not including information beyond 1990 is that the wage data do not appear reliable for these more recent waves.

[6] We lost about 17% of the sample due to missing information regarding family income and about about 6% due to missing information regarding parents' education.

school or not. This question allows us to identify those individuals who are still acquiring schooling and therefore to take into account that education length is right-censored for some individuals. It also helps us to identify those individuals who have interrupted schooling. Overall, young individuals tend to acquire education without interruption. In our sample, only 306 individuals have experienced at least one interruption (Table 1). This represents only 18% of our sample and it is along the lines of results reported in Keane and Wolpin (1997). As well, we note that interruptions tend to be short. Almost half of the individuals (45 %) who experienced an interruption, returned to school within one year while 73% returned within 3 years.

Second, unlike many studies set in a reduced-form which use potential experience (age -education- 5), we use data on actual experience. The availability of data on actual employment rates allows use to estimate the employment security return to schooling. More details can be found in Belzil and Hansen (2001).

4 Empirical Results

In Section 4.1, we discuss the effects of household human capital on the utility of attending school and on labor market outcomes. In Section 4.2, we investigate the relative importance of household human capital and unobserved ability in explaining differences in schooling attainments and wages. In Section 4.3, we evaluate the true intergenerational education correlation and its macroeconomic counterpart; the impact of human capital based economic growth on schooling attainments of the next generation.

4.1 Parameter estimates

To facilitate presentation of the results, we split the parameter estimates in 3 tables. The effects of household human capital on the utility of attending school and labor market outcomes are in Table 2A. The remaining structural parameters of the utility of attending school and the return to schooling are in Table 2B. Finally, the estimates summarizing the distribution of idiosyncratic unobserved abilities are found in Table 2C.

First, we have estimated a model where the deterministic components of wage and employment abilities ($\upsilon_i^w, \upsilon_i^e$) are made functions of household human capital (Model 1). For illustrative purposes, we have also estimated a restricted model specification where household human capital does not affect labor market outcomes (Model 2).[7]

As the principal objective of this paper is to evaluate the relative importance of household human capital and unobserved abilities, we do not discuss all parameter

[7]The reader should note that all household characteristics (especially education, income and siblings) are highly correlated.

estimates in details. Instead, we focus on those that will enable us to answers the basic questions raised above. An in-depth discussion of the return to schooling and the goodness of fit for a similar model specification is found in Belzil and Hansen (2001).[8] The respective values of the mean log likelihood (-13.7227 and -13.7399) indicate that the restricted version of the model is strongly rejected. As a consequence, our discussion of the parameter estimates will be based primarily on those of Model 1.

The parameter estimates for the effects of household human capital on the utility of attending school and labor market outcomes (found in Table 2A) indicate clearly that, other things equal, the utility of attending school is increasing in father's education (0.0231) and household income (0.0018). Interestingly, the effect of female education is negative (-0.0031) but insignificant. The relatively weak effect of female education may be explained by the fact that more educated females tend to work more in the labor market and spend less time with their children. The results for siblings (-0.0157) indicate that those raised in families with smaller number of children tend to have a higher utility of attending school.

While the effects of household human capital on labor market outcomes are weaker, there is support for the hypothesis that labor market ability is correlated with household human capital. The positive effects of father's education (around 0.0120) on log wages and the negative effect on log inverse employment rates (-0.0135) indicate that father's education increase both wages and employment rates by more than 1%. As for the utility of attending school, the effect of female education on wages is found to be negative (-0.0083). However, female education has virtually no effect on employment rates. Household income increases wages (0.0012) but has no significant effect on employment rates. Finally, the number of siblings has a significant negative effect on wage ability (-0.0077) and an insignificant negative effect on employment rates. Taken as a whole, there is therefore overwhelming evidence that school and labor market abilities are strongly correlated with household human capital.

The differences in the parameter estimates of the household human capital variables between Model 1 and Model 2 (found in column 2) indicate that ignoring the effects of household characteristics on labor market outcome will lead to a serious under-estimation of the effect of household background variables on the utility of attending school. This is particularly true for father's education (0.0096), household income (0.0006) and siblings (-0.0067). All these values are much below their equivalent estimate in Model 1. This is explained by the fact that, in the most general (unrestricted) model, household human capital raises absolute advantages in the labor market.

[8]Overall, our model is able to fit the data very well. As documented in Belzil and Hansen (2001), the estimates of the wage equation reveal that assuming constant marginal returns to schooling is a serious mistake. The high level of significance of the parameter estimates for the spline functions (Table 2B) indicate that a model with constant marginal (local) returns would be strongly rejected.

The estimates reported in Table 2C illustrate the importance of unobserved abilities. There is a relatively important variation in the individual specific intercept terms of the utility of attending school as well as in the intercept terms of the wage function. In Model 1, the intercept terms of the wage function range from 1.1323 (type 3) to 2.1083 (type 5) while the intercept terms of the utility of attending school range from -3.7970 (type 3) to -2.1232 (type 5). Overall, those types endowed with a high school ability are also endowed with a high wage intercept. This is evidence of a positive correlation between school and market ability.[9] More detailed comparisons of the effects of household human capital and unobserved abilities is delayed to Section 4.2.

4.2 The Relative Importance of household Human Capital and Ability in Explaining Individual Schooling Attainments and Wages.

At this stage, two questions naturally arise. Given that predicted schooling attainments can be decomposed into two orthogonal components, what is the relative importance of household human capital and individual unobserved abilities in explaining individual schooling attainments? What is the relative importance of household human capital and individual unobserved abilities in explaining labor market wages? To answer these questions, we have evaluated the variations in predicted schooling explained by both sources.

4.2.1 Schooling Attainments

The variations in predicted schooling attainments, explained by a particular variable or parameter, are computed as follows: $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(PRED(S_i) - E(PRED(S))^2}$ where $PRED(S_i)$ is the predicted schooling attainment of individual i obtained when we fix all attributes other than the one of interest at their respective sample average and where $E(PRED(S))$ denotes the sample average of the predicted schooling attainments (when all variables and parameters are allowed to vary). The relative dispersion observed for both sources (such as parents' human capital and ability heterogeneity) will provide a good indication of the relative importance of each factor as predicted by the structural parameters.[10]

The measures of dispersion characterizing predicted schooling attainments are presented in Table 3. Overall, there is strong evidence that father's and mother's schooling are by far the most important household background variables. When

[9] For more details on the "Ability Bias" and the "Discount Rate Heterogeneity Bias", see Belzil and hansen (2001).

[10] As the model is non linear, the variance of predicted schooling cannot be decomposed linearly.

taken as a whole, individual variations in household human capital account for a much larger share of total variations in schooling than does ability heterogeneity. The estimated measure of variation in individual schooling attainments imputed to idiosyncratic ability heterogeneity is equal to 0.5449 in Model 1 and represents only 50% of the variation imputed to all household attributes (equal to 1.0977). Undoubtedly, household human capital endowments are more important than unobserved abilities in explaining cross-sectional differences in schooling attainments.

4.2.2 Wages

While household background variables account for a larger share of cross-sectional differences in schooling than do individual abilities, it is far from obvious that they have a similar explanatory power on labor market wages. Both school and market abilities have an effect on wages through schooling but market ability has also a direct effect on wages through the intercept terms of the wage function. To investigate this issue, we have computed a measure of variation in predicted wages that can be imputed to household background variables and ability heterogeneity. Without loss of generality, we used predicted entry wages. The results are in column 2 of Table 3.

As expected, the respective variations in explained wages due to ability heterogeneity and household background variables are quite different from those observed for predicted schooling attainments. The variation in predicted wages (0.2448) explained by abilities is 3 times larger than the variation explained by all household background variables (0.0768). These results are easily explained. First, household human capital has a much larger effect on the utility of attending school than on labor market outcomes. Second, the wage return to schooling is found to be quite low so that individual differences in schooling cannot explain differences in wages. Third, labor market ability appears to be the prime factor explaining predicted wages.

4.3 What is the True Intergenerational Education Correlation ?

In the reduced-form literature, it is customary to document the intergenerational education correlation using OLS estimates. However, OLS estimates are likely to be unreliable. The effects of household human capital on schooling attainments, obtained from OLS regressions, ignore dynamic dimensions and cannot distinguish between the utility of attending school and labor market outcomes. They are also incapable of identifying the relative importance of individual ability and pure stochastic shocks. As our model allows us to separate the effects of household human capital from unobserved abilities, it is easy to generate data on schooling attainments, letting vary all observable attributes or parameters that are subject to heterogeneity, and compute partial correlations between realized schooling attainments and household background variables. An OLS regression of simulated schooling attainments on household background variables will provide a good estimate of the various partial correlations predicted by the structural dynamic programming model. In turn, these can be compared to the sample partial correlations obtained from a reduced-form OLS regression of actual schooling on household background variables.

The partial correlations measured in the data are found in the last column of Table 4. The OLS estimate of father's schooling is around 0.2073, while the estimate of mother's education is 0.1683. The effect of household income is 0.0154 and the effect of sibling is -0.1454. These results are relatively standard in the literature. As seen from Table 4, the structural dynamic programming model predicts much smaller effects of household human capital variables than what is revealed by OLS estimates obtained from actual schooling attainments. The parameter estimates for father's education (0.1724 in model 1) indicates a much weaker correlation between individual schooling attainments and father's education than the sample correlation. It is approximately 17% lower than the OLS estimate found in column 2. The estimates for mother's education (0.1066) is even smaller when compared with the correlation measured in the data (0.1683). It is 40% lower than the OLS estimate of mother's education. The effects of household income (0.0119 and siblings (-0.1284) predicted by the structural model are also much weaker than those measured in the data. They are approximately 30% lower (in the case of household income) and 12% lower (in the case of siblings) than their OLS counterparts in column 2. Overall, there is strong evidence that OLS estimates of the correlation between household human capital variables and individual schooling attainments tend to over-predict the effect of all variables. This seems to be particularly true for mother's education and household income.

As argued before, the intergenerational education correlation, inferred from cross-section data, has a macroeconomic counterpart. More precisely, knowledge of the true intergenerational education correlation can be used to measure the average increase in the level of schooling of the next generation explained by an exogenous increase in the level of human capital of the current generation. While the effect of human capital and education on growth is one of the central questions addressed by empirical macroeconomists, it is also important to investigate how household human capital affects schooling attainments of the next generation. Although, following Lucas (1988), more general theoretical models have been introduced, which involve overlapping generations and human capital transfers across generations, very few of them have been tested empirically.[11] In our model, the intergenerational human capital transmission mechanism is relatively simple. An increase in education increases household income of the current generation. This increase in schooling and income will, in turn, increase the util-

[11] See Barro and Sala-i-Martin, 1995, for a survey.

ity of attending school and reduce the opportunity cost of schooling for the next generation. In other words, education may be seen as a by-product of economic growth.

To investigate this issue, we increased exogenously the level of schooling of both the father and mother by one year and imputed the relevant increase in household income indicated by our estimates of the returns to schooling. Then, we computed the average increase in schooling attainments of the next generation. We have also performed the same experiment without changing household income. The results are found in Table 5. On average, increasing both parents' education by one year (with the appropriate increase in family income) will raise schooling attainment of the next generation by 0.40 year. This increase is explained mostly by an increase in education. However, there exist no well-defined benchmark result which is equivalent in the macroeconomic literature devoted to economic growth. As a consequence, our result cannot be evaluated easily. It nevertheless illustrates some persisting effects of human capital growth and indicate that an increase in the average level of education is, at the same time, one of the consequences as well as one of the causes of economic growth.

5 Conclusion

We have estimated a structural dynamic programming model of schooling decisions where individual heterogeneity (observed as well as unobserved) has several dimensions; ability in school, ability in the labor market and initial endowments in household human capital. The econometric specification of the model is quite general. The structure of the model has allowed us to investigate the relative importance of household human capital and individual unobserved abilities in explaining cross sectional differences in schooling attainments and wages. It also enabled us to investigate the link between the intergenerational education correlation (typically measured from cross-section data) and the effect of human capital based economic growth on schooling attainments of the next generation (the aggregate counterpart to the intergenerational education correlation).

Our estimates indicate that the differences in predicted schooling explained by household human capital are generally twice as large as the differences explained by unobserved abilities while the differences in predicted wages explained by unobserved abilities are 3 times as large as the differences explained by household human capital. These results may be explained intuitively. First, household human capital has a much larger effect on the utility of attending school than on labor market outcomes. Second, the wage return to schooling is found to be quite low so that individual differences in schooling can hardly explain differences in wages. Third, labor market ability appears to be the prime factor explaining predicted wages.

We find that the true intergenerational education correlation predicted by the dynamic programming model is much lower than what is revealed by standard OLS regressions of actual schooling on various household human capital variables. The true partial correlation between son and father's schooling (0.17) is around 17% lower than the sample correlation. The true partial correlation between son and mother's education (0.11) is approximately 40% lower than the sample correlation. The effects of household income (0.0119 and siblings (-0.1284) predicted by the structural model are also much weaker than the sample correlations.

Various simulations indicated that an exogenous increase of 1 year in the level of schooling of the current generation will increase schooling attainments of the next generation by 0.4 year. While there is no benchmark result in the growth literature based on cross-country growth rate comparisons, our findings illustrate the link between the intergenerational education correlation (typically found in cross-section data) and the intergenerational effects of human capital growth at the aggregate level. Our findings also illustrate the need for economic models in which education is a consequence as well as a cause of economic growth.

Our results suggest interesting topics of future research. If data on parental transfers were available, it would be interesting to distinguish between the structural (direct) effect of parents' education from the ability effect. In particular, it would be interesting to evaluate how household labor supply behavior affects schooling attainments and labor market outcomes of the children. Finally, as education financing requires less parental transfers in a welfare state than in a liberal economy, it would be interesting to compare the intergenerational education correlation in countries where post-secondary schooling is heavily subsidized to the one obtained for the US economy.

References

[1] Barro, Robert and Xavier Sala-i-Martin (1995) *Economic Growth*, New-York: McGraw Hill.

[2] Belzil, Christian and Hansen, Jörgen (2001) "Unobserved Ability and the Return to Schooling" IZA Working paper, Concordia University.

[3] Cameron, Stephen and Heckman, James (1998) "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males" *Journal of Political Economy, 106 (2)*, 262-333.

[4] Eckstein, Zvi and Kenneth Wolpin (1999) "Why youth Drop Out of High School: The Impact of preferences, Opportunities and Abilities" *Econometrica,* vol. 67, No. 6 (November), 1295-1339.

[5] Kane, Thomas (1994) "College Entry by Blacks since 1970: The Role of College Costs, Family Background, and the Returns to Education" *Journal of Political Economy, 102*, 878-911.

[6] Keane, Michael P. and Wolpin, Kenneth (1997) "The Career Decisions of Young Men" *Journal of Political Economy, 105 (3)*, 473-522.

[7] Lazear, Edward (1980) "Family Background and Optimal Schooling Decisions" *Review of Economics and Statistics, 62 (1)*, 42-51.

[8] Lucas, Robert (1988) "On the Mechanics of Economic Development" *Journal of Monetary Economics 22:3-42*

[9] Magnac, Thierry and David Thesmar (1998) "Identifying Dynamic Discrete Choice Models : An Application to School-Leaving in France" Working Paper, CREST, Paris, France

[10] Rust, John (1987) "Optimal Replacement of GMC Bus Engines: An Empirical Analysis of Harold Zurcher" *Econometrica, 55 (5)*, 999-1033.

[11] Topel, Robert (1999) "Labor Markets and Economic Growth", Working Paper, University of Chicago.

Table 1 - Descriptive Statistics

	Mean	St dev.	# of individuals
Household Income/1000	36,904	27.61	1710
father's educ	11.69	3.47	1710
mother's educ	11.67	2.46	1710
# of siblings	3.18	2.13	1710
prop. raised in urban areas	0.73	-	1710
prop. raised in south	0.27	-	1710
prop in nuclear family	0.79	-	1710
Schooling completed (1990)	12.81	2.58	1710
# of interruptions	0.06	0.51	1710
duration of interruptions (year)	0.43	1.39	1710
wage 1979 (hour)	7.36	2.43	217
wage 1980 (hour)	7.17	2.74	422
wage 1981 (hour)	7.18	2.75	598
wage 1982 (hour)	7.43	3.17	819
wage 1983 (hour)	7.35	3.21	947
wage 1984 (hour)	7.66	3.60	1071
wage 1985 (hour)	8.08	3.54	1060
wage 1986 (hour)	8.75	3.87	1097
wage 1987 (hour)	9.64	4.44	1147
wage 1988 (hour)	10.32	4.89	1215
wage 1989 (hour)	10.47	4.97	1232
wage 1990 (hour)	10.99	5.23	1230
Experience 1990 (years)	8.05	11.55	1230

Note: Household income and hourly wages are reported in 1990 dollars. Household income is measured as of May 1978. The increasing number of wage observations is explained by the increase in participation rates.

Table 2A
The Effects of Household Human Capital on the Utility of Attending School and labor Market outcomes

	Model 1	**Model 2**
	Param (st. dev)	**Param (st. dev)**
Utility of attending School		
Father's Educ	0.0231 (0.0024)	0.0091 (0.0010)
Mother's Educ	-0.0031 (0.0026)	0.0056 (0.0025)
household Income	0.0018 (0.0003)	0.0006 (0.0003)
# of Siblings	-0.0157 (0.0012)	-0.0067 (0.0012)
Wages		
Father's Educ (υ_1^w)	0.0120 (0.0021)	-
Mother's Educ (υ_2^w)	-0.0083 (0.0020)	-
household Income (υ_3^w)	0.0012 (0.0003)	-
# of Siblings (υ_4^w)	-0.0077 (0.0025)	-
Employment		
Father's Educ (υ_1^e)	-0.0135 (0.0045)	-
Mother's Educ (υ_2^e)	0.0026 (0.0050)	-
household Income (υ_3^e)	-0.0004 (0.0005)	-
# of Siblings (υ_4^e)	0.0076 (0.0049)	-

Note: Household income is divided by 1000.

Table 2B
Other Structural Parameters

	Model 1 Param.(Std error)	Model 2 Param.(Std error)
Utility in School		
Nuclear Family	0.0183 (0.0057)	0.0187 (0.0046)
Rural	-0.0039 (0.0048)	-0.0037 (0.0043)
South	-0.0190 (0.0051)	-0.0194 (0.0049)
Stand.Dev.(σ_{ξ})	0.1940 (0.0105)	0.2165 (0.0116)
Splines δ_{7-10}	0.1035 (0.0105)	0.1058 (0.0078)
Splines δ_{11}	0.4831 (0.0218)	0.4810 (0.0214)
Splines δ_{12}	-1.8526 (0.0258)	-1.9135 (0.0230)
Splines δ_{13}	-1.4753 (0.0547)	-1.6561 (0.0230)
Splines δ_{14}	3.0402 (0.0118)	3.0744 (0.0132)
Splines δ_{15}	-0.5811 (0.0234)	-0.4331 (0.0141)
Splines δ_{16}	1.0164 (0.0244)	1.1518 (0.0087)
Splines $\delta_{17-more}$	-0.5497 (0.0084)	-0.5974 (0.0235)
Interruption Prob.	0.0749 (0.0036)	0.0749 (0.0036)
Discount Rate	0.0030 (0.0001)	0.0032 (0.0001)
Emp. Return to Schooling		
schooling	-0.0682 (0.0041)	-0.0683 (0.0026)
experience	-0.0153 (0.0026)	-0.0151 (0.0026)
experience^2	0.0001 (0.0001)	0.0001 (0.0001)
std. dev (σ_e)	1.3473 (0.0096)	1.3461 (0.0020)
Wage return to schooling		
Spline grade 7-12	0.0104 (0.0002)	0.0132 (0.0003)
Spline grade 13	0.0131(0.0016)	0.0153 (0.0013)
Spline grade 14	0.0848 (0.0018)	0.0919 (0.0017)
Spline grade 15	-0.0105 (0.0020)	-0.0047 (0.0016)
Spline grade 16	0.0167 (0.0022)	0.0233 (0.0019)
Spline grade 17-more	-0.0050 (0.0013)	-0.0016 (0.0012)
experience	0.0835 (0.0016)	0.0822 (0.0016)
experience^2	-0.0025 (0.0001)	-0.0025 (0.0002)
std. dev (σ_w)	0.2966 (0.0024)	0.2965 (0.0024)
mean log Likelihood	-13.7227	-13.7399

Note: The local returns computed from the spline parameter estimates are as follows 0.0104 (7-12), 0.0235 (13), 0.1083 (14), 0.0978 (15), 0.1145(16), 0.1095 (17 and more). In Model 2, the corresponding estimates are 0.0132, 0.0285, 0.1204, 0.1157, 0.1390 and 0.1374.

Table 2C
Individual Specific Intercept Terms and Type Probabilities

			Model 1	Model 2
			Param. (St Error)	**Param. (St Error)**
Type 1	υ_1^ξ	**School ab.**	-2.9248 (0.0108)	-2.9189 (0.0090)
	υ_1^w	**Wage**	1.4594 (0.0105)	1.4656 (0.0098)
	κ_{01}	**Employment**	-3.2637 (0.0312)	-3.2823 (0.0221)
	q_1	**Type Prob.**	1.0146 (0.0560)	0.9634 (0.0226)
Type 2	υ_2^ξ	**School ab.**	-2.5286 (0.0125)	-2.5488 (0.0088)
	υ_2^w	**Wage ab.**	1.8687 (0.0107)	1.8739 (0.0094)
	κ_{02}	**Employment**	-3.1568 (0.0384)	-3.1501 (0.0077)
	q_2	**Type Prob**	0.5338 (0.0518)	0.6036 (0.0075)
Type 3	υ_3^ξ	**School ab.**	-3.2681 (0.0131)	-3.2560 (0.0096)
	υ_3^w	**Wage**	1.1323 (0.0156)	1.1321 (0.0136)
	κ_{03}	**Employment**	-3.0886 (0.0381)	-3.1053 (0.0060)
	q_3	**Type Prob**	0.0713 (0.0185)	-0.0080 (0.0076)
Type 4	υ_4^ξ	**School ab.**	-3.7970 (0.0243)	-3.9498 (0.0187)
	υ_4^w	**Wage**	1.4490 (0.0162)	1.4651 (0.0070)
	κ_{04}	**Employment**	-1.4903 (0.0362)	-1.5014 (0.0268)
	q_4	**Type Prob**	-0.1636 (0.0415)	-0.1847 (0.0067)
Type 5	υ_5^ξ	**School ab.**	-2.1232 (0.0289)	-2.0870 (0.0185)
	υ_5^w	**Wage**	2.1083 (0.0221)	2.1587 (0.0101)
	κ_{05}	**Employment**	-3.6275 (0.0224)	-3.6834 (0.0105)
	q_5	**Type Prob**	-1.1892 (0.0817)	-1.0816 (0.0008)
Type 6	υ_6^ξ	**School ab.**	-2.6797 (0.0184)	-2.6302 (0.0139)
	υ_6^w	**Wage**	1.6612 (0.0120)	1.6909 (0.0130)
	κ_{06}	**Employment**	-3.6508 (0.0173)	-3.7121 (0.0157)
	q_6	**Type Prob**	0.0 (normalized)	0.0 (normalized)

Note: The type probabilities are estimated using a logistic transform. The resulting probabilities are 0.36 (type 1), 0.22 (type 2), 0.14 (type 3), 0.11 (type 4), 0.04 (type 5) and 0.13 (type 6). In Model 2, the probabilities are 0.34 (type 1), 0.24 (type 2), 0.13 (type 3), 0.11 (type 4), 0.04 (type 5) and 0.14 (type 6).

Table 3
Sources of Variations in Schooling Attainments and Wages

Variable/Parameter	**Model 1** **Variations in pred. schooling**	**Model 1** **Variations in pred. wages**
Household background		
Parents' education	0.8162	0.0436
Parents'educ and income	0.9843	0.0700
All household variables	1.0977	0.0768
School and Market Abilities $(\tilde{\upsilon}_k^w, \tilde{\upsilon}_k^\xi, \tilde{\upsilon}_k^e)$	0.5449	0.2448
All Sources	1.3071	0.2762

Note: Our estimates of the variations in the predicted endogenous variable of interest Y (either schooling attainments or log entry wages) explained by a particular source of variation (either household human capital or unobserved abilities) are computed as follows:

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(PRED(Y_i) - E(PRED(Y))^2}$$

where $PRED(Y_i)$ is computed at the sample average of all variables or parameters other than the one of interest and where $E(PRED(Y)$ denotes the sample average of the variable.

Table 4
Estimates of the Partial Correlations between Individual Schooling Attainments and Household Human Capital

	Realized schooling (Model 1)	**Actual schooling (Data)**
Father's educ	0.1724 (10.50)	0.2073 (10.7)
Mother's educ	0.1066 (4.51)	0.1683 (6.20)
Household Income	0.0119 (6.25)	0.0154 (7.40)
Siblings	-0.1284 (5.05)	-0.1454 (5.66)
$\mathbf{R}^2$	0.242	0.306

Note: T statistics are in parentheses.

Table 5
Human Capital, Growth and Intergenerational Transfers: The effect of an Exogenous Increase in Parents' Education on Schooling Attainments of the Next Generation

Experiment	**Model 1**	**Model 1**
Δ EDUCATION OF CURRENT GENERATION	1 year	1 year
Δ INCOME OF CURRENT GENERATION	no	yes
Δ EDUCATION OF NEXT GENERATION	0.295 year	0.383 year

Note: Household income is increased according to the estimated returns to schooling

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