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Subjective Discount Rates, Intergenerational Transfers and the Return to Schooling

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ABSTRACT

Subjective Discount Rates, Intergenerational Transfers and the Return to Schooling*

Using a dynamic programming model of schooling decisions, we investigate the relationship between subjective discount rates and the labor market ability (the discount rate bias) on a panel taken from the National Longitudinal Survey of Youth (NLSY). Given household human capital and Armed Forces Qualification test scores (AFQT), subjective discount rates, which vary between 1% and 5% per year, are found to be negatively correlated with labor market ability. The true return to schooling is estimated around 6% per year. Estimates obtained from a model where neither the ability bias nor the discount rate bias are considered, indicate that one percentage point can be imputed to the correlation between discount rates and labor market ability and at least another percentage point can be imputed to the positive correlation between the per-period utility of attending school and labor market ability. The model is used to simulate the effects of an increase in the level of human capital of one generation on both schooling attainments and labor market productivity of the next generation. We find the true intergenerational education correlation to be relatively low; an increase of 1 year in the average level of schooling will raise the level of human capital of the next generation by approximately 0.15 year of schooling and translates into a 1% productivity (wage) growth.

JEL Classification: J2, J3

Keywords: Intergenerational transfers, returns to education, subjective discount rates, human capital, schooling decisions

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1 Introduction

Estimating the economic return to schooling plays a central part in modern labor economics. Although theoretical models of schooling decisions are naturally set in a dynamic and stochastic framework, the empirical literature is largely dominated by linear wage equations in which education is sometimes instrumented out.[1] This is understandable. The environment in which young individuals make schooling decisions is difficult to model comprehensively. In the early phase of their life, young individuals give up potential income in favor of higher future (but uncertain) wages and, perhaps, higher employment security. While enrolled in school, they must face costs such as tuition or transportation as well as psychic costs but may also receive parental support (intergenerational transfers) which reduce the opportunity costs of schooling and therefore raises the utility of attending school. Furthermore, native ability, affecting both labor market wages and educational achievements, are arguably correlated with parental educational background (see Lazear, 1980, Kane, 1994 and Cameron and Heckman, 1998). Not surprisingly, labor economists have, up to now, ignored most surrounding dimensions of schooling decisions and focussed on wage regression frameworks in order to estimate the return to schooling. It has however been recognized for a long time that ordinary least squares (OLS) estimates can seriously over estimate the true return to schooling. If individuals with higher unobserved ability (earning higher wages) are also those who obtain more schooling, the utility of attending school is correlated with the error term of the wage equation and OLS estimates of the return to schooling will suffer the 'ability bias' (see Card, 1998, for an enlightening discussion and Taber, 1998, for empirical evidence in a dynamic programming framework).

Although individual discount rates are fundamental parameters of intertemporal decision making, there exist very few empirical estimates of individual discount rates in a human capital investment decision framework. In the context of schooling decisions, the relationship between subjective discount rates and unobserved ability can also shed light on the direction of the bias of OLS estimates of the return to schooling. If individuals who have lower discount rates also have higher labor market ability (and therefore achieve higher levels of schooling), OLS estimates of the return to schooling would clearly be biased upward; that is they would suffer the 'discount rate bias' (Card, 1998). As far as we know, the discount rate bias has never been investigated empirically so there exists no evidence

[1]Authors such as Taubman (1975) and Ashenfelter and Krueger (1994) have proposed to use samples of twins (or siblings) while Blackburn and Neumark (1993) have used instruments such as IQ tests in order to eliminate ability bias. At the same time, others have concentrated on the possibility of using "exogenous influences" on the schooling decision such as the season of birth (Angrist and Krueger, 1991), military service lotteries (Angrist and Krueger,1992), geographical location (Card, 1993) or changes in the minimum schooling age (Harmon and Walker, 1995).

of its importance.[2] Similarly, empirical studies documenting the role of parents' background in both educational and labor market achievements are still in its infancies. Although the effect of parental background on educational achievements has been well documented (see Cameron and Heckman, 1998 and Kane, 1994, for recent examples), reduced-form models based on standard wage equations are not suitable to distinguish between the effects that parental background might have on the utility of attending school and those effects that it might have on labor market ability through human capital transmission. As well, reduced-form models cannot provide any information about the importance of the discount rate bias. As a consequence, investigating the relationships between individual discount rates, unobserved ability and intergenerational human capital transfers undoubtedly requires researchers to use structural econometric techniques.

Although structural dynamic programming models have become increasingly popular in recent years, few authors have estimated structural models of schooling decisions. Keane and Wolpin (1997) have used a structural dynamic programming model of schooling and occupational decisions using a cohort of the NLSY and payed a particular attention to the capacity of a dynamic programming model to fit data on occupational choices and mobility patterns while Belzil and Hansen (1999) and Taber (1998) have used a structural dynamic programming model to estimate the returns to schooling and investigated the importance of the ability bias. Eckstein and Wolpin (1998) use a dynamic programming model to evaluate the effect of youth employment on academic performance of young Americans.

The main objective of the present paper is to estimate a structural model of the decision between staying at school or entering the labor market in which the separate effects of subjective discount rates, labor market ability and household human capital on schooling attainments can be identified. We estimate the economic return to schooling as well as a set of surrounding structural parameters using a dynamic programming model. We formulate a model where individuals choose between an additional year of schooling and entering the labor market and assume that individuals know that they must retire when they are sixty-five years old and that wages grow stochastically with experience between entrance in the labor market and retirement. To be realistic, we allow individuals to take into account that they might experience unemployment over their lifetime. Using recursive methods, we can solve for the value functions in closed-form and set an exact likelihood for the number of years of education obtained by a given individual.[3]

Using a nonstationary dynamic programming model to model human capital investment decisions has several advantages. First, solving the dynamic program-

[2] The first reference to the discount rate bias appears to be Lang (1993).

[3] Our model has the structure of an optimal stopping problem; a very common type of dynamic discrete choice model which has seen several applications in the recent literature (see Eckstein and Wolpin (1989) for a survey, Wolpin (1987) for an example with finite horizon and Rust (1987) for an example with physical capital investment).

ming problem faced by a given agent allows us to identify surrounding parameters such as the income while at school (parental transfers) and the subjective discount rate which are not identified in standard reduced-form models. Second, the identification of new parameters provides an opportunity to introduce multivariate individual heterogeneity in discounting and ability and, in particular, investigate the discount rate bias. However, in order to be convincing, the identification requires that we use a large set of household and individual characteristics which can take into account that parental ability, parental wealth and child's ability are correlated. To do so, we use data on household characteristics such as parents' education, number of siblings, presence of both biological parents at age 14, and family income, which are likely to control for household ability (human capital) and financial resources (wealth), and data on Armed Force Qualification Tests (AFQT) score achievements, which are likely to control for individual ability.[4] We construct a model in which the utility of attending school is allowed to be correlated with the intercept term of the wage equation (after controlling for household characteristics). The correlation between the utility of attending school and labor market wages arises because AFQT score affects both the level of net earnings while at school (say, through psychic costs reduction) and the intercept term of the wage equation. This allows us to control for the ability bias. After controlling for the correlation between the utility of attending school and labor market wages (the ability bias), and after introducing discount factor heterogeneity, we allow unobserved labor market ability to be correlated with individual discount factors (using a discrete bi-variate distribution). In order to investigate the effects of allowing for a correlation between ability and discount rates on the estimates of the return to schooling, we estimate the model under the null hypothesis (there is no correlation between ability and discount rates) as well as under the alternative. We also test for the presence of a discount rate bias and evaluate the sensitivity of the return to schooling to the introduction of a control for the discount rate bias.

The main features of the paper are the following. First, we discuss the structural parameter estimates and their capacity to fit the data well. We also illustrate the effects of accumulated human capital on expected rates of unemployment and the effect of discount rate heterogeneity on schooling attainments. We summarize the estimates of the returns to schooling for various model specifications and discuss the importance of the discount rate bias as compared to the ability bias. We use the structural parameters to simulate the effects on schooling attainments of an increase in the wage return to schooling, an increase in the employment security return to schooling and an increase in the rate of unemployment. Finally, we discuss the implication of our model for the "true intergenera-

[4]Not surprisingly, test scores are found to be positively related to household human capital. In the NLSY, a regression of test scores (in log) on household characteristics (parents' education, family income, siblings, nuclear family indicator) leads to a R^2 of 0.29

tional education correlation" and evaluate the impact of economic growth driven by human capital on schooling attainments and labor market productivity of the next generation.

The model is implemented on a panel of white males taken from the National Longitudinal Survey of Youth (NLSY). The panel covers a period going from 1979 until 1990. The likelihood function is constructed from data on years of education completed as well as data on both labor market wages and individual employment rates observed over the panel. The identification of all structural parameters other than those belonging to the wage equation and the employment rate equation is explained by the fact that our model fully imposes the theoretical restrictions of dynamic programming. The main results are the following. First, discounting heterogeneity is found to be important. One of our most robust finding is a group endowed with a very low discount rate (around 1% per year) and a second group with a higher rate (around 5% per year). These estimates appear very close to average risk free interest rates computed from historical time series (Kocherlakota, 1996). Second, AFQT scores are found to have a strong positive effects on the per-period utility of attending school and labor market wages. Third, after controlling for the positive correlation between the utility of attending school and labor market wages, we find a negative correlation between individual discount factors and unobserved ability. This result is very robust. Fourth, the most reliable estimates indicate that the true return to schooling is around 6% per year. Fifth, allowing for correlation between discount factors and ability had a particularly remarkable impact on the estimates of the return to schooling. We find that both the discount rate bias and the ability bias are important. Estimates obtained from a model where neither the ability bias nor the discount rate bias are considered, can seriously over-estimate the true return. More precisely, there is a 1% return to schooling which can be imputed to the correlation between discount rates and ability while there is at least another 1% which can be imputed to the positive correlation between the per period utility of attending school and labor market ability. Sixth, various simulations indicate that schooling attainments are much more elastic to changes in the wage return to schooling than changes in the employment security return to schooling. Finally, an increase of 1 year in the average level of schooling, accompanied by a 6% growth rate in income, will raise the level of human capital of the next generation by approximately 0.15 year of schooling. In terms of productivity growth, and assuming that the return to schooling is time invariant, this increase in schooling attainments translates into a 1% productivity (wage) growth. This means that the true intergenerational education correlation is much lower than the cross-sectional correlation between parents' education and children's education.

The main features of the paper are the following. Section 2 is devoted to the presentation of the theoretical model as well as its econometric specification. Section 3 contains a brief description of the NLSY. The main empirical results are discussed in Section 4. The conclusion is in Section 5.

2 The Model

We model education choices as a dynamic discrete choice exercise in a nonstationary environment. We assume that individuals choose between two human capital accumulation strategies; acquiring general human capital (schooling) and entering the labor market (to obtain benefits from schooling and acquire additional human capital from labor market experience). The decision to remain at school (obtain an additional year of schooling) is modeled as an optimal stopping problem; that is when an individual decides to enter the labor market, it is impossible to return to school. We assume that individuals take into account that, over their lifetime, they may experience unemployment. This is important as unemployment is relatively common amongst those with a low level of schooling. In order to be realistic, we therefore assume that education and accumulated experience affect employment security as well as wages.

2.1 Theoretical Structure

In this sub-section, we present the theoretical structure of our empirical model.

- Assumption 1- The Preferences

Each individual maximize his expected discounted lifetime utility, according to discount factor $\beta = \frac{1}{1+\rho}$ (where ρ is the subjective discount rate), by choosing the optimal time to interrupt schooling and enter the labor market. The control variable, d_t, is such that

$\mathrm{d}_t = 1$ if an individual, endowed with S_t years of schooling, invests in an additional year of schooling at period t.
$\mathrm{d}_t = 0$ if an individual leaves school at the beginning of period t (to enter the labor market).
Individual preferences are represented by the following per-period (instantaneous) utility function $U(y_t, S_t)$,

$$U(y_t, S_t) = \log(y_t) + \lambda \cdot \log(S_t) + \varepsilon_t \tag{1}$$

where y_t is income at date t and S_t is schooling acquired by date t. The inclusion of S_t in the utility function can be interpreted as the consumption value of schooling and maybe justified if, for instance, individuals perceive social status or prestige associated to schooling. Income can be earned from working in the labor market (denoted $\tilde{\mathrm{w}}_t$) or from intergenerational transfers obtained from the household (denoted ξ_t).

$$\text{When } d_t = 1,\ \mathrm{I}_t = \xi_t$$
$$\text{When } d_t = 0,\ \mathrm{I}_t = \tilde{w}_t.$$

- **Assumption 2- The utility of Attending School**

The net income while at school, ξ_t, is assumed to be stochastic and reflects the difference between parental transfers and costs such as tuition, books, transportation as well as other psychological costs associated to the disutility of learning. The per period utility of attending school is therefore

$$U(\xi_t, S_t) = \log \xi_t + \lambda \log(S_t) + \varepsilon_t^{\xi}$$

where ε_t^{ξ} represents a sequence of i.i.d. stochastic shocks affecting the utility of attending school. When an individual leaves school, ξ_t is set to 0.

- **Assumption 3- Human Capital and Employment Security**

In order to be realistic we must take into account that individuals can experience unemployment during their lifetime. As the unit of time is a year, we ignore the distinction between the incidence and the duration of unemployment and model employment as the fraction of the year spent employed. This fraction, e_t, is assumed to be a non-stationary stochastic process. This means that, at any year t, the income process (y_t) can be expressed as

$$y_t = (d_t \cdot \xi_t) + ((1 - d_t) \cdot \tilde{w}_t) \tag{2}$$

where

$$\tilde{w}_t = e_t \cdot w_t$$

We assume that, at the beginning of each period, individuals observe a realization of w_t and decide to enter the labor market or not based on the expected employment rate. In other words, the actual employment rate, e_t, for a given year, is unknown at the beginning of each year.

- **Assumption 4- The Utility of Work**

The return to human capital is captured in the equation for the log wage paid in the labor market. The log wage regression equation is

$$\log w_t = \varphi_0 + \varphi_s(S_t\ ) + \varphi_e(Exp_t) + \varepsilon_t^w \tag{3}$$

where ε_t^w represents a sequence of i.i.d. stochastic shocks and where $\varphi_s(.)$ represents the return to education and $\varphi_e(.)$ represents the return to experience. At the estimation step, $\varphi_e(.)$ is chosen to be quadratic. It follows that the ex-post utility of working in the labor market with S_t years of schooling (given a realized value for e_t) is simply

$$U(w_t, e_t, S_t) = \log(e_t) + \varphi_0 + \varphi_s(S_t\ ) + \varphi_e(Exp_t) + \lambda \log(S_t) + \varepsilon_t^w$$

- **Assumption 5- The Stochastic Process for Employment Security**

To characterize the stochastic process of the employment security variable, e_t, we start from the log inverse employment rate, e_t^*, that is

$$e_t^* = \log(\frac{1}{e_t}) \tag{4}$$

and assume that

$$\log(e_t^*) \sim N(\mu_t, \sigma_e^2) \tag{5}$$

It follows that

$$E \log e_t = -\exp(\mu_t + \frac{1}{2}\sigma_e^2)$$

and

$$Var(\log e_t) = \exp(2\mu_t + \sigma_e^2) \cdot (\exp(\sigma_e^2) - 1)$$

2.2 The Solution

Given assumptions 1 to 5, it is clear that the expected utility of working at wage w_t for a fraction e_t of the year, is simply

$$EU(\tilde{w}_t, S_t) = E \log \tilde{w}_t + \lambda \cdot \log S_t$$

or

$$EU(\tilde{w}_t, S_t) = E \log e_t + E \log w_t + \lambda \cdot \log S_t$$

and can be expressed as

$$EU(\tilde{w}_t, S_t,) = -\exp(\mu_t + \frac{1}{2}\sigma_e^2) + (\varphi_0 + \varphi_s(S_t\ ) + \varphi_e(Exp_t)) + \lambda \log(S_t)$$

As it is done often in dynamic optimization problems, the solution to the stochastic dynamic problem can be characterized using recursive methods. Noting that beyond T (at retirement) earnings are set to 0, the expected value of entering period T is simply given by

$$EV_T = -\exp(\mu_T + \frac{1}{2}\sigma_e^2) + (\varphi_0 + \varphi_s(S_T\ ) + \varphi_e(\mathrm{Exp}_T)) + \lambda \cdot \log(S_T)$$

The value functions associated to the decision to remain in school with $S(t)$ years of schooling already accumulated, $V_t^s(S_t)$, can be expressed as

$$V_t^s(S_t) = \log(\xi_t) + \lambda \log(S_t) + \varepsilon_t^{\xi} + \beta EMax[V_{t+1}^s(S_{t+1}), V_t^w(S_{t+1})]$$

or, more compactly, as

$$V_t^s(S_t) = \log(\xi_t) + \lambda \log(S_t) + \varepsilon_t^{\xi} + \beta E(V_{t+1} \mid d_t = 1) \tag{6}$$

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). The expected value is taken over the distribution of potential wages and employment rates. Setting d_t to 1 reduces the total time in the labor market but raises entering wages.

The value of stopping schooling (that is entering the labor market) with S_t years of schooling at wage w_t and taking into account the distribution of e_t (because e_t is unknown when w_t is drawn),$V_t^w(S_t)$, is given by

$$V_t^w(S_t) = -\exp(\mu_t + \frac{1}{2}\sigma_e^2) + \log(w_t) + \lambda \log(S_t) + \beta E(V_{t+1} \mid d_t = 0) \tag{7}$$

and denotes the discounted expected value of lifetime earnings of starting work in the labor market with S_t years of schooling, no labor market experience and $T - t$ years of potential specific human capital accumulation ahead. Clearly, $E(V_{t+1} \mid d_t = 0)$ is simply

$$E(V_{t+1} \mid d_t = 0) = \sum_{j=t+1}^{T} \beta^{j-(t+1)}(-\exp(\mu_j + \frac{1}{2}\sigma_e^2) + (\varphi_0 + \varphi_s(S_j) + \varphi_e(Exp_j)) + \lambda \log(S_j))$$

2.3 Econometric Specification

In order to implement the model empirically, we must make some additional assumptions. First, we only model the decision to acquire schooling beyond 6 years. Furthermore, no one reports having completed 20 years of education (or more). Accordingly, we set a maximum of 20 years of schooling. Finally, we assume a terminal value of 0 at age 65. Given that the model allows three distinct states (school, work and unemployment), we ignore occupation decisions as well as university majors.[5]

- **Assumption 6- Household Characteristics and the Utility of Attending School**

The per period utility of attending school is obviously a complicated relationship to model. Both direct and psychic learning costs, which can vary with the level of schooling, are likely to affect schooling decisions. Because individuals raised in wealthy families are likely to receive higher intergenerational transfers or experience a lower level of disutility of attending school, parents' human capital and financial wealth are expected to have a strong effect on the probability of transiting from one grade level to the next. As it is impossible to write down the "full" structural model which would include all these aspects, we specify a reduced-form function for ξ_{it} (the net earnings while at school net). The function is allowed to depend on various family background variables and household characteristics as well as individual (measured) ability so that the effects of household ability on schooling attainments can be identified from individual own ability.

To preserve positivity of the level of income while at school, we assume that

$$\log \xi_{it} = X_i'\delta + \zeta(S_t) \cdot S_t + \varepsilon_{it}^{\xi} \tag{8}$$

The vector X_i contains the following variables; parents' education (both mother and father), household income, number of siblings, family composition at age 14 and regional controls while $\zeta(S_t) \cdot S_t$ captures the changes in parental transfers with the level of schooling.[6] The marginal effect of schooling level on parental transfers, $\zeta(S_t)$, is modeled using spline functions. The number of siblings is used to control for the fact that, other things equal, the amount of parental resources spent per child is declining with the number of siblings. The household composition variable (Nuclear Family) is equal to 1 for those who have been raised 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. Finally, in order to control for individual ability (affecting the psychic costs of obtaining schooling), we use AFQT test scores.[7] Yearly family income is measured in \$1,000 while AFQT test scores (reported as a number between 0 and 100) are divided

[5] For an empirical model of occupation decisions, see Keane and Wolpin, 1997.

[6] In the NLSY, household income is measured as of 1979.

[7] Several issues concerning the linked between Armed Force Qualification Test scores and schooling attainments are discussed in Cameron and Heckman (1998) and Taber (1998).

by 10. In order to allow the earnings while at school (and, therefore, the utility of attending school) to depend on the level of schooling in a flexible fashion, we use 8 splines (6 to 9, 10 years,11 years, 12 years, 13 to 14, 15 years, 16 years and 17 years or more). The variables are defined as follows;

$$
\begin{gathered}
Education_{6-9} = Education \\
Education_{10} = Education - 9 \; if \; Education > 9 \; and \; 0 \; if \; not. \\
Education_{11} = Education - 10 \; if \; Education > 10 \; and \; 0 \; if \; not \\
Education_{12} = Education - 11 \; if \; Education > 11 \; and \; 0 \; if \; not \\
Education_{13-14} = Education - 12 \; if \; Education > 12 \; and \; 0 \; if \; not. \\
Education_{15} = Education - 14 \; if \; Education > 10 \; and \; 0 \; if \; not \\
Education_{16} = Education - 15 \; if \; Education > 14 \; and \; 0 \; if \; not. \\
Education_{17-more} = Education - 16 \; if \; Education > 16 \; and \; 0 \; if \; not.
\end{gathered}
$$

- **Assumption 7**

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

$$\log w_{it} = \varphi_{0i} + \varphi_1.S_{it} + \varphi_2.Exp_{it} + \varphi_3.Exp_{it}^2 + \varepsilon_{it}^w \tag{9}$$

where

$$\varphi_{0i} = \varphi_4 \cdot (AFQT_i/10) + \;\upsilon_i^w$$

and where

$$\varepsilon_{it}^w \sim i.i.d \; N(0, \sigma_w^2)$$

represents a purely random innovation to wages paid in the labor market. The term υ_i^w plays the role of unmeasured labor market ability while test scores represent measured ability.

- **Assumption 8**

The employment rate, e_{it}, is allowed to depend on accumulated human capital (S_{it} and Exp_{it}) and ability ($AFQT_i$) so that

$$E(\log e_{it}^*) = \mu_{it} = \kappa_0 + \kappa_1 \cdot S_{it} + \kappa_2 \cdot Exp_{it} + \kappa_3 \cdot (AFQT_i/10)$$

where κ_0 is an intercept term, κ_1 represents the employment security return to schooling, κ_2 represents the employment security return to experience and κ_3 represents the effect of ability (as measured by AFQT scores) on employment security. After controlling for test scores, the probability of experiencing unemployment is assumed to be independent from the stochastic shock affecting wages
.

- **Assumption 9- Discount Rate Bias and Ability Bias**

As discussed before, ordinary least squares (OLS) estimates can seriously over-estimate the true return to schooling if individuals with higher unobserved ability (earning higher wages) are also those who obtain more schooling or if individuals who have lower discount rates also have higher labor market ability and therefore achieve higher levels of schooling (the discount rate bias). Given the specification of equation (8) and equation (9), income while at school and wages share a common factor (namely AFQT scores). Our model therefore controls for the ability bias. In order to investigate the discount rate bias, we estimate the correlation between ρ_i and υ_i^w using a flexible approach. We assume that υ_i^w and ρ_i follow a joint distribution which can be approximated with a bi-variate discrete distribution. The probabilities are expressed as follows:

$$Pr(\upsilon^w = \upsilon_1^w, \rho = \rho_1) = p_1$$

$$Pr(\upsilon^w = \upsilon_2^w, \rho = \rho_1) = p_2$$

$$Pr(\upsilon^w = \upsilon_1^w, \rho = \rho_2) = p_3$$

$$Pr(\upsilon^w = \upsilon_2^w, \rho = \rho_2) = p_4$$

where $\upsilon_1^w > \upsilon_2^w$ and $\rho_1 > \rho_2$ and

$$\sum_{j=1}^{J} p_j = 1 \text{ and } p_j \geq 0 \text{ j=1,2...J (where J=4)} \tag{10}$$

The covariance can be expressed as

$$cov(\upsilon^w, \rho) = (p_1.p_4 - p_2.p_3)(\upsilon_1^w - \upsilon_2^w).(\rho_1 - \rho_2)$$

and, conditional on $(\upsilon_1^w \neq \upsilon_2^w)$ and $(\rho_1 \neq \rho_2)$, testing for independence (or no correlation) requires testing for $p_1.p_4 - p_2.p_3 = 0$.[8]

[8] We actually estimate the probabilities using logistic transforms, that is we define

$$\mathsf{p_i} = \frac{\exp(\mathsf{q_i})}{\sum_{\mathsf{j}=1}^{4} \exp(\mathsf{q_j})}$$

for i=1,2,3,4 and normalize q_4 to 0. This method is often used in bi-variate duration models. See van den Berg, Lindeboom and Ridder (1994) for an example.

2.4 The Likelihood Function

The likelihood function is constructed from data on years of education completed as well as data on both labor market wages and individual employment rates observed over the panel. The construction of the likelihood function requires to evaluate the following probabilities; the probability of stopping school after completed $S_t = \tau$ years, the probability of entering the labor market at wage $w_{i,\tau+1}$ and the density of observed wages and employment rates from $\tau + 2$ until 1990. The probability of stopping school after τ years, is given by

$$\Pr(S_{it} = \tau) = \left\{ \prod_{s=1}^{\tau} P(d_{i,s} = 1) \right\} P(d_{i,\tau+1} = 0) \tag{11}$$

The probability of entering the labor market at wage $w_{i,\tau+1}$, $P(d_{i,\tau+1} = 0, w_{i,\tau+1})$, can be factored as

$$P(d_{i,\tau+1} = 0, w_{i,\tau+1}) = P(d_{i,\tau+1} = 0 \mid w_{i,\tau+1}) \cdot \frac{1}{\sigma_w} \phi(\frac{w_{i,\tau+1}}{\sigma_w}) \tag{12}$$

where $\phi(.)$ denotes the standard normal density and where $P(d_{i,\tau+1} = 0 \mid w_{i,\tau+1})$ is a normal conditional probability. Finally, the contribution to the likelihood for log $(w_{i,s})$ and log $(e^*_{i,s})$ observed from $\tau_i + 2$ until 1990 is given by[9]

$$Pr\left(\{w_{i,\tau+2}, \log e^*_{i,\tau+2}\}....\{w_{i,1990}, \log e^*_{i,1990}\}\right) =$$

$$\prod_{s=\tau+2}^{1990} \left\{ \frac{1}{\sigma_w} \phi(\frac{w_{i,s}}{\sigma_w}) \cdot \frac{1}{\sigma_e} \phi(\frac{log(e^*_{i,s})}{\sigma_e}) \right\} = \prod_{s=\tau+2}^{1990} \left\{ H(w_{is}, \log(e^*_{i,s}) \right\} \tag{13}$$

Using (11), (12) and (13) the likelihood function, for a given individual (conditional on unobserved heterogeneity), is given by

$$L_i(. \mid \upsilon^w, \rho) = \left\{ \prod_{s=1}^{\tau_i} P(d_{i,s} = 1) \cdot P(d_{i,\tau+1} = 0, w_{i,\tau+1}) \cdot \prod_{\tau+2}^{1990} \left\{ H(w_{is}, \log(e^*_{i,s}) \right\} \right\} \tag{14}$$

Maximizing the log likelihood function simply requires to write the individual contributions (14) conditional on every possible combinations $\vartheta_j = (\upsilon^w, \rho)_j$ and taking a weighted average of all contributions according to the $p's$. That is the contribution to the likelihood for individual i is given by

$$\log L_i = \log \sum_{j=1}^{J} p_j \cdot L_i(. \mid \vartheta_j) \tag{15}$$

[9] For those who are still in school at the survey time or those for whom wages are missing, the contribution to the likelihood is easily adjusted.

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.[10]

The original sample contained 3,790 white males. However, we lacked information on family background variables (such as family income as of 1978 and parents' education) and on AFQT score for 1,161.[11] The age limit and missing information regarding actual work experience further reduced the sample to 1,254. Of these 1,254 individuals, about 25% had interrupted their schooling attainment for at least one year. This figure, similar to the one reported by Keane and Wolpin (1997), appears to be inconsistent with the optimal stopping assumption and could suggest that some individuals use labor market earnings to finance future schooling attainment.[12] Before going further, it is important to undertake a deeper investigation of the characteristics of those who choose to interrupt schooling.

Overall, it has been proven difficult to impute a particular behavioral pattern for those who interrupt school. First, and as pointed out also by Keane and Wolpin (1997), a relatively large fraction of those who leave school non permanently (around 50%) seem to stay out of the labor force totally as their individual records show no wages. The remaining individuals work in the labor market before returning in school but a relatively large fraction work for a small number of weeks. In order to evaluate if the interrupters are systematically different from those who acquire education continuously, we split the individuals between those who had obtained 12 years of schooling or less and those who had obtained 13 years or more, and estimated a simple Probit model with an indicator for interruption as the dependent variable. We included eight explanatory variables; parents' education (two variables), family income, number of siblings, family composition (nuclear family), area of residence at the age of 16 (urban vs rural area), indicator if growing up in a southern state and AFQT score. The results, not reported

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

[11]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.

[12]Keane and Wolpin (1997) argued that a 20% interruption rate may be overstated because of categorizing rules. For instance, if an individual completes a year of college by going to school half-time in two years, he will be recorded as an interrupter and dfined as having attanded school in the second year only.

to save space, were similar for both groups. For those who have obtained more than 12 years of schooling, all parameter estimates were found insignificant at the 10% level (the lowest p-value was 0.14 for the family income variable). For those who obtained 12 years or less, all parameters are also estimated without any precision. The lowest p-values were 0.06 for mother's education and 0.08 for the nuclear family variable.

We take these results as evidence that the decision to interrupt schooling (and return later) can be treated as exogenous and uninformative. Empirical evidence shows that it is certainly uncorrelated with family background and, for a larger number of individuals, the decision is most likely dictated by random events such as physical or mental health problems, desire to involve in particular non-market activities or any other events of this type. Given that excluding interrupters would most likely not introduce selection bias problems and in order to be consistent with our theoretical structure, we decided to exclude these interrupters in the core sample used in this paper, yielding a final sample size of 942 white males, and focus only on wages observed after individuals have left school.[13]

Before discussing descriptive statistics, it is important to describe the construction of some important variables. 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 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. Second, actual experience accumulated by period t (exp_t) is constructed as

$$\exp_t = \sum_{s=\tau_{i+1}}^{t} e_{it} \text{ for } t \geq \tau_{i+1}$$

where e_{it} denotes the fraction of year t that the individual was employed.

Descriptive statistics for the sample used in the estimation can be found in Table A1 (in Appendix). The frequencies for various schooling attainments and completions are in Table B1 (in Appendix). There is a large fraction of young individuals who terminate school after 12 years (high school graduation). The next largest frequency is at 16 years and is most likely corresponding to college graduation. The average schooling completed (by 1990) is 12.9 years.[14]

[13]Arguably, wages observed while an individual is still enrolled in school are mostly earned in part-time jobs and are not representative of the true effects of human capital on wages.

[14]The average schooling attainment at age 16 is between 10 and 11 years.

4 Empirical Results

This section is devoted to the presentation of the empirical results. First, we discuss the structural parameter estimates (Section 4.1) for a model with no consumption value of schooling as well as a model with consumption value. We discuss the capacity of the model to fit the data well and we also illustrate the effects of accumulated human capital on expected rates of unemployment and the effect of discount rate heterogeneity on schooling attainments. In 4.2, we summarize the estimates of the returns to schooling for various model specifications and discuss the importance of the discount rate bias compared to the ability bias. In 4.3, we use the structural parameters to simulate the effects of an increase in the wage return to schooling, an increase in the employment security return to schooling and an increase in the rate of unemployment on schooling attainments. Finally, in Section 4.4, we discuss the implications of our model for the "true intergenerational education correlation" and for intergenerational human capital transfers caused by economic growth driven by human capital accumulation.

4.1 The Parameter Estimates

The parameter estimates found in Table 1A are those obtained under the maintained assumption that there is no consumption value of schooling ($\lambda = 0$). The estimates found in column 1 have been obtained from the estimation of the model under the alternative hypothesis (allowing for the correlation between discount rates and ability). The restricted version of the model, where Corr $(\rho, \upsilon^w) = 0$, is in column 2. The structural estimates can be split into 4 main groups; those related to the income received while at school (parental support) and capturing the effects of family background on the utility of attending school, those related to the wage function, those related to employment rates and, finally, the preference parameters such as discount rates and the marginal utility of schooling (when estimated).

The estimates of the parameters capturing the effects of household characteristics on the utility of attending school are all of the expected sign. The parameter estimates for father's education (0.0202), mother's education (0.0153) and family income (0.0016) are positive significant and indicate that the utility of attending school is increasing with the level of human capital in the household. The parameter estimate for the "nuclear family" indicator is also positive significant (0.0796) and indicates that, other things equal, those raised by both biological parents when they were 14 years old experience a higher utility of attending school. As expected, AFQT scores have also a large positive (significant) effect on the utility of attending school (0.0990). Although of the expected sign, the other estimates (rural, south and siblings) are found to be less significant. Their lower level of significance, along with the relatively modest effects of parents' education and income, is largely explained the introduction of test scores.[15] Finally, the standard deviation of the stochastic shock affecting the utility of attending school is found to be important (0.385).

Turning to the estimates of the wage function and employment security, we note that the estimated wage return to schooling is relatively low (0.0696) and that, as expected, there is a positive significant correlation between test scores (AFQT) and individual wages. The estimates for AFQT scores (0.0213) indicate a return of 2% per decile. The estimates for actual experience (0.0684) and its square (-0.0009) show that our panel in sufficiently long to capture concavity in age earnings profile. The estimates for the effects of education (-0.0907), actual experience (-0.0377) and AFQT scores(-0.0507) on the log inverse employment rate indicate that there is a clear negative significant (positive) relationship between individual unemployment (employment) rates and human capital. More detailed discussions are presented below.

Finally, our estimates of the discount rates (0.0680 for half of the population and 0.0100 for the remaining half), along with their respective sample proportions found in the note below Table 1A, indicate a negative correlation between individual discount rates and individual unobserved ability.[16] The correlation is found to be -0.64. Given that test scores affect the utility of attending school and labor market ability simultaneously, it is also easy to compute the correlation between ability and parental support. The correlation is positive and found to be 0.95. This indicates that, without controlling for measured ability, our estimates would suffer from the ability bias and that the negative correlation between ability and discount rates therefore prevails at the same time as the positive correlation between the utility of attending school and ability in the labor market.

The estimates obtained under the null hypothesis that unobserved labor market ability and individual discount rates are independent, are found in column 2 of Table 1A. Given that AFQT scores still affect parental support and labor market ability (as well as employment security), this model specification is therefore adequate to control for the presence of ability bias. This means that changes in structural parameters, when compared to estimates found in column 1, are most likely attributable to the discount rate bias. Indeed, the restricted model can now be used to test for the presence of a discount rate bias. The effects of ignoring discount rate bias appear relatively obvious. While the parameters capturing the effects of household characteristics on the utility of attending school and the parameters representing the effect of human capital on employment security have not changed significantly, the wage return to schooling is now substantially higher. Ignoring the discount rate bias raises the return to schooling by 1 percentage point per year (from 0.0696 to 0.0800) while both the return to experience

[15] Similar results are reported in Cameron and Heckman (1997) and Belzil and Hansen (1999).

[16] We have tried to extend the model to more than 2 discount factor types but all attempts have indicated that 2 types were sufficient to capture all discount factor heterogeneity.

(0.0668) and the AFQT score premium (0.019) remain more or less at the same level. A likelihood ratio test for the null that individual discount rates and unobserved ability are independent results in a p-value much smaller than 1% and therefore rejects strongly the null hypothesis that there is no discount rate bias. At the same time, the correlation between ability and parental support is still very high (0.93). The large difference between the return to schooling obtained in column 1 and column 2 (0.0696 vs 0.0800) as well as the very low standard errors also indicates a clear evidence that ignoring the discount rate bias can result in a serious over-estimation of the return to schooling. Further discussions of the relative importance of the discount rate bias and the ability bias are delayed to Section 4.2

Before going further, it is natural to ask whether or not our structural model is able to fit the data accurately. As indicated from Table A2 found in appendix, there is a large fraction of young individuals who terminate school after 12 years (high school graduation). The next largest frequency is at 16 years and is most likely corresponding to college graduation. These features are most likely driven by the fact that the utility of continuing school beyond a given level are likely to vary with the level of schooling. For instance, regulations of the minimum school enrollment age (16 years in most states), large increase in tuition costs and fees beyond high school or the like could explain the large frequency at 12 years. Because we allow the effect of parental support to vary with the level of schooling in a quite flexible way (using spline functions), we can expect the frequencies predicted by our model to be relatively close to observed frequencies.

The predicted frequencies (for the restricted as well as the unrestricted model of Table 1A) are found in Table 1B and indicate that the model which controls for the discount rate bias is indeed able to predict schooling attainments quite accurately. This is true at low levels of schooling (6 to 10 years) as well as at higher levels (17 years or more). For the unrestricted model (column 1 of Table 1A), a simple χ^2 test statistic (with 4 degrees of freedom) fails to reject the null hypothesis that the model is properly specified at the 1% level.[17] The critical value (at the 1% level) is 13.3. In particular, we note that model specifications allowing for the correlation between discount rates and labor market unobserved ability is found to fit data on schooling attainments much better than the model specification which ignores the discount rate bias. In particular, a model which ignores the potential correlation between discount rates and unobserved ability appears to underestimate seriously the frequencies at 11-12 years and over-estimates the frequency at 15-16 years.

The estimates for the version of the model where individual preferences allow for a consumption value of schooling are found in Table 2A. It is important to

[17]The goodness of fit is largely explained by the usage of spline functions which capture the irregular behaviour of the utility of attending school as the level of schooling increases. Our estimates of the spline functions indicate very important decrease in parental support after high school graduation.

investigate the properties of the model with a consumption value of schooling as the estimates of the rate of time preference (and therefore the correlation between ability and discount rates) could be affected. Again, we have estimated the model under the null (in column 2) as well as under the alternative (column 1) hypothesis. Given the structure of the instantaneous utility function, the values of the parameter λ (0.13 in column 1 and 0.11 in column 2) indicate that, for a given level of income, accumulated schooling increases utility. The estimates of the discount rates are around 0.05 for type 1 and 0.01 for type 2 and have therefore not changed very much. Apart from some minor changes in the parameter estimates indicating the effect of family background on the utility of attending school, none of the parameters capturing the wage return to human capital or the employment security return to human capital have changed. This is not surprising given that identification of these parameters come from data on wages and unemployment. Ignoring the discount rate bias raises the return to schooling from 0.0665 (column 1) to 0.0779 (column 2) and, again, there is clear evidence that discount rates are negatively correlated with unobserved ability (the correlation is estimated to be -0.54) after controlling for potential ability bias (the correlation between parental support and labor market ability is around 0.93). The likelihood ratio test rejects strongly the null hypothesis that there is no correlation between unobserved labor market ability and individual discount rates.

The capacity of the model to fit observed schooling frequencies is, however, not the only criterion by which the empirical relevance of our model can be judged. Within a dynamic framework, our estimates of the subjective discount factor can also be used to evaluate the accuracy of our model. Equally, given that employment rates play a central part in the model structure, it is important to investigate the implications of the structural parameter for the life cycle behavior of predicted unemployment rate. In order to illustrate the effects of human capital (education and experience) on predicted unemployment rates, we have computed predicted rates at various schooling levels for new entrants in the labor market (experience=0) and for individuals who have accumulated 10 years of experience. These predicted values, along with actual rates of unemployment measured as of 1990, are found in Table 2B. The observed rates of unemployment in 1990 at various schooling levels are averaged over individuals who have accumulated different levels of experience by 1990. The level of experience ranges between 1 to 11 years. Overall, the estimates imply a reasonable decline in individual unemployment rates and predicted unemployment are typically comparable with those observed in the data as of 1990. In particular, our predicted rates of unemployment appear to be very accurate for all those having obtained more than 10 years of schooling. As well, our estimates of the effect of experience indicate a significant decline in unemployment as individuals accumulate labor market experience.

One of our most robust finding is a group endowed with a very low discount rate around 1% per year (type 2) and a second group with a higher rate around 5% per year (type 1). These estimates appear very close to average risk free interest rates computed from historical time series (Kocherlakota, 1996). Given our most reliable estimates of the return to schooling (between 6% and 7% per year), it follows that discounting heterogeneity must have implications for predicted schooling attainments. To illustrate the difference in schooling attainments across discount rate types, we report expected schooling attainments for each type for 4 different model specifications. These are found in Table 2C. The impact of discount factor heterogeneity is easily seen. The average schooling attainments of individuals belonging to type 1 are between 11.0 and 11.5 years (depending on the model specification) while average attainments of those belonging to type 2 average 13 to 14 years of schooling. This indicates that, even after conditioning on individual ability and household human capital, discounting heterogeneity explains a large portion of observed schooling attainments.

4.2 The Return to Schooling: Discount Rate Bias vs Ability Bias

It has been recognized for a long time that ordinary least squares (OLS) estimates can seriously over estimate the true return to schooling. As a consequence, several economists have tried to use instrumental variables or institutional changes in order to obtain more reliable estimates of the effect of an additional year of education. Although many authors have reported that the estimates of the returns to schooling obtained by instrumental variable methods tend to exceed OLS estimates, many estimates are meant to measure a local return to schooling (say around high school graduation or around minimum school leaving age) and it is often difficult to generalize the results to higher and lower levels of schooling.[18] As pointed out by Staiger and Stock (1997), estimates of the returns to schooling obtained using instrumental methods are often faced with the “weak instrument” problem and reported standard errors may be misleading

In the context of the present paper, in which test scores (measured ability) affect wages as well as the utility of attending school, and where a large number of variables measuring household ability are allowed to affect the utility of attending school, it is reasonable to impute the residual correlation between wages and schooling to the correlation between wages and discount factors. However, in the case where test scores are not included in the analysis, our model would fail to capture the positive correlation between the utility of attending school and

[18] Estimates of the return to schooling between 12% and 15% are often reported. The reader will note that such large estimates are hardly compatible with evidence on long run risk free interest rates (averaging 1% to 3%). Card (1998) discusses various reasons why IV estimates may sometimes over-estimate the true return to schooling. Further research on the effect of population unobserved heterogeneity on the returns to schooling (in a random effect framework) appears to be a promising avenue for research.

unobserved ability. This would introduce an additional bias; the ability bias. In order to investigate the relative importance of the ability bias and the discount rate bias, we have re-estimated our most general model, with a consumption value of schooling and we gradually removed AFQT scores from the model specification.

A summary of all estimates of the returns to schooling are found in Table 3.[19] The estimates range from the most restricted model specification, in which test scores affect neither wages nor parental support and in which the correlation between discount rates and ability is 0 (in column 1 of Table 3) to the most general version, already presented in Table 2A, which controls for the ability bias and the discount rate bias (in column 5). The estimate found in column 3 has been obtained after having eliminated AFQT scores from the utility of attending school only and therefore illustrates the effect of assuming that measured ability affects wages but not the utility of attending school (or parental support). The return to schooling reported in column 3 is therefore likely to suffer from the ability bias. The estimate reported in column 2 is just a restricted version of column 3; that is a version where discount rates and ability are forced to be uncorrelated.

The results are consistent with what would normally be expected. The estimate reported in column 1, 0.0973, is the highest and is actually not far from the OLS estimates that would be obtained on any particular cross-section (between 1979 and 1990).[20] The estimate found in column 2, although suffering from both the ability and the discount rate bias, is significantly lower (0.0842) and reflects the importance of introducing test scores in the wage equation. The estimate obtained in column 3, when compared to the most reliable estimate of column 1, illustrates the importance of controlling for the ability bias. After removing AFQT scores from the utility of attending school, the return to schooling increases from 0.0665 (column 5) to 0.0818 (column 3). This increase is therefore even larger than the increase in the return to schooling explained by the discount rate bias; that is the increase from 0.0665 (column 5) to 0.0779 (column 4). To summarize, we find that both the discount rate bias and the ability bias to be important. Our most general and most reliable estimates seem to indicate that the return to schooling, obtained from a model where neither the ability bias nor the discount rate bias are considered, can seriously over-estimate the true return. Indeed, the discount rate bias and the ability bias appear to be of the same size. Our results indicate that there is a 1% return to schooling which can be imputed to the correlation between discount rates and ability while there is at least another 1% which can be imputed to the positive correlation between the per period utility of attending school and labor market ability. Finally, it should be noted that our estimates of the return to schooling appear particularly reliable

[19] As the estimates for the model with no consumption value of schooling are virtually identical, we only report those obtained for the model with a consumption value.

[20] During the period covered by the panel, OLS estimates of the return to schooling range between 0.09 and 0.12.

in view of our estimates of discount factors and empirical evidence on risk free interest rates.

4.3 The Return to Human Capital, Unemployment and Schooling Attainments: Some Simulations

One of the most striking advantages of estimating structural dynamic programming models is the possibility to perform counterfactual simulations. In our model, human capital affects labor market outcomes through wages and through employment security and it would therefore be interesting to investigate the sensitivity of schooling attainments to changes in any of these various aspects. In what follows, we investigate how schooling attainments vary when the wage return to schooling increases, when the employment security return to schooling increases and when the overall rate of unemployment increases (for a fixed employment security return). To illustrate the sensitivity of schooling attainments with respect to these parameter changes, we report mean schooling attainment elasticities. Computing a percentage change in the employment security return to schooling simply requires to modify the slope of the employment security equation (κ_1) and to compute the implied marginal effect on e_{it} . Computing a percentage change in the unemployment rate simply requires to modify the intercept term of the employment security equation (κ_0) and to compute the implied change in the unemployment rate using the fact that the expected rate of unemployment can be approximated by 1-exp(-exp(μ_{it})) .

The elasticities, reported in Table 4, indicate that young males would react much stronger to a change in the wage return to schooling than a change in the employment security to schooling or a change in the rate of unemployment. Elasticities of schooling attainments with respect to the wage return are found to be around 0.30 for both unrestricted model (Table 1A and Table 2A). Although increasing the job security return to schooling also increase schooling attainments, the elasticity appears very small. It averages 0.004. This result can be explained by the fact that, although individuals are assumed to be risk averse, the degree of risk aversion imbedded in a logarithmic utility function is relatively mild.[21] A similar argument applies to the reported elasticity with respect to a change in the rate of unemployment. When there is an overall increase in the rate of unemployment (obtained by changing the intercept term of the employment security function), individuals respond by increasing their schooling attainments. The relatively low elasticity (0.04) indicates that the percentage increase in schooling attainment is much lower than the percentage increase in the rate of unemployment.

[21] Belzil and Hansen (1999) estimate a dynamic programming model of schooling decisions where the per-period utility function is a power utility function. They find a degree of risk aversion commensurate with a logarithmic utility function.

4.4 Human Capital, Growth and the Intergenerational Education Correlation

The correlation between individual schooling attainments and parents' education (the intergenerational education correlation) is well established. In the panel analyzed in this paper, a regression of father's and mother's education on individual schooling attainments (as of 1990) lead an effect of 0.244 for father's education and 0.216 for mother's education. These values, found in the last column of Table 5A, measure the cross-sectional correlation between parents' and children's education. However, as for the correlation between wages and education, economists should be reluctant to view the sample correlation as a measure of the causal relationship between parents' and children's education. Indeed, our estimates (Table 1A and Table 2A) indicate that after controlling for various measures of individual and household ability, the true effect of parents' schooling on children's schooling attainment is small. As such, our structural estimates can be used to simulate the effect of a counterfactual increase in the level of human capital (years of schooling) of the parents holding individual ability and the like constant. To do so, we have computed expected schooling attainments obtained when parents' education are increased by one year each. The results, in Table 5A, indicate that the true effect of an increase of 1 year in parents' education is around 0.09 year for the father (the effects vary between 0.06 and 0.10) and around 0.07 year (for both unrestricted models) for the mother. The true intergenerational education correlation is therefore 2 to 3 times smaller than the cross-sectional correlation.

In view of the recent revival of neo-classical growth models, which are based on human capital theory (Lucas, 1988, Barro and Sala-i-Martin, 1995), our model can be used to simulate the macroeconomic counterpart of our microeconomic estimates.[22] In particular, a model that captures the true intergenerational correlation and the true effect of household income (holding other factors such as the distribution of observed and unobserved ability) can therefore be used to evaluate the intergenerational human capital transfers that would take place if the average level of schooling was increased exogenously in a stationary economy.[23] In order to perform this simulation, we increase the overall level of schooling by 1 year (for both fathers and mothers) and accompany this increase by the change in household income which would normally follow an exogenous increase in human capital using the estimated return to schooling for each particular model. This exercise can therefore be used to measure the increase in both schooling attainments and labor market productivity of the next generation explained by

[22]It seems to be widely accepted (in the empirical growth literature) that the average level of schooling affects growth rates but that changes in schooling have only limited effects. However, Topel (1999) presents empirical evidence which contradicts that result.

[23]In practice, such exogenous increases are rarely observable. However, changes in schooling attainments explained by increased public investments in schools, or increase in school quality can be seen as policies targeted at the same objectives. For a discussion, see Topel (1999).

economic growth resulting from a exogenous increase in the level of schooling of the previous generation.

The results, found in Table 5B, indicate that an increase of 1 year in the average level of schooling, accompanied by a 6% growth rate in income, will raise the level of human capital of the next generation by approximately 0.15 year of schooling. In terms of productivity growth, and assuming that the return to schooling is time invariant, this increase in schooling attainments translates into a 1% productivity (wage) growth. Inasmuch as these estimates indicate a clear decreasing return to scale to intergenerational human capital transfers, they also illustrate the dynamics of human capital growth. In particular, they illustrate the lagged effects of human capital accumulation. Although, following Lucas (1988), more general theoretical growth models have been introduced, which involve overlapping generations and human capital transfers across generations, our results have arguably no benchmark in the empirical growth literature based on cross-country growth rate comparisons. Nevertheless, they suggest that the links between microeconomic model of human capital accumulation and empirical growth models should be an interesting avenue for future research.

5 Conclusion

We have estimated a dynamic programming model of schooling decisions in which individual ability, household human capital and individual discount factor heterogeneity played a substantial role. The model is general enough to capture the fact that parental educational background is correlated with the utility of attending school and that individual ability (as measured by AFQT scores) has an effect on both the utility of attending school and labor market wages. As a consequence, our model is capable of capturing the true correlation between unobserved ability and individual discount rates while controlling for a potential ability bias.

Not surprisingly, we have found that parents' education background increase the utility of attending school but also found that the true intergenerational education correlation is quite low. The positive correlation between income while at school and parents education can be explained by the fact that parents with higher social status provide more generous intergenerational transfers or reduce the disutility of school enrollment. After controlling for individual and household ability, discounting heterogeneity is found to be important. Our estimates of individual discount factors fluctuate between 1% and 5% per year. These estimates appear very close to average risk free interest rates computed from historical time series (Kocherlakota, 1996). The flexible estimation of the joint distribution of individual discount rates and unobserved ability in the labor market (also allowed to be correlated with parents' education) has clearly indicated that individual subjective discount rates and labor market ability are negatively correlated.

Allowing for correlation between discount factors and ability had a particularly remarkable impact on the estimates of the return to schooling. We find that both the discount rate bias and the ability bias to be important. Our most general and most reliable estimates seem to indicate that the return to schooling, obtained from a model where neither the ability bias nor the discount rate bias are considered, can seriously over-estimate the true return. Our results indicate that there is a 1% return to schooling which can be imputed to the correlation between discount rates and ability while there is at least another 1% which can be imputed to the positive correlation between the per period utility of attending school and labor market ability. Our estimates of the true return to schooling are quite robust; they range between 6.5% and 6.9% per year.

Various simulations indicated that young males would react much stronger to a change in the wage return to schooling than a change in the employment security to schooling or a change in the rate of unemployment. As our model has implications for the intergenerational human capital transfers, it has been used to simulate the effects of an increase in human capital of one generation on schooling attainments and labor market productivity of the next generation. We found that an increase of 1 year in the average level of schooling, accompanied by a 6% growth rate in income, will raise the level of human capital of the next generation by approximately 0.15 year of schooling. In terms of productivity growth, and assuming that the return to schooling is time invariant, this increase in schooling attainments translates into a 1% productivity (wage) growth. Although our results have arguably no benchmark in the empirical growth literature, we believe that microeconomic models of human capital accumulation can be used to learn about the process by which human capital is transferred across generations and, therefore, explain cross country differences in economic growth.

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Table 1A.
Structural Estimates without Schooling Consumption Value
(Asymptotic standard errors in parentheses)

Variable	Parameter	(1)	(2)
Income at school			
Intercept	δ_1	1.0541 (0.007)	0.8360 (0.006)
Nuclear family	δ_2	0.0796 (0.027)	0.0967 (0.043)
Siblings	δ_3	-0.0031 (0.007)	-0.0027 (0.009)
Rural	δ_4	-0.0118 (0.002)	-0.0216 (0.032)
South	δ_5	0.0237 (0.031)	-0.0192 (0.027)
Fam. income / 1,000	δ_6	0.0016 (0.0005)	0.0025 (0.001)
Father's education	δ_7	0.0202 (0.002)	0.0242 (0.005)
Mother's education	δ_8	0.0153 (0.005)	0.0073 (0.008)
Test score (AFQT/10)	δ_9	0.0990 (0.006)	0.0899 (0.007)
Standard error	σ_ξ	0.3850 (0.011)	0.4491 (0.016)
Wage equation			
Education	φ_1	0.0696(0.005)	0.0800 (0.003)
Experience	φ_2	0.0684 (0.006)	0.0668 (0.002)
Experience^2	φ_3	-0.0009 (0.0001)	-0.0009 (0.0001)
Test score (AFQT/10)	φ_4	0.0213 (0.003)	0.0187 (0.003)
Individual effect	υ_1^w	1.4891 (0.076)	1.4048 (0.048)
Individual effect	υ_2^w	1.0377 (0.064)	0.9676 (0.059)
Standard error	σ_w	0.3185 (0.003)	0.3208 (0.003)
Employment security			
Intercept	κ_0	-2.7715 (0.306)	-2.7827 (0.056)
Education	κ_1	-0.0907 (0.009)	-0.0902 (0.011)
Experience	κ_2	-0.0377 (0.003)	-0.0376 (0.003)
Test score (AFQT/10)	κ_3	-0.0507 (0.008)	-0.0491 (0.009)
Standard error	σ_e	1.4728 (0.013)	1.4730 (0.013)
Preferences			
Taste for schooling	λ	0.0 (restricted)	0.0 (restricted)
Discount rate	ρ_1	0.0680 (0.002)	0.0551 (0.001)
Discount rate	ρ_2	0.0100 (0.001)	0.0127 (0.001)
Corr (ρ, υ^w)		-0.64	0.0 (restricted)
Corr (ξ_i, φ_{0i})		0.9492	0.9267
P-value for L.R. test Corr = 0		0.001	
Mean Log Lik.		-15.0113	-15.0662

Notes: The sample proportions for (υ_1^w, ρ_1), (υ_2^w, ρ_1), (υ_1^w, ρ_2), and (υ_2^w, ρ_2) are 0.06, 0.40, 0.42, and 0.12 respectively in Column 1, and 0.22, 0.29 0.21, and 0.28 respectively in column 2. Estimates for the splines are not reported to save space.

Table 1B.
Model Fit: Actual vs Predicted Schooling Attainments

	Predicted (%) (Table 1A, Col. 1)	Predicted (%) (Table 1A, Col. 2)	Actual (%)
Schooling:			
6-10 years	9.17	11.37	12.21
11-12 years	52.22	43.51	50.53
13-14 years	11.02	6.84	11.04
15-16 years	19.20	28.11	18.90
17 or more	8.39	10.17	7.32
$\chi^2_{4d.f.}$	11.61	72.37	-
P-value	0.022	0.000	-

Note: The critical value, at a 1% level, is 13.3

Table 2A.
Structural Estimates with Schooling Consumption Value
(Asymptotic standard errors in parentheses)

Variable	Parameter	(1)	(2)
Income at school			
Intercept	δ_1	-0.5314 (0.015)	-0.8330 (0.117)
Nuclear family	δ_2	0.0441 (0.016)	0.1184 (0.040)
Siblings	δ_3	-0.0056 (0.005)	-0.0097 (0.008)
Rural	δ_4	-0.0344 (0.014)	-0.0269 (0.038)
South	δ_5	0.0038 (0.014)	-0.0249 (0.036)
Fam. income / 1,000	δ_6	0.0014 (0.0001)	0.0013 (0.0007)
Father's educ	δ_7	0.0138 (0.005)	0.0262 (0.006)
Mother's educ	δ_8	0.0181 (0.007)	0.0074 (0.007)
Test score (AFQT/10)	δ_9	0.1123 (0.005)	0.1037 (0.008)
Standard error	σ_ξ	0.4576 (0.017)	0.4124 (0.011)
Wage equation			
Education	φ_1	0.0665 (0.002)	0.0779 (0.003)
Experience	φ_2	0.0669 (0.002)	0.0663 (0.002)
Experience^2	φ_3	-0.0009 (0.0001)	-0.0008 (0.0001)
Test score (AFQT/10)	φ_4	0.0232 (0.003)	0.0193 (0.003)
Individual effect	υ_1^w	1.5060 (0.022)	1.4155 (0.021)
Individual effect	υ_2^w	1.0604 (0.020)	0.9834 (0.021)
Standard error	σ_w	0.3193 (0.003)	0.3210 (0.003)
Employment security			
Intercept	κ_0	-2.7785 (0.0438)	-2.7891 (0.052)
Education	κ_1	-0.0885 (0.009)	-0.0893 (0.007)
Experience	κ_2	-0.0375 (0.003)	-0.0377 (0.003)
Test score (AFQT/10)	κ_3	-0.0501 (0.008)	-0.0513 (0.008)
Standard error	σ_e	1.4731 (0.013)	1.4728 (0.014)
Preferences			
Taste for schooling	λ	0.1299 (0.007)	0.1139 (0.016)
Discount rate	ρ_1	0.0529 (0.001)	0.0459 (0.001)
Discount rate	ρ_2	0.0109 (0.0001)	0.0129 (0.0001)
Corr (ρ, υ^w)		-0.54	0.0 (restricted)
Corr (ξ_i, φ_{0i})		0.9683	0.9470
P-value for L.R. test Corr= 0		0.001	
Mean Log Lik.		-15.0051	-15.0604

Notes: The sample proportions for (υ_1^w, ρ_1), (υ_2^w, ρ_1), (υ_1^w, ρ_2), and (υ_2^w, ρ_2) are 0.04, 0.34, 0.41, and 0.21 respectively in Column 1, and 0.16, 0.16, 0.34, and 0.34 respectively in column 2. Estimates for the splines are not reported to save space.

Table 2B.
Unemployment and Education: Predicted and Actual Unemployment Rates

Level of Schooling	Unemployment Rates Predicted Exp = 0	 Predicted Exp = 10 years	 Actual (in 1990)
10 years	0.067	0.048	0.010
12 years	0.045	0.031	0.070
14 years	0.027	0.020	0.030
16 years	0.023	0.017	0.020
18 years	0.018	0.011	0.010
20 years	0.014	0.007	0.010

Notes: Predicted unemployment rates are calculated using the average AFQT score for each schooling attainment level.

Table 2C.
Discount Rates and Mean Schooling attainments

	Table 1A Column 1	Table 1A Column 2	Table 2A Column 1	Table 2A Column 2
Type 1				
ρ_1	0.068	0.055	0.053	0.046
E (Education)	11.5 years	11.4 years	11.3 years	11.2 years
Type 2				
ρ_2	0.010	0.013	0.011	0.013
E (Education)	14.2 years	14.4 years	14.2 years	13.4 years

Notes: Schooling attainment is calculated for a representative agent with family background variables set to averages (medians for the dummy variables).

Table 3.
Discount Rate Bias, Ability Bias and the Returns to Schooling:
The Case with Consumption Value of Schooling

	The Return to Schooling				
	(1)	(2)	(3)	(4)	(5)
AFQT in ξ_t	no	no	no	yes	yes
AFQT in log w_t	no	yes	yes	yes	yes
Corr (ρ_i, φ_{0i})	0.0	0.0	-0.20	0.0	-0.54
Corr (ξ_i, φ_{0i})	0.0	0.0	0.0	0.31	0.30
Return	0.0973	0.0842	0.0818	0.0779	0.0665

Table 4.
Mean Schooling Elasticities with respect to
the Wage Return and the Job Security Return to Schooling

Parameter	Table 1A Column 1 $\frac{\Delta\% E(Educ)}{\Delta\%\ param.}$	Table 1A Column 2 $\frac{\Delta\% E(Educ)}{\Delta\%\ param.}$	Table 2A Column 1 $\frac{\Delta\% E(Educ)}{\Delta\%\ param.}$	Table 2A Column 2 $\frac{\Delta\% E(Educ)}{\Delta\%\ param}$
Wage Return	0.326	0.151	0.286	0.305
Job Security Return	0.003	0.004	0.005	0.005
Unemployment Rate	0.042	0.039	0.040	0.040

Note: Schooling attainment is calculated for a representative agent with family background variables set to averages (medians for the dummy variables).

Table 5A.
The True Intergenerational Education Correlation

Parameter	Table 1A Column 1 $\frac{\Delta E(Educ)}{\Delta parents^{\prime}.educ}$	Table 1A Column 2 $\frac{\Delta E(Educ)}{\Delta parents^{\prime}.educ.}$	Table 2A Column 1 $\frac{\Delta E(Educ)}{\Delta parents^{\prime}.educ.}$	Table 2A Column 2 $\frac{\Delta E(Educ)}{\Delta parents^{\prime}.educ}$	Cross-section $\frac{\Delta E(Educ)}{\Delta parents^{\prime}.educ}$
Father's educ	0.09	0.09	0.06	0.10	0.24
Mother's educ	0.07	0.03	0.07	0.03	0.22

Note:Schooling attainment is calculated for a representative agent with other family background variables set to averages (medians for the dummy variables).

Table 5B.
Human Capital, Growth and Intergenerational Transfers

Parameter	Table 1A Column 1	Table 1A Column 2	Table 2A Column 1	Table 2A Column 2
$\frac{\Delta E(Educ)}{\Delta\ parents^{\prime}educ}$	0.17	0.13	0.14	0.14
$\frac{\Delta E(\log w)}{\Delta parents^{\prime}.educ}$	0.01	0.01	0.01	0.01

Note: Schooling attainment is calculated for a representative agent with other family background variables set to averages (medians for the dummy variables). The change in parents' education is accompanied by the equivalent increase in income (obtained from the estimated return to schooling).

Table A1. Descriptive Statistics.

Variable	Mean	Std. Dev.	# Individuals
prop. raised in urban areas	0.72	-	942
father's educ (years)	11.84	3.44	942
mother's educ (years)	11.69	2.53	942
family income in 1978	40,282	28,179	942
number of siblings	3.05	2.02	942
prop. growing up in nuclear family	0.81	-	942
prop. raised in southern states	0.26	-	942
AFQT score	47.03	29.00	942
education completed (as of May 1990)	12.94	2.54	942
prop. students (in 1990)	0.01	-	942
wage 1979 (per hour)	5.84	0.62	4
wage 1980(per hour)	6.51	2.40	120
wage 1981 (per hour)	6.78	2.71	251
wage 1982 (per hour)	6.99	3.00	412
wage 1983 (per hour)	6.77	2.86	503
wage 1984 (per hour)	7.21	3.36	594
wage 1985 (per hour)	7.79	3.40	649
wage 1986 (per hour)	8.61	3.79	670
wage 1987 (per hour)	9.42	4.39	717
wage 1988 (per hour)	10.30	4.97	762
wage 1989 (per hour)	10.41	5.05	767
wage 1990 (per hour)	11.06	5.32	766
actual work experience 1979	0.10	1.81	941
actual work experience 1980	0.26	1.92	915
actual work experience 1981	0.55	2.06	899
actual work experience 1982	0.98	2.23	886
actual work experience 1983	1.52	2.43	861
actual work experience 1984	2.18	2.63	842
actual work experience 1985	2.85	2.62	809
actual work experience 1986	3.61	2.82	775
actual work experience 1987	4.46	2.95	742
actual work experience 1988	5.37	3.04	714
actual work experience 1989	6.30	3.12	685
actual work experience 1990	7.25	3.21	639

Notes:
Family income and hourly wages are reported in 1990 dollars. Family income is measured as of May 1979 (for 1978). The increasing number of wage observations (until 1988) is explained by the increase in participation rates (schooling completion).

Table A2. Observed Schooling Attainments in the NLSY (1990).

Schooling	Freq. (%)	# of individuals
7 years	0.4	4
8 years	1.9	18
9 years	4.4	41
10 years	5.5	52
11 years	8.3	78
12 years	42.3	398
13 years	5.5	52
14 years	5.5	52
15 years	2.1	20
16 years	16.8	158
17 years	2.1	20
18 years	2.2	21
19 years	1.2	11
20 years	1.8	17