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STRUCTURAL ESTIMATES OF THE INTERGENERATIONAL EDUCATION CORRELATION**

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SUMMARY

Using a structural dynamic programming model, we investigate the relative importance of family background variables and individual specific abilities in explaining cross-sectional differences in schooling attainments and wages. Each type of ability is the sum of one component correlated with family background variables and a residual (orthogonal) component which is purely individual specific. Household background variables (especially parents' education) account for 68% of the explained cross-sectional variations in schooling attainments, while ability correlated with background variables accounts for 17% and pure individual specific ability accounts for 15%. Interestingly, individual differences in wages are mostly explained by pure individual specific abilities as they account for as much as 73% of the explained variations in wages. Family background variables account for only 19%, while ability endowments correlated with family background account for 8%. Copyright © 2003 John Wiley & Sons, Ltd.

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.[1] At the micro level, it is customary to assume a strong correlation between one's schooling attainment and household background variables (especially parents' 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 background variables. At the same time, innate ability, also correlated with household background variables, should have an impact on the decision to attend school and on labour market wages.

The net effects of household background variables on individual schooling attainments are far from obvious. On the one hand, households that have higher income may transfer more resources to their children and reduce the opportunity cost of school attendance. On the other hand, wealthier

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[1] Indeed, the recent revival of neo-classical growth models is largely based on human capital theory (Lucas, 1988). 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).

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households also face a higher opportunity cost of spending time with children and may reduce their time investment in children. The effect of innate ability on school attendance is also unclear. If skill endowments are strongly correlated with household background variables (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 labour market).

The simultaneous effects of parents' background variables on the opportunity cost of schooling and on both school and market abilities are at the centre of the strong cross-sectional correlation between household background variables and individual schooling attainments. Whether individual schooling attainments are more affected by household background variables or innate ability remains an open question.

The main objective of the present paper is to estimate a structural model of schooling decisions which will allow us to answer the following two questions.

1. How much of individual differences in schooling attainments is explained by individual ability heterogeneity as opposed to differences in household background variables?
2. How much of predicted wages is explained by individual ability heterogeneity as opposed to differences in household background variables?

As far as we know, and despite the amount of work devoted to the determinants of schooling, neither of these questions have been precisely answered to date. In this paper, we estimate two complementary versions of a finite horizon dynamic programming model on a panel of white males taken from the National Longitudinal Survey of Youth (NLSY). The panel covers the period from 1979 until 1990.

First, we estimate a model specification (Model 1) where individuals are endowed with exogenous household characteristics and innate abilities. Labour 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 background variables and an unobserved component representing idiosyncratic ability which is orthogonal to household background variables. Using the parameter estimates, we simulate the model and recover the implied correlations between schooling attainments and all the determinants of interest. In this framework, it is impossible to distinguish the effects of parents' background on the per-period utility of attending school from the effects of household background variables on scholastic ability.

As a second step, we estimate a version of the model in which Armed Forces Qualification Tests (AFQT) scores are used as an observable (although imperfect) measure of scholastic ability. As AFQT scores are known to be strongly correlated with household background variables, it is possible to distinguish between an ability component correlated with household characteristics and a residual component which is orthogonal to family background variables. This approach allows us to measure the direct effects of household background variables on the per-period utility of attending school (net of the effects of these same variables on scholastic ability).

Altogether, the results provide a relatively clear picture of the importance of family background variables. Given scholastic ability, household background accounts for 68% of the explained cross-sectional variations in schooling attainments. Interestingly, more than half of this 68% is explained by father's and mother's schooling alone. However, around half of the residual source (approximately 15%) of explained variations due to abilities is also explained by family background variables. When taken as a whole, family background variables may therefore account for 85% of the explained cross-sectional variations in schooling attainments. However, individual differences in wages are mostly explained by ability endowments. Parents' background variables account for 27% of the explained variations in wages, while unobserved abilities (orthogonal to family background variables) account for 73%. When scholastic ability is correlated with family background variables, the role of ability is even stronger. Ability endowments explain as much as 81% of wages, while only 19% is explained by family background variables.

The main features of the paper are the following. A brief review of the literature is found in Section 2. Section 3 is devoted to the presentation of the dynamic programming model. The main empirical results are discussed in Section 4. The conclusion is in Section 5.

2. THE CORRELATION BETWEEN FAMILY BACKGROUND VARIABLES AND SCHOOLING ATTAINMENTS

In recent years, numerous papers concerned with the dynamics of schooling attainments have stressed the importance of parental background and family environment as one of the major determinants of the probability of transiting from one grade level to the next. This positive correlation between individual schooling attainments and parents' education is well established in simple correlation analysis (Kane, 1994), in reduced-form dynamic models such as Cameron and Heckman (1998, 2001), as well as in structural dynamic programming models such as Keane and Wolpin (1997), Eckstein and Wolpin (1999) and Belzil and Hansen (2001, 2002). Most studies set in a dynamic framework also point out that the other major determinant is permanent unobserved heterogeneity, which may represent unobservable factors such as individual specific taste for schooling, academic ability, motivation, differences in discount rates or any other unobservable trait which is time-invariant.[2]

As a starting point, the strong intergenerational education correlation may be best illustrated by simple OLS estimates of the effects of parents' background variables on schooling. These are in Table I. The parents' background variables are those normally used by researchers who use the NLSY and are discussed in more detail in the next section. The regressions indicate that schooling increases with father's schooling, mother's schooling, family income and that schooling is higher for those who have been raised by both parents (we refer to this variable as the 'nuclear family'). On the other hand, schooling decreases with the number of siblings and is lower for those living in the south and in rural areas. None of these results are surprising. As pointed out by Cameron and Heckman, father's and mother's education are by far the most important family background variables (they account for as much as 83% of the explained variations).

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 behaviour. While their model does not allow them to estimate the direct effect of household background variables and perform a variance decomposition, 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 their model, the utility of attending school depends explicitly on household background variables but, after conditioning on schooling, labour market outcomes are unaffected by parental background

[2] Cameron and Heckman refer to parents' education and individual abilities as 'long run factors'.

Table I. OLS estimates of the effects of family background variables on schooling attainments

	(1)	(2)	(3)	(4)
Intercept	1.1500	1.3070	2.1159	2.1043
	(0.0834)	(0.0818)	(0.09380)	(0.1031)
Father's education	0.2565	0.2199	0.2073	0.2073
	(0.0061)	(0.0061)	(0.0061)	(0.00610)
Mother's education	0.2279	0.1948	0.1776	0.1683
	(0.0086)	(0.0085)	(0.0085)	(0.0085)
Household income		0.0178	0.0173	0.0155
		(0.0006)	(0.0006)	(0.0007)
Siblings			−0.1391	−0.1454
			(0.0081)	(0.0081)
Nuclear family				0.4312
				(0.0420)
Rural				−0.0496
				(0.0378)
South				−0.3478
				(0.0379)
R^2	0.2553	0.2864	0.2985	0.3060
Sample size	1708	1708	1708	1708

variables.[3] While empirical evidence reported in all the papers cited above indicates that school attendance increases with household background variables, the relative importance of household characteristics and unobserved abilities remains difficult to evaluate.

3. THE MODEL

Individuals are initially endowed with household background variables, 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 labour market or continue to 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 labour market). Every decision is made at the beginning of 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 background 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

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

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

[3] Sauer (2001) investigates the impact of education financing means on lifetime earnings. His analysis is targeted towards a very particular sample of elite Law School graduate students.

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 reported as of 1978 and measured in units of \$1000. The term v_i^{ξ} represents individual heterogeneity (ability) affecting the utility of attending school. It is discussed in more detail 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 $I_t = 1$, the decision problem is frozen for one period. If $I_t = 0$, 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.[4]

Once the individual has entered the labour 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 is

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

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

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

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 v_i^w is unobserved labour 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 $e_{it}^* = \log(1/e_{ti})$ and where ε_{it}^e is a random shock normally distributed with mean 0 and variance σ_e^2.[5] The employment rate is also allowed to depend on accumulated human capital (S_{it} and $Exper_{it}$) so that

$$\mu_{it} = \kappa_1(S_{it}) + \kappa_2(Exper_{it}) + \kappa_3(Exper_{it}^2) + v_i^e \tag{3}$$

where v_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 return to experience. As is

[4] 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.

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

usually the case in the literature, we assume that all random shocks ($\varepsilon_{it}^{\xi}, \varepsilon_{it}^{w}, \varepsilon_{it}^{e}$) are 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_t^{ξ}), the wage shock (ε_t^{w}), accumulated experience $(Exper_t)$ and a set of individual characteristics. As is often done in dynamic optimization problems, the solution to the stochastic dynamic problem can be characterized using recursive methods (backward induction). After dropping the individual subscript for convenience, the decision to remain in school, given state variables S_t and η_t, denoted $V_t^s(S_t, \eta_t)$, can be expressed as

$$V_t^s(S_t, \eta_t) = X'\delta + \psi(S_t) + \upsilon^{\xi} + \varepsilon_t^{\xi} + \beta\{\zeta \cdot EV_{t+1}^I(S_{t+1}, \eta_{t+1}) + (1-\zeta) \cdot EMax[V_{t+1}^s(S_{t+1}, \eta_{t+1}), V_{t+1}^w(S_{t+1}, \eta_{t+1})]\}$$

or, more compactly, as

$$V_t^s(S_t, \eta_t) = X'\delta + \psi(S_t) + \upsilon^{\xi} + \varepsilon_t^{\xi} + \beta E(V_{t+1}|d_t = 1) \tag{4}$$

where $V_t^I(S_t, \eta_t)$ denotes the value of interrupting schooling acquisition and where $E(V_{t+1}|d_t = 1)$ 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, $V_{t+1}^I(S_t, \eta_t)$, can be expressed in a similar fashion.

The value of stopping school (that is entering the labour 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), $V_t^w(S_t, \eta_t)$, is given by

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

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

$$E(V_{t+1}|d_t = 0) = \sum_{j=t+1}^{T} \beta^{j-(t+1)} \left[-\exp\left(\mu_j + \frac{1}{2}\sigma_e^2\right) + \varphi_1(S_j) + \varphi_2(Exper_j) + \varphi_3(Exper_j^2) \right]$$

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.

3.1. Abilities in School and in the Labour Market

The first model specification (Model 1) is constructed so as to separate and quantify the contributions of individual specific endowments according to two groups; individual specific attributes correlated with household background variables and purely individual specific abilities/tastes (orthogonal to parents' background). By conditioning on scholastic ability, Model 2 will allow us to disentangle the effects of family or environmental influences from innate genetic endowments of ability.

Model 1

Ability heterogeneity has three dimensions: school ability (v_i^ξ), market ability affecting wages (v_i^w) and market ability affecting employment rates (v_i^e). In the first model specification, the unobserved ability regression function is given by the following expression:

$$v_i^s = X_i' \gamma^s + \tilde{v}_i^s \tag{6}$$

for $s = \xi$, w and e. We assume that there are K types of individuals and set $K = 6$. Each type is endowed with a vector $(\tilde{v}_k^w, \tilde{v}_k^\xi, \tilde{v}_k^e)$. 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 to normalize q_6 to 0.

Estimation of this 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 background variables on the utility of attending school (the δ's) from the effect of household background variables on individual school ability. As a consequence, we set $\gamma^\xi = 0$. In practice, this normalization implies that our estimates of the effect of parents' background are the sum of a direct effect on the utility of attending school and an indirect effect capturing the transmission of ability across generations.[6]

Model 2

The availability of data on AFQT scores is a promising avenue for disentangling the effects of household background variables on the utility of attending school from its effects on scholastic ability. While a simple option is to estimate the model conditional on AFQT scores,[7] we construct our estimation strategy on the idea that AFQT scores are a noisy estimator of relevant scholastic ability (v_i^s) and on the fact that the relevant measure of scholastic ability (v_i^s) is given by equation (6). That is

$$AFQT_i = v_i^\xi \cdot \lambda + \eta_i = (X_i' \gamma^\xi + \tilde{v}_i^\xi) \cdot \lambda + \eta_i \tag{7}$$

A consistent estimator of the effects of household background variables on $AFQT(\gamma^\xi \cdot \lambda)$ is easily obtained using OLS and may be used at the structural estimation stage. The orthogonal components of school and market abilities are treated as in Model 1.

3.2. 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 six 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 ($\tilde{t}$) to 22. Constructing the likelihood

[6] The degree of under-identification faced in the estimation of a dynamic programming model necessitates some parametric assumptions as discussed in detail in Rust (1994) and Magnac and Thesmar (2001).

[7] This approach implies that $v_i^\xi = \lambda \cdot AFQT_i + \tilde{v}_i^\xi$.

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

$$\Pr(d_{t+1} = 0|d_t = 1) = (1 - \zeta) \cdot \Pr(V_t^w(S_t) \geq V_t^s(S_t)) \tag{8}$$

$$\Pr(d_{t+1} = 1|d_t = 1) = (1 - \zeta) \cdot \Pr(V_t^w(S_t) < V_t^s(S_t)) \tag{9}$$

$$\Pr(I_{t+1} = 1|d_t = 1) = \zeta \tag{10}$$

where $\Pr(V_t^w(S_t) \geq V_t^s(S_t))$ is easily evaluated using equations (4) and (5). Equation (8) represents the probability of exercising the right to leave school permanently in $t+1$ (implicitly assuming $I_{t+1} = 0$), while equation (9) represents the probability of staying in school to acquire an additional year of human capital (also implicitly assuming $I_{t+1} = 0$). Equation (10) 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 easily be derived from equations (8), (9) and (10):

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

- The probability of entering the labour 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:

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

- 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 labour market histories observed from $\tau + 2$ until 1990 is given by

$$L_3 = \Pr(\{\tilde{w}_{\tau+2}\} \ldots \{\tilde{w}_{1990}\}) = \Pr(\{w_{\tau+2} \cdot e_{\tau+2}\} \cdot \cdots \cdot \Pr\{w_{1990} \cdot e_{1990}\})$$

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

$$\log L_i = \log \sum_{j=1}^{K=6} p_j \cdot L_i(\cdot|v_j) \tag{11}$$

where each p_j represents the population proportion of type v_j.

4. EMPIRICAL RESULTS

In Section 4.1, we discuss the structural estimates of the effects of household background variables on the utility of attending school and on labour market outcomes. In Section 4.2, we perform some variance decompositions in order to investigate the relative importance of household background variables and abilities in explaining differences in schooling attainments and wages. In Section 4.3, we briefly discuss the true intergenerational education correlation implied by the model and compare it with the reduced-form correlation estimates.

4.1. The Effects of Family Background Variables

To facilitate presentation of the results, we split the parameter estimates between three tables. The effects of household background variables on the utility of attending school and labour market outcomes are in Table IIA. The remaining structural parameters of the utility of attending school and the return to schooling are in Table IIB. The estimates summarizing the distribution of unobserved heterogeneity (labour market ability, taste for schooling) are found in Table IIC.

As the principal objective of this paper is to evaluate the relative importance of household background variables and unobserved abilities, we do not discuss all parameter estimates in detail. Instead, we focus on those that will enable us to answer 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 (2002).[8]

Parameter Estimates in Model 1

The parameter estimates for the effects of household background variables on the utility of attending school and labour market outcomes for Model 1 are found in Table IIA (column 1). As explained before, this model specification does not allow for a separate identification of the effects of household background variables on the utility of attending school and on scholastic ability. The normalization imposed at the estimation stage implies that all effects of household background variables on schooling attainments are captured in the utility of attending school (the δ's).

The estimates indicate clearly that, other things equal, the utility of attending school is increasing in father's education (0.0205) and household income (0.0017). Interestingly, the effect of female education is negative (−0.0080). The relatively weak effect of female education may be explained by the fact that more educated females tend to work more in the labour market and spend less time with their children. The results for siblings (−0.0157) indicate that those raised in families with a smaller number of children tend to have a higher utility of attending school while those raised in a nuclear family enjoy a higher utility of attending school (0.0387). Finally, those raised in the south (−0.0412) and in rural areas (−0.0618) experience a lower utility of attending school. Our estimate of the yearly discount rate (0.33% per year) is relatively low. It may however be a reflection of the young age at which schooling decisions are made and, in particular, of the very high survival probability of young white males.

[8] As documented in Belzil and Hansen (2002), 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 IIB) indicates that a model with constant marginal (local) returns would be strongly rejected.

Table IIA. The effects of household background variables on the utility of attending school and labour market outcomes

	Model 1 Parameter (std. dev.)	Model 2 Parameter (std. dev.)
Utility of attending school (δ)		
Father's education	0.0205 (0.0024)	0.0154 (0.0010)
Mother's education	−0.0080 (0.0025)	−0.0131 (0.0026)
Household income	0.0017 (0.0002)	0.0009 (0.0003)
No. siblings	−0.0156 (0.0012)	−0.0111 (0.0027)
Nuclear family	0.0387 (0.0065)	0.0633 (0.0142)
Rural	−0.0618 (0.0125)	−0.0176 (0.0130)
South	−0.0412 (0.0045)	−0.0390 (0.0130)
Ability in school ($\gamma^{\epsilon} \cdot \lambda$)		
Father's education	–	0.0069 (0.0021)
Mother's education	–	0.0065 (0.0014)
Household income	–	0.0008 (0.0001)
No. siblings	–	−0.0040 (0.0019)
Nuclear family	–	0.0025 (0.0013)
Rural	–	−0.0023 (0.0010)
South	–	−0.0131 (0.0007)
Wages (γ^{w})		
Father's education	0.0106 (0.0021)	0.0131 (0.0023)
Mother's education	−0.0144 (0.0022)	−0.0141 (0.0027)
Household income	0.0012 (0.0003)	0.0013 (0.0003)
No. siblings	−0.0084 (0.0023)	−0.0088 (0.0025)
Nuclear family	0.0225 (0.0062)	0.0486 (0.0136)
Rural	−0.0591 (0.0126)	−0.0131 (0.0146)
South	−0.0363 (0.0046)	−0.0474 (0.0122)
Employment (γ^{e})		
Father's education	−0.0221 (0.0051)	−0.0145 (0.0057)
Mother's education	−0.0031 (0.0055)	−0.0089 (0.0066)
Household income	−0.0006 (0.0006)	−0.0007 (0.0007)
No. siblings	0.0123 (0.0059)	0.0055 (0.0063)
Nuclear family	−0.0100 (0.0080)	−0.0232 (0.0371)
Rural	0.0559 (0.0146)	0.0555 (0.0352)
South	−0.0986 (0.0083)	−0.0713 (0.0310)

Note: Household income divided by 1000.

While the effects of household background variables on labour market outcomes are weaker, there is support for the hypothesis that labour market ability is correlated with household background variables even after conditioning on schooling. The positive effects of father's education (around 0.0106) on log wages indicate that father's education increases wages by 1%. As for the utility of attending school, the effect of female education on wages is found to be negative (−0.0144). Not surprisingly, household income, which is a measure of parents' market skills, increases wages. The estimate (0.0012) is highly significant. The number of siblings present in the household has a significant negative effect on wage ability (−0.0084). Being raised by both parents (in a nuclear family) increases wages (0.0225), while being raised in the south or in rural areas reduces wages (−0.0363 and −0.0591 respectively). Taken as a whole, there is therefore overwhelming evidence that school and labour market abilities are strongly correlated with household background variables. Furthermore, all seven

Table IIB. Other structural parameters

	Model 1 Parameter (std. err.)	Model 2 Parameter (std. err.)
Utility in school		
Std. dev. (σ_ξ)	0.3793 (0.0105)	0.2175 (0.0116)
Splines δ_{7-10}	−0.0418 (0.0105)	0.0181 (0.0078)
Splines δ_{11}	0.3793 (0.0218)	−0.1250 (0.0214)
Splines δ_{12}	−1.6601 (0.0258)	−1.4689 (0.0230)
Splines δ_{13}	−1.2814 (0.0547)	−0.9828 (0.0230)
Splines δ_{14}	3.2614 (0.0118)	3.5721 (0.0132)
Splines δ_{15}	−0.6729 (0.0234)	−0.8231 (0.0141)
Splines δ_{16}	0.8004 (0.0244)	0.5456 (0.0087)
Splines $\delta_{17-\text{more}}$	−0.6330 (0.0084)	−0.6190 (0.0235)
Interruption probability	0.0749 (0.0036)	0.0749 (0.0036)
Discount rate	0.0033 (0.0001)	0.0045 (0.0001)
Employment return to schooling		
Schooling	−0.0258 (0.0041)	−0.0361 (0.0026)
Experience	−0.0146 (0.0026)	−0.0148 (0.0026)
Experience^2	0.0001 (0.0001)	0.0001 (0.0001)
Std. dev. (σ_e)	1.3160 (0.0096)	1.3250 (0.0020)
Wage return to schooling		
Spline grade 7–10	0.0042 (0.0002)	0.0053 (0.0003)
Spline grade 11	0.0079 (0.0010)	0.0051 (0.0013)
Spline grade 12	0.0046 (0.0011)	0.0156 (0.0012)
Spline grade 13	0.0171 (0.0016)	0.0236 (0.0013)
Spline grade 14	0.0787 (0.0018)	0.0803 (0.0017)
Spline grade 15	−0.0154 (0.0020)	−0.0246 (0.0016)
Spline grade 16	0.0092 (0.0022)	−0.0002 (0.0019)
Spline grade 17–more	−0.0124 (0.0013)	−0.0183 (0.0012)
Experience	0.0877 (0.0016)	0.0876 (0.0016)
Experience^2	−0.0030 (0.0001)	−0.0029 (0.0002)
Std. dev. (σ_ω)	0.2966 (0.0024)	0.2920 (0.0024)
Mean log likelihood	−13.6638	−13.6362

variables are found to have a significant effect on wages as well as on the utility of attending school.[9] Overall, the effects of parents' background variables on employment rates are of the same sign as the effects on wages, but less significant. For instance, female education, family income and the nuclear family indicator have an insignificant impact on employment rates.[10]

[9] For illustrative purposes, we have also estimated a restricted version of Model 1 where household human capital does not affect labour market outcomes after conditioning on schooling. The differences in the parameter estimates of the household human capital variables between the restricted and unrestricted versions indicate that ignoring the effects of household characteristics on labour 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, household income and siblings. This is explained by the fact that, in the most general model, household human capital raises absolute advantages in the labour market. Based on standard likelihood ratio tests, the restricted version of the model is strongly rejected.

[10] The estimates reported in Table IIC 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. 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. For more details on the 'Ability Bias' and the 'Discount Rate Heterogeneity Bias', see Belzil and Hansen (2001).

Table IIC. Unobserved heterogeneity and type probabilities

			Model 1 Parameter (std. err.)	Model 2 Parameter (std. err.)
Type 1	v_1^{ξ}	School ability	−2.9693 (0.0108)	−3.0184 (0.0169)
	v_1^{ω}	Wage	1.5374 (0.0105)	1.3643 (0.0098)
	κ_{01}	Employment	−3.4537 (0.0312)	−3.4077 (0.0221)
	q_1	Type probability	0.6286 (0.0560)	−0.2707 (0.0226)
Type 2	v_2^{ξ}	School ability	−2.7838 (0.0125)	−2.9329 (0.0528)
	v_2^{ω}	Wage	1.8672 (0.0107)	1.9673 (0.0094)
	κ_{02}	Employment	−2.4784 (0.0384)	−1.4417 (0.0077)
	q_2	Type probability	−0.3823 (0.0518)	−2.6253 (0.0075)
Type 3	v_3^{ξ}	School ability	−3.2766 (0.0131)	−3.3411 (0.0217)
	v_3^{ω}	Wage	1.1951 (0.0156)	1.0062 (0.0136)
	κ_{03}	Employment	−3.3351 (0.0381)	−3.1869 (0.0060)
	q_3	Type probability	−0.4227 (0.0185)	−1.7000 (0.0076)
Type 4	v_4^{ξ}	School ability	−3.3891 (0.0243)	−3.3538 (0.0445)
	v_4^{ω}	Wage	1.5055 (0.0162)	1.4291 (0.0070)
	κ_{04}	Employment	−1.5840 (0.0362)	−1.7157 (0.0268)
	q_4	Type probability	−0.4513 (0.0415)	−0.9400 (0.0067)
Type 5	v_5^{ξ}	School ability	−2.3878 (0.0289)	−2.3975 (0.0182)
	v_5^{ω}	Wage	2.1162 (0.0221)	2.0000 (0.0101)
	κ_{05}	Employment	−3.6242 (0.0224)	−3.5838 (0.0105)
	q_5	Type probability	−0.0776 (0.0817)	−0.9443 (0.0008)
Type 6	v_6^{ξ}	School ability	−2.7010 (0.0184)	−2.7358 (0.0166)
	v_6^{ω}	Wage	1.8016 (0.0120)	1.6707 (0.0130)
	κ_{06}	Employment	−3.7365 (0.0173)	−3.4238 (0.0157)
	q_6	Type probability	0.0 (normalized)	0.0 (normalized)

Note: The respective type probabilities are 0.32, 0.12, 0.11, 0.11, 0.16 and 0.17 in Model 1, and 0.27, 0.03, 0.06, 0.14, 0.14 and 0.36 in Model 2.

Parameter Estimates in Model 2

In the second model specification, the separate effects of household background variables on the utility of attending school and on ability in school are estimated consistently. This procedure requires the correlation between AFQT scores and parents' background variables be estimated initially by OLS. Thereafter, λ may be estimated at the same time as other parameters or be replaced by an estimator obtained through a full maximum likelihood procedure where AFQT scores are used as a direct measure of ability.[11] As a consequence, the effects of some of the parents' background variables on the utility of school should be lower than those reported in column 1 (for Model 1). This claim is easily verified upon looking at the structural estimates reported in the second column of Table IIA.

Except for mother's education, the estimates of the effects of household background variables on scholastic ability are of the same sign as the effects on the utility of attending school. In particular, we find that mother's education, father's education and family income are positively correlated with scholastic ability. After conditioning on scholastic ability, two of the most important household background variables, father's education and household income, are strongly reduced.

[11] It turns out that the two procedures are practically equivalent. In what follows, we report the estimates obtained when $\hat{\lambda}$ is 0.0308 (the value obtained when the structural model was estimated with AFQT scores adjusted for age).

Father's education is lowered from 0.0205 to 0.0154 and household income from 0.0017 to 0.0009. The effect of mother's education remains negative and increases in absolute value from −0.0080 to −0.0131. This may be explained by the fact that, given ability, mother's labour supply (highly correlated with mother's schooling) might be detrimental to child development. While this hypothesis is often advanced to explain the weak (or negative) correlation between schooling attainments and mother's schooling observed in reduced-form estimates, there exists no strong empirical evidence on the causal effect of female labour supply on schooling attainments (Blau and Grossberg, 1992). A similar pattern is observed for the regional indicator and the rural/urban indicator. The indicator for the family composition (Nuclear) is the only parameter estimate that has increased.

4.2. The Relative Importance of Household Background Variables and Ability in Explaining Individual Schooling Attainments and Wages

At this stage, two questions naturally arise. What is the relative importance of household background variables and individual unobserved abilities in explaining individual schooling attainments? What is the relative importance of household background variables and individual unobserved abilities in explaining labour market wages? To investigate these issues, we simulated the model and generated 200 000 observations on schooling attainments and wages. Using standard regression techniques, we estimated the effects of individual specific endowments on schooling attainments. Using the simulations, it is possible to impute a fraction of schooling and wages explained by each set of determinants (parents' background variables vs. unobserved abilities and tastes). These variance decompositions are summarized in Table III.

Schooling Attainments
The results of the simulations obtained for both model specifications illustrate the complementary benefits of estimating these two models. An inspection of the variance decomposition of generated schooling attainments for Model 1, which is found in the first column of Table III, indicates that 85% of the explained variation is imputed to observed household characteristics while only 15% is imputed to purely individual specific unobserved abilities. While this breakdown does not offer

Table III. Sources of variations in schooling attainments and wages

	Model 1		Model 2	
	(1) % Schooling explained by	(2) % Wages explained by	(3) % Schooling explained by	(4) % Wages explained by
Household background				
Parents' education	71.3%	18.7%	54.8%	12.5%
Parents' education and income	77.4%	23.3%	62.2%	16.9%
All household variables	84.8%	27.4%	67.6%	19.3%
Abilities				
Abilities (unobserved)	15.2%	72.6%	—	—
Abilities (observed & unobserved)			32.4%	80.7%

Note: The percentages are expressed as a fraction of the total variations imputed to parents' background variables and unobserved heterogeneities.

the possibility to distinguish between scholastic ability and other factors, it provides a measure of the relative importance of household background variables and pure individual specific unobserved components. It should be noted that this does not necessarily contradict the results recently reported in the literature which point out that individual schooling attainments are largely explained by differences in individual taste for schooling (Keane and Wolpin, 1997; Eckstein and Wolpin, 1999).[12]

As this might have been anticipated from the structural estimates, the variance decomposition obtained for Model 2 (found in the third column of Table III) indicates that, after taking into account that scholastic abilities are potentially explained by parents' background, the fraction of schooling attainments explained by individual abilities is substantially increased. Indeed, it is practically doubled and the fraction goes from 15% to 32%. Accordingly, after conditioning on abilities, household background variables explain 68% of the explained variations in schooling attainments.

Altogether, the results provide a relatively clear picture of the importance of family background variables. Given scholastic ability, household background accounts for 68% of the explained cross-sectional variations in schooling attainments. Interestingly, more than half of the parents' background variable variations are explained by father's and mother's schooling alone and around half of the residual source of explained variations due to abilities is indeed explained by family background variables. This means that, when taken as a whole, family background variables may explain up to 85% of the cross-sectional variations in schooling attainments.

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 should have a similar explanatory power on labour market wages. Both school and market abilities have an effect on wages through schooling, but market ability also has a direct effect on wages through the intercept terms of the wage function. The wage variance decompositions are also in Table III.

The respective variations in explained wages due to ability heterogeneity and household background variables are quite different from those observed for predicted schooling attainments. Unlike what was observed for schooling, individual differences in wages are mostly explained by ability endowments. This is true in both models. In the first model specification, parents' background variables account for 27% of the explained variation while unobserved abilities (orthogonal to family background variables) account for 73%. When scholastic ability is correlated with family background variables, the role of ability is even stronger. Ability endowments explain as much as 81% of wages, while only 19% is explained by family background variables.

There are two main reasons for the relatively weak effects of parents' background variables on wages (as compared to schooling). First, as shown by the structural estimates in Table IIA, household background variables have a much larger effect on the utility of attending school than on labour market outcomes. Second, as in Belzil and Hansen (2002), the wage return to schooling is found to be quite low so that individual differences in schooling cannot explain differences in wages.

[12] In Keane and Wolpin (1997) and Eckstein and Wolpin (1999), parents' background variables are not used as observable characteristics.

4.3. The Implied Intergenerational Education Correlation and Goodness-of-Fit

The effects of individual specific endowments (household background variables and abilities) on schooling attainments, which have been obtained from the simulations of both models, are also useful to investigate the intergenerational correlation implied by the structural model and to assess the validity of our model. These estimates may be viewed as the net effects of each specific variable on schooling attainments and wages. While OLS estimates cannot be used to investigate the relative importance of household background variables and individual specific unobserved heterogeneity, they may nevertheless provide a good descriptive measure of the total (unconditional) correlation between household background variables and schooling attainments. For this reason, the correlations implied by the simulations of Model 1 may be compared to OLS estimates.

The results of these regressions are found in Table IV. As normally expected, the estimates reported indicate that individual schooling attainments increase with parents' education, income and nuclear family status but decrease with number of siblings and both the south and rural indicators. They also indicate that schooling attainments increase with scholastic ability ($\tilde{v}_i^{\xi}$) but decrease with market ability ($\tilde{v}_i^{w}$).

A comparison between OLS estimates (already presented in column 4 of Table I) and the implied correlations associated to Model 1 (in columns 1 and 2) indicate the validity of our approach. Virtually all the estimates are close to their OLS counterparts. This is a clear indication

Table IV. Correlations between schooling attainments and parents' background variables implied by the structural estimates

	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Father's education	0.1934	0.1932	0.1539	0.1707
	(0.0019)	(0.0018)	(0.0057)	(0.0057)
Mother's education	0.1444	0.1439	0.0935	0.0526
	(0.0227)	(0.0026)	(0.0076)	(0.0079)
Household income	0.0106	0.0106	0.0122	0.0106
	(0.0002)	(0.0002)	(0.0006)	(0.0006)
Siblings	−0.1531	−0.1527	−0.0967	−0.1308
	(0.0025)	(0.0024)	(0.0075)	(0.0075)
Nuclear family	0.4136	0.4163	0.3242	0.4104
	(0.0132)	(0.0127)	(0.0389)	(0.0389)
Rural	0.0943	0.0894	−0.0353	−0.0551
	(0.0118)	(0.0114)	(0.0337)	(0.0349)
South	−0.3981	−0.3976	−0.2507	−0.3324
	(0.0119)	(0.0115)	(0.0351)	(0.0351)
$\tilde{v}_i^{\xi} \times 10$	0.4533		0.2401	
	(0.0164)		(0.0544)	
$\tilde{v}_i^{w} \times 10$	−0.5495		−0.2222	
	(0.1550)		(0.0487)	
$\tilde{v}_i^{e} \times 10$	0.2991		0.0547	
	(0.0906)		(0.01320)	
R^2	0.3143	0.2667	0.2975	0.2373

that our model is able to fit the data well.[13] On the other hand, the correlations implied by Model 2 (columns 3 and 4) measure the marginal effects of family background variables, holding scholastic ability constant. As suggested by the structural estimates, these correlations are indeed weaker and reflect the relatively strong correlation between scholastic ability and family background variables.

Overall, both the simulations and the variance decompositions provide strong evidence that father's and mother's schooling are by far the most important household background variables. For instance, an increase of 1 year in both parents' education will lead to a mean increase as large as 0.3 year of schooling. To obtain a similar increase based on family income, one would require an increase in household income greater than \$30 000. These results are consistent with those reported in reduced-form literature (Cameron and Heckman, 1998).

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 labour market, initial endowments in household background variables and subjective discount rates. The econometric specification of the model is quite general. The structure of the model has allowed us to investigate the relative importance of household background variables and individual unobserved abilities in explaining cross-sectional differences in schooling attainments and wages.

Overall, we find that parents' background variables have a major impact on cross-sectional differences in schooling levels. Depending on whether or not ability endowments are allowed to be correlated with family background variables, household characteristics are 2.5 to 5 times more important than purely individual specific ability endowments. However, the effects of parents' background variables on labour market wages are found to be very minor. Wages are mostly explained by individual specific factors which are orthogonal to family environment factors. Indeed, purely individual specific factors are 3 to 4 times more important than parents' background variables.[14]

Our results suggest interesting topics for future research. Given the negative effect of mother's schooling on individual schooling attainments (after conditioning on scholastic ability), it would be interesting to evaluate how household labour supply behaviour (especially mother's labour supply) affects schooling attainments and labour 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.

DATA APPENDIX

The sample used in the analysis is extracted from 1979 youth cohort of 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

[13] A more conventional approach to model fit is to compute predicted frequencies to empirical frequencies. As indicated in a companion paper (Belzil and Hansen, 2001), our model is also able to fit the data very well according to this criterion.
[14] This has also been pointed out in the sociological literature (see Hauser, 1998).

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 employment rates for each individual from the time the individual is age 16 up to December 31, 1990.[15]

The original sample contained 3790 white males. However, we lacked information on household background variables (such as household income as of 1978 and parents' education).[16] The age limit and missing information regarding actual work experience further reduced the sample to 1710. Descriptive statistics are found in Table AI.

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 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

Table AI. Descriptive statistics

	Mean	Std. dev.	No. individuals
Household income/1000	36 904	27.61	1710
Father's education	11.69	3.47	1710
Mother's education	11.67	2.46	1710
No. siblings	3.18	2.13	1710
Proportion raised in urban areas	0.73	–	1710
Proportion raised in south	0.27	–	1710
Proportion in nuclear family	0.79	–	1710
Schooling completed (1990)	12.81	2.58	1710
No. 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.

[15] The reason for not including information beyond 1990 is that the wage data do not appear reliable for these more recent waves.
[16] We lost about 17% of the sample due to missing information regarding family income and about 6% due to missing information regarding parents' education.

individuals have experienced at least one interruption (Table AI). 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 three years.

Second, unlike many studies set in a reduced form which use potential experience (age–education–6), we use data on actual experience. The availability of data on actual employment rates allows us to estimate the employment security return to schooling. More details can be found in Belzil and Hansen (2001).

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