

Education Decisions and Policy Interventions: A General Equilibrium Evaluation¹

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Preliminary and incomplete draft: October 2006

Abstract

This paper examines the effects of alternative policies on the distribution of education in both partial and general equilibrium. We build a life-cycle model with endogenous labor supply, consumption/saving, and education choices, allowing for agents' heterogeneity in several dimensions and for incomplete insurance markets. PSID data are used to estimate relevant characteristics of education-specific dynamic earnings processes. Through numerical simulations, we compare the effects of alternative policy interventions on education decisions, endogenous selection, income inequality, and welfare. In this preliminary version, we experiment with college tuition subsidies. While in partial equilibrium such policies can be very effective in increasing education levels and reducing inequality, in general equilibrium the results are starkly different: the main effect of a subsidy there is to increase the supply of human capital as one would expect. However, it is the more able but liquidity constrained individuals who take up extra education, while the education levels of the less able can actually decrease (they are crowded out). Thus the subsidy strongly acts on the composition of those in education.

¹Special thanks go to Lars Nesheim for useful discussions about the computational aspect of the problem. We are also grateful to Orazio Attanasio, Richard Blundell, Michele Boldrin, Hamish Low, Nicola Pavoni, and Josep Pijoan-Mas for comments.

1 Introduction

This paper examines policies designed to alter the equilibrium distribution of education and their wider economic consequences. It also looks at the nature of education decisions and the role that such decisions play in shaping life cycle earnings and wealth profiles. Individual choices are analyzed in the context of a general equilibrium model with separate, education-specific spot markets for jobs. The unit price of (efficiency-weighted) labor differs by education group and equals marginal product.

We are interested in the equilibrium, long-term effects of policy interventions targeting the wider population rather than limited groups, with relative labor prices endogenously adjusting to changes in the aggregate supply of educated people. We examine traditional policies, such as tuition transfers and loan subsidies, but we also devise and evaluate alternative forms of policy intervention.² The policy experiments are carried out through numerical simulations, with some of the model's parameters directly estimated from PSID and CPS data and others calibrated to match specific long-term features of the US economy. By simulating and comparing equilibrium outcomes we aim to explore the quantitative aspects of the relationship among schooling decisions, wages inequality and education policy. The impact of diverse education policies on equilibrium measures of productivity, consumption and welfare is also considered.

Research linking human capital (HC) investment to life cycle earnings dates back to original work by Mincer (1958), Becker (1964) and Ben-Porath (1967). The first studies ignored the important issue of self selection into education, as described by Rosen (1977) and Willis and Rosen (1979). Permanent and transitory individual characteristics are now acknowledged as important determinants of education choices and have become a standard feature of HC models. Empirical evidence supporting the plausibility of a link between human capital accumulation and economic inequality has been provided, among others, by Mincer (1994).

In work relating education policies and individual preferences Fernandez and Rogerson (1995) originally point out that heterogeneity among individuals, whether in terms of income, ability or locality, can generate conflicting preferences as to the kind of policies

²Standard education policy is just one of the possible types of human capital policy. For example, changes in proportional income taxation affect the life-cycle returns on human capital and the opportunity costs of education, altering human capital investment decisions.

that are most desirable.³

Studies on the evaluation of policy interventions in equilibrium are more recent. Heckman, Lochner, and Taber (1998b, 1998c) have led the way in advocating an approach to policy evaluation which does not overlook equilibrium effects induced by the policy.⁴ In fact, statements regarding the effects of policy interventions which ignore price changes induced by such interventions are misleading. Fernandez and Rogerson (1998) provide an interesting application of general equilibrium (G.E.) modelling to the evaluation of education-finance reform in the US. Later work by Cunha, Heckman, and Navarro (2004) reinforces the view that models that are able to construct equilibrium counterfactuals are essential to understanding the wider consequences of policy interventions.

In the empirical literature on education policy, early work by Keane and Wolpin (1997) focuses on the partial equilibrium effect of a tuition subsidy on young males' college participation. A valuable generalization of their approach within a dynamic GE framework is due to Lee (2001). Also Abraham (2001) examines wage inequality and education policy in a GE model of skill biased technological change. All these studies restrict labor supply to be fixed, although earlier theoretical research has uncovered interesting aspects of the joint determination of life cycle labor supply and HC investment, among others Blinder and Weiss (1976).

Our model incorporates several important extensions with respect to earlier work: first, optimal individual labor supplies are an essential part of the lifetime earnings mechanism; second, agents' heterogeneity has different dimensions, including a permanent (ability) component and uninsurable efficiency shocks; third, ability is transmitted across generations; fourth, inter-vivos transfers from parents to offsprings are permitted to ease liquidity constraints in the education decision.

Recent empirical evidence in Hyslop (2001) indicates that labor supply explains over 20 % of the rise in (both permanent and transitory) family inequality during the period of rising wage inequality in the early 1980's. Moreover, even if individual labor supplies do not deviate much from the average levels of their demographic group, it is the case that average levels differ substantially between groups.

³Fernandez and Rogerson (1995) consider ex-ante identical individuals who differ only in income

⁴Heckman, Lochner, and Taber estimate and simulate a dynamic general equilibrium model of education accumulation, assets accumulation and labor earnings with skill-biased technological change.

The other second extension in our model is the introduction of individual uncertainty over the returns to HC in the form of idiosyncratic multiplicative shocks to labor efficiency. As Levhari and Weiss (1974) originally emphasized, uncertainty is of exceptional importance in human capital investment decisions as the risk associated to such decisions is usually not insurable nor diversifiable. Using a multiplicative form of earnings risk, Eaton and Rosen (1980) show how earnings taxation has an ambiguous effect on investment in human capital because it impinges on two important parameters of the decision problem: for one, taxation reduces the riskiness of returns to human capital investment.⁵ In addition, taxation induces an income effect that can influence the agents' willingness to bear risk. Thus, ignoring the riskiness of education decisions can partly sway the results in the analysis of the effects of earnings taxation and education policies.

Gale and Scholz (1994) show that inter vivos transfer for education are sizeable, thus they should be incorporated in the mechanism of a model of education acquisition, especially if one is interested in quantifying the role of credit constraints.

We also calibrate the level of correlation between ability of parents and kids. Besides genetic transmission, this can be thought of as a way to incorporate the effect of parental background on ability formation, as extensively documented in the literature, see Heckman and Carneiro (2003) for a review.⁶

We model three levels of education obtained through formal schooling and corresponding to three types of HC which enter the production technology.⁷ Education and employment are mutually exclusive in each period. Foregone earnings and tuition charges are the direct costs of schooling, and a utility cost comes in the form of reductions in leisure when studying.

In general, the model provides a way to look at endogenous equilibrium levels of aggregate human capital, with associated wages, as a function of agents' optimizing schooling choices and demographic factors. Through its policy functions, it provides a mapping

⁵As the proportional tax rate increases, agents earn less from high realization of the shock but also lose less from the bad ones. Therefore the overall risk is decreased.

⁶The simulations reported in the current draft do not yet embed inter-vivos transfers and inter-generational correlation in ability.

⁷We distinguish among people with less than high school degrees (LTHS), high school graduates (HSG) and college graduates (CG). The distinction between LTHS and HSG is based on different earning and labor supply characteristics. Schooling is the only way to accumulate human capital (no children nurturing or on-the-job training). The possible effects of OJT are accounted for through an age-efficiency profile which is estimated for each education group and is maintained to be policy-invariant.

from a set of initial conditions (that is, initial agents' distribution over states such as permanent and persistent idiosyncratic shocks and assets) into distributions over educational and economic attainments: this mapping turns out to be ideal to study the economic implications of alternative policy interventions.

2 Model

2.1 Overview

We consider an economy where a unique good is produced, and it can be either consumed or used as physical capital. We specify an overlapping generations general equilibrium model for this economy that focuses on education and labour supply. Consumers maximise an intertemporal utility function over their finite life-cycle, by choosing education, labour supply and consumption/savings. Agents can accumulate assets representing ownership shares on physical capital, but cannot borrow. They have a maximum lifetime and they plan to consume their entire assets. However they may die before that leaving accidental bequests. Individuals can work up to an exogenous retirement age but not beyond. They can however decide not to work before that. Retirement is financed by the accumulated assets.⁸ The population consists of overlapping generations, each with an ex-ante identical distribution of heterogeneity.

Young and old households are not linked in any direct way. Bequests are pooled together and redistributed to all newly born individuals according to the steady state equilibrium wealth distribution. This reflects both inter-vivo transfers for education and actual bequests. Since we assume that assets must always be non-zero (due to liquidity constraints), these transfers are the only source of funding for education, other than possible government transfers. Education can only take place at the beginning of the life-cycle and the individual can attain one of three education levels, corresponding to less than high school, high school, and college. The costs of education consist of the opportunity cost, tuition fees net of any government subsidy and the psychic/utility costs of education. In addition individuals are endowed with different abilities which lead to different efficiency units of human capital and thus earnings. Thus wage differences among individuals are the consequence of differences in education (between group inequality) and

⁸In the next version, we will incorporate social security.

differences in labor efficiency (within group inequality). Workers are perfect substitutes within schooling groups, regardless of their individual efficiency.

There is no aggregate uncertainty in the model. Once out of school the individual has to decide on the proportion of his/her time to devote to work and on consumption. All these decisions take place in an incomplete markets environment: individual can only save using a risk-free asset.

There is an aggregate production function with four inputs: The three levels of human capital, measured in total efficiency units supplied and physical capital. We solve the model as a closed economy with the interest rate determined endogenously.

The model is partly estimated and partly calibrated. First we estimate a wage equation and extract relative prices for our three human capital measures. This allows us to compute the total supply of efficiency units of human capital in each of the three groups. From the residuals of the wage equation, we also estimate the stochastic process of efficiency units, which we take to be the process of uncertainty facing the individual.⁹ The stochastic process of wages is taken to be education specific.

Next we estimate the aggregate production function which is taken initially to be Cobb-Douglas. However, it proved to be quite difficult to obtain reliable estimates, so we carry out sensitivity analysis based on a number of different production function structures. Moreover, since there seems to have been a change in the production structure mainly due to skill biased technological change we use as our basis for the Cobb-Douglas specification the average shares over the period.

To obtain the parameters characterising preferences we use risk aversion coefficients taken from the literature and then we set the preference for labour supply to match the proportion of people working in the economy. Given these parameters we then calibrate the utility costs of education to match the proportions in each education group during 1978-82. The individual discount rate is calibrated to match the ratio of physical capital over total output.

⁹This may overestimate the degree of uncertainty; see Cuhna, Heckman and Navarro (2004).

2.2 Individual demographics and preferences

We use the index j to denote age. Agents have a probability to survive in each period, denoted as s_j , which is decreasing in age. The demographics are stable, so that age j agents make up a constant fraction ζ_j of the population at any point in time. The ζ_j values are normalized to sum up to 1 and are such that $\zeta_{j+1} = s_j \zeta_j$. The maximum attainable age is denoted by J .

The period utility $u(c, l)$ is concave in consumption c and leisure $l = (1 - n)$; it satisfies standard regularity conditions and in particular the Inada conditions. The education level is denoted by e , it takes three values, with $e = e_1$ the lowest and $e = e_3$ the highest. Permanent (unobserved) individual characteristics are denoted by θ and distributed over the domain $[\theta_{\min}, \theta_{\max}]$. We denote by $\{z\}_{j=1}^{\bar{j}}$ the sequence of uninsurable idiosyncratic shocks. Their law of motion is summarized by a stationary transition function π denoted as $\pi_{z_{j+1}|z_j} = \pi\{z_{j+1} \mid z_j\}$.

While in school, individual utility is given by $u(c_j, f(\theta))$, where the function $f(\theta)$ reflects the psychic costs of schooling which may be thought of as leisure costs but may include other aspects of effort and like or dislike of the education process. These costs will depend on ability with the idea that more able individuals will suffer lower costs.

Given some initial values \bar{x}_1 for the state variables, household/individual utility over sequences of consumption and leisure, $c = \{c_1, \dots, c_{\bar{j}}\}$ and $l = \{l_1, \dots, l_{\bar{j}}\}$, as of age 1 is denoted $U(\bar{x}_1, c, l)$ and can be written as the expected discounted sum of period utilities

$$U(\bar{x}_1, c, l) = E_{z \in Z} \left\{ \sum_{j=1}^{j_{edu}} S_j \beta^{j-1} [d_j u(c_j, f(\theta)) + (1 - d_j) u(c_j, l_j)] + \sum_{j=3}^{\bar{j}} S_j \beta^{j-1} u(c_j, l_j) \right\} \quad (1)$$

where d_j is a binary variable which is 1 if the agent is in education and 0 otherwise, j_{edu} denotes the last period of education, $S_j = \left(\prod_{i=1}^j s_i \right)$ denotes the probability of surviving to age j and β is the intertemporal discount factor. For the first three periods the individual may decide to be in education which is why there are two alternative forms for the utility function depending on the action they take. Note that, once in education, $f(\theta)$ is fixed and only depends on ability θ .

The period budget constraint is given by

$$c_j + a_{j+1} = [1 + r(1 - \tau_k)] a_j + w_e e^{\epsilon_j} n_j (1 - \tau_{n^e}) (1 - d_j) - (D_e - T_e) d_j^{10} \quad (2)$$

where and a_j denotes individual asset holdings at age j and r is the risk-free interest rate.¹¹ For the purposes of policy analysis we distinguish between the taxation of capital income τ_k and the taxation of labour income τ_n .¹² The term D_e is the direct cost of schooling and T_e summarizes government subsidies towards education e . The term e^{ϵ_j} is individual labor efficiency, and ϵ_j is defined as

$$\epsilon_j(\theta, e, z) = \theta + \xi_j(e) + z_j \quad (3)$$

where $\xi_j(e)$ is an education-specific age profile.

2.3 Solving the individual problem

The individual's problem may be solved recursively by backwards induction. Denote by x_j the value of the state variables in period j and by $W_j(x_j)$ the optimum value function at age j . The state includes the current value of the shock z , which is assumed to arrive at the beginning of the period, as well as permanent characteristics, past values that are relevant for predicting future outcomes and of course current assets and education levels. Following the third year of life when no more education choices can be made the individual chooses consumption and labour supply to solve the problem

$$W_j(x_j) = \max_{c,n} \left\{ u(c_j, 1 - n_j) + s_j \beta \int_Z \pi_{z_{j+1}|z_j} W_{j+1}(x_{j+1}) dz_{j+1} \right\} \quad (4)$$

subject to the budget constraint 2 with $d_j = 0$ and subject to the constraint $a_{t+1} \geq A$ where A is some exogenous minimum level of assets, possibly zero or possibly negative.

Previously, during the first three years of life, the individual's problem is complicated by the fact that she/he needs to decide on whether to obtain education. In this case, for $j \leq 3$, the problem solved is

$$W_j(x_j) = \max_{c,n,d} \left\{ d_j u(c_j, f(\theta)) + (1 - d_j) u(c_j, l_j) + s_j \beta \int_Z \pi_{z_{j+1}|z_j} W_{j+1}(x_{j+1}) dz_{j+1} \right\} \quad (5)$$

subject to the budget constraint, the asset constraint mentioned above and subject to the constraint that $n = 0$ if $d_j = 1$, i.e. we do not allow for work and education at the same time.

¹¹Individual asset holdings satisfy: $a_j \geq a_{\min}$ for every j and $a_{\bar{j}+1} \geq 0$. The first inequality is a borrowing constraint, whereas the second is a transversality condition for agents reaching age \bar{j} .

¹²Heckman (1976) first noted the importance of this distinction when considering investments in human capital. Changing the cost of intertemporal substitution will affect investment decisions.

2.4 Aggregate variables

We study equilibrium allocations and assume a stationary population. The relevant aggregate variables of the economy are physical capital K and efficiency-weighted aggregate labor supplies (referred to as human capital aggregates) H_1 , H_2 , and H_3 . Relative price variation is key because as the policy alters the supply of each education group, relative prices will change and this will lead to different steady state levels of supply for H_1 , H_2 , and H_3 . The total stock of human capital of type e is the sum over the efficiency weighted individual labor supplies defined by

$$h_j(\theta, e, z, a) = e^{\epsilon_j(\theta, e, z)} n_j(\theta, e, z, a) \quad (6)$$

2.5 Technology

Firms maximize profits using a CRS technology and set wages competitively. The aggregate technology employs physical and human capital and is denoted as $F(H, K)$ with $H = \{H_1, H_2, H_3\}$. The relationship between human capital factors (H) and physical capital is expressed as a Cobb-Douglas :

$$F(H, K) = \bar{A} H^{1-\alpha} K^\alpha \quad (7)$$

\bar{A} is a TFP coefficient and the general, unconstrained definition of the HC input is

$$H = \left\{ A_1 H_1^{\rho_1} + [A_2 H_2^{\rho_2} + A_3 H_3^{\rho_2}]^{\frac{\rho_1}{\rho_2}} \right\}^{\frac{1}{\rho_1}}$$

which allows for the elasticity of substitution to differ between unskilled labour H_1 and the other two inputs.¹³

The equilibrium conditions require that marginal products equal pre-tax prices so that $w_e = \frac{\partial F}{\partial H_e}$ for any education level e , and $r + \delta = \frac{\partial F}{\partial K}$, where δ is the depreciation rate for capital.

2.6 Market structure

Our setup is an incomplete markets one where idiosyncratic risk cannot be insured, other than by self-insurance through precautionary savings. However we also impose liquidity

¹³In practice, the data suggest a Cobb-Douglas specification with $\rho_1 = \rho_2 = 0$. However we do use this general specification as a basis for sensitivity analysis.

constraints, which will be biting for the more able young people, unless they have inherited wealth.

We consider model specifications with and without missing annuity markets. In the simulations where we allow non-zero asset holdings for newborns, we also experiment with different degrees of correlation between initial wealth and permanent characteristics θ .¹⁴

2.7 Government

Government has revenues from proportional taxation of labor and asset income at respectively τ_{ne} and τ_k rate, and uses part of these revenues to subsidize education via a transfer T_e . We call G the residual non-education general government expenditure and assume that G is lost in non-productive activities. The government's behaviour is fully described by the budget constraint, which requires that expenditures equal revenues obtained from taxation:

$$G + \sum_j^{\bar{j}} \zeta_j \int_X T_e d_j(x) d\psi_j(x) = \sum_j \zeta_j \left\{ \int_X [1 - d_j(x)] \tau_{ne} w_e h_j(x) d\psi_j(x) + \int_{\bar{A}} r \tau_k a_j d\psi_j(a) \right\}$$

The government has a balanced budget in each period.

3 Equilibrium

We use the notion of stationary recursive competitive equilibrium, as in Lucas (1980).¹⁵ Let $(X, F(X), \psi_j)$ be an age-specific measure space with state space X and $F(X)$ be a σ -algebra on X .

Given some state vector $x \in X$, a stationary equilibrium for this economy is a set of decision rules $d_j(x)$, $a_{j+1}(x)$, $c_j(x)$, $n_j(x)$, value functions $W_j(x)$, price functions w_e , r , densities $(\psi_1, \dots, \psi_{\bar{j}})$ and $(\zeta_1, \dots, \zeta_{\bar{j}})$, and a law of motion Q , such that:

1. $d_j(x)$, $a_{j+1}(x)$, $c_j(x)$ and $n_j(x)$ are optimal decision rules and solve the household's problem, and $W_j(\theta, e, z, a)$ are the associated value functions;

¹⁴Imposing different patterns of dependence between such marginal densities turns out to be useful if ability is correlated with socio-economic background factors such as family wealth.

¹⁵Our model satisfies the conditions for defining a measure ψ_j , such that $\mu(x, j) = \zeta_j \psi_j(x)$ is stationary as a function of the Markov process $\pi\{z_{j+1} | z_j\}$ and of the decision rules $d_j(x)$ and $a_{j+1}(x)$, where x is an element of the state space.

2. Firms employ inputs so that

$$\begin{aligned} w_e &= F_{H_e} \quad \text{for } e \in \mathfrak{E} \\ r + \delta &= F_K ; \end{aligned}$$

3. $\psi_j(x)$ is a stationary measure, that is $\psi_j(F) = Q(F, \psi_j)$, where $Q(\cdot, \cdot)$ is the law of motion of $\psi_j(\cdot)$ and is generated by the optimal decisions $d_j(x)$, $a_{j+1}(x)$, $c_j(x)$;¹⁶

4. The good, asset and labour markets clear.

From Walras' Law, the goods market clearing equation is derived residually by integrating the individual budget constraint.

4 Parameterization

We now describe in detail how we parameterize our model economy.

4.1 Demographics and preferences

Individuals are assumed to be born at the real age of 16, and they can live a maximum of $\bar{j} = 84$ years, after which, at the real age of 99, death is certain (retirement is not modelled, so that agents die at the end of their working life). The sequence of conditional survival probabilities $\{s\}_{j=1}^{99}$ is based on mortality tables for the US and we don't differentiate mortality rates by sex or race.

For the preference parameters, we rely on existing Euler equation estimates, as well as on matching aggregate labour supply levels. Thus we specify the utility function to be of the CRRA type, i.e.

$$u(c_j, l_j \mid d_j = 0) = \frac{[c_j^\nu l_j^{1-\nu}]^{1-\lambda}}{1-\lambda}$$

$$u(c_j \mid d_j = 1) = \frac{[c_j^\nu f^e(\theta)^{1-\nu}]^{1-\lambda}}{1-\lambda}$$

The parameters ν and λ of the period utility jointly pin down the intertemporal elasticity of substitution of consumption $\frac{1}{1-\nu(1-\lambda)}$ (ISE) as well as the level of labour supply over the lifecycle. We set the ISE to 0.75 as in Blundell, Browning and Meghir

¹⁶Given ζ_j , also $\mu(x, j) = \zeta_j \psi_j(x)$ is a stationary measure.

(1994) and Attanasio and Weber (1993). Given this a value of $\nu = 0.33$ and hence $\lambda = 2.00$ matches the labour supply data very well.

4.2 Education cost parameters

The direct cost of education D_e is set to be equal to 0.3 times the average earnings in the economy, which corresponds to an estimate of average (in-state) tuition costs for public and private colleges in the US.¹⁷

Tuition subsidies (T_e) as a share of average earnings have changed over the last 30 years. A long term average stands at roughly 1/2 of the tuition costs. We run several experiments based alternative levels of tuition subsidization.

4.3 Skill prices and age profiles

An important characteristic of the model is that the three types of human capital represent different inputs to the production function, not necessarily perfectly substitutable and may have relative prices that vary over time in response to changes in either supply or demand for skills. So as to be able to simulate our model, we need to extract from the data the distribution of unobserved heterogeneity affecting wages and education choices as well as the stochastic process of the shocks.

We start by specifying an education specific wage equation for individual i wages in period t , w_{eit}

$$\ln w_{eit} = w_{et} + g_e(\text{age}_{eit}) + u_{eit} \quad (8)$$

where w_{et} represents the log of the aggregate price of human capital for education group e and where $g_e(\text{age}_{eit})$ is the education specific profile of wages. The unobservable component u_{eit} is specified to be

$$u_{eit} = \theta_i + z_{eit} + m_{it} \quad (9)$$

where θ_i represents unobserved fixed effects, z_{eit} is the (persistent) shock to wages and m_{it} is measurement error, assumed *iid*. Self-selection implies that fixed effects are correlated with both education decisions and observed wage rates. However, a within groups transformation eliminates the source of self-selection and identifies the changes in the returns

¹⁷Source: Education digest, NCES, National Center for Education Statistics.

to education over time as well as the way wages grow with age by education group. Thus we estimate by OLS

$$(\ln w_{eit} - \ln \bar{w}_{ei}) = (\ln w_{et} - \ln \bar{w}) + g(\text{age}_{eit}) - \overline{g(\text{age}_{eit})} + (u_{eit} - \bar{u}_{ei}) \quad (10)$$

where the upper-bar denotes an (individual) time average and where g is a polynomial of order two for the lowest education group and of order 4 for the two higher education groups. The term $(\ln w_{et} - \ln \bar{w})$ is modelled as time dummies. The residuals from this equation can be used to identify the persistence of wage shocks, and we discuss this below.

For the estimation of wage equations we use longitudinal data from the PSID. The sample is based on annual interviews between 1968 and 1997 and on bi-annual interviews from 1999 onwards. We do not use individuals associated with the Census low income sample, the Latino sample or the New Immigrant sample and focus instead on the SRC core sample, which did not suffer any systematic additions or reductions between 1968 and 2001 and was originally representative of the US population.

The main earnings' variable in the PSID refers to the head of the household, and is described as total labor income of the head.¹⁸ We use this measure, deflated into 1992 dollars by the CPI-U for all urban consumers. By selecting only heads of household we ignore other potential earners in a family unit and restrict our attention to people with relatively strong attachment to the labor force. We include both men and women as well as whites and non-whites.

Information on the highest grade completed is used to allocate individuals to three education groups: high school drop-outs (LTHS), high school graduates (HSG) and college graduates (CG). A detailed description of our sample selection is reported in the appendix: in brief, we select heads of household aged 25-60 who are not self-employed and have positive labor income for at least 8 (possibly non continuous) years.

The age polynomials from the wage equation are presented in Table (1). Figure (1) plots the age profiles implied by the polynomial estimates for different education groups.

¹⁸In the PSID the head of the household is a male whenever there is a cohabiting male/female couple. Women are considered heads of household only when living on their own. We do not address the related sample issues explicitly, but any gender effects are likely to be captured in the ability estimates. The earnings variable includes the labor part of both farm and business income, wages, bonuses, overtime, commissions, professional practice and others. Labour earnings data are retrospective, as the questions refer to previous year's earnings, which means that 1968 data refer to 1967 earnings.

Table 1: Age polynomials' coefficients

Dependent variable: log hourly earnings		
coeff.	point estimate	S.E.
<i>Education=LTHS</i>		
age	0.0412505	0.0081143
age ²	-0.0004179	0.0000905
<i>Education=HSG</i>		
age	0.4928285	0.1071015
age ²	-0.0162768	0.0039883
age ³	0.0002413	0.0000644
age ⁴	-1.34e-06	3.82e-07
<i>Education=CG</i>		
age	0.8697329	0.1560285
age ²	-0.0282	0.0058548
age ³	0.0004149	0.0000953
age ⁴	-2.30e-06	5.69e-07

By fitting the within group specification of the wage (log of hourly earnings) equation we also obtain $\ln \hat{w}_{et}$, estimates of the growth of log-price of labor by education and year, which are plotted in figure (2). The time effects have a natural interpretation as time varying prices of skills associated to different education groups. The fact that the relative prices vary this much is a key justification for treating the different education levels as different types of human capital.

4.4 Permanent characteristics and their distribution

For the purposes of simulation we require the unconditional distribution of ability as reflected by the fixed effect θ_i . We thus use the estimate

$$\hat{\theta}_i = \frac{\sum_{t=1}^{T(i)} \ln w_{it} - \widehat{\ln w}_t - g(\widehat{age}_{it})}{T(i)}$$

where $T(i)$ is the total number of observation available on agent i . If we assume that the unconditional distribution of ability has not changed over the time period covered by our sample, we can use the estimated fixed-effects as an estimate of the $\{\theta_i\}$ distribution over the working population. In Figure (3) we report the empirical frequencies of $\hat{\theta}$ obtained by aggregating both cross-sectionally and longitudinally.

The estimation variance of $\hat{\theta}_i$ will inflate the overall variance of unobserved hetero-

geneity. To mitigate this problem we have traded off some representativeness by taking individuals who are observed for at least five periods. As a further check we compare our distribution of ability with the one-off IQ reported in the 1972 sample. Figure (4) reports the measured IQ densities for the whole 1972 sample and a selected sub-sample based on our criterion. It seems that both the IQ density and the estimated fixed effect density exhibit a long left tail.

4.5 Labor efficiency shocks

We now use the residuals from the wage equation to estimate our assumed stochastic process for wages. First note that we can treat as observable the following:

$$u_{eit} = \ln w_{eit} - g_e(\text{age}_{eit}) - \ln w_{et} - \theta_i \quad (11)$$

We assume that u_{eit} can be decomposed into two components

$$u_{eit} = z_{eit} + m_{eit}$$

where z_{eit} is an autocorrelated error process and m_{eit} is classical measurement error $iid(0, \sigma_{em}^2)$ and where $\{z_{ei}\}_t$ is a autocorrelated process with education specific parameters

$$z_{eit} = \rho_e z_{eit-1} + \varepsilon_{eit}$$

in which $\varepsilon_{eit} \sim iid(0, \sigma_\varepsilon^2)$, we can achieve identification of the autoregressive parameters in one of several ways. With an external estimate of the measurement error variance we can use the following expressions to estimate σ_ε^2 and ρ :

$$\rho = \frac{COV(z_{eit}, z_{eit-1})}{VAR(z_{eit})} = \frac{COV(u_{eit}, u_{eit-1})}{VAR(u_{eit}) - VAR(m_{it})} \quad (12)$$

$$VAR(u_{eit}) = \frac{\sigma_{\varepsilon_e}^2}{1 - \rho_e^2} + \sigma_m^2$$

where we can substitute the covariances of u with sample analogues. However it is also possible to use the variance of u and its first two auto-covariances to identify the variance of the measurement error as well. Thus we have that

$$\rho_e = \frac{COV(u_{eit}, u_{eit-2})}{COV(u_{eit}, u_{eit-1})}$$

Table 2: Estimated autoregressive coefficient $\hat{\rho}$

Group 1	Group 2	Group 3	Pooled
0.651	0.557	0.608	0.584
(0.130)	(0.042)	(0.058)	(0.034)

and the rest follows immediately. In practice we replace the error terms u with the residuals for the wage regression as defined in (11).

We present estimates of the autoregressive coefficients obtained using external estimates of measurement error by French (2000), who provides a lower and a upper bound estimate for measurement error (respectively 0.0172 and 0.0323). Our results are based on an average of the two. The (bootstrapped) standard errors are in parentheses.

The estimated values for $\hat{\rho}_e$ seem indicate that group 2 (High school graduates) experience the lowest earnings' risk.¹⁹ These findings are apparently in contrast with some of the recent literature, among others Storesletten, Telmer, and Yaron (2002) and Meghir and Pistaferri (2004). However, using the upper estimate of measurement error we get parameters very close to one. Of course, with near unit-root persistence of wage shocks the identification of fixed effects suffers from severe initial conditions problems. An alternative on which we are currently working is using an exogenous distribution of ability based on 1972 test scores while assuming unit-root behaviour of labor efficiency shocks.

4.6 Human capital aggregates

Estimation of the aggregate production function requires the total wage bills for each of the education groups, and in the general CES case we also require measures of human capital in each of these groups. We use the March supplement of the Current Population Survey (CPS) to obtain these. The CPS is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics.²⁰ The wage bills are straightforward to obtain. We just add up the earnings of each of the three

¹⁹The point estimates of σ_ε^2 for the pooled case is 0.01156, whereas for the LTHS, HSG and CG cases is, respectively, 0.01040, 0.01250 and 0.0098. We also perform tests based on the autocovariance structure of the AR(1) residuals, in order to check for the goodness of the specification. They validate the specification choice and are available from the authors.

²⁰The survey has been conducted for more than 50 years. Statistics on the employment status of the population and related data are compiled by the Bureau Labor Statistics (BLS) using data from the Current Population Survey (CPS).

education groups and then scale up the figures to match the entire US economy.

When we need to estimate a CES production function the issue is more involved because we also need to estimate the *quantity of human capital* in each year. To achieve this we need an aggregate price series for each of the education groups; our estimates from the PSID provide the growth of prices over time and we can normalise one of the initial prices to one.²¹

The adult universe (i.e., population of marriageable age) is comprised of persons 15 years old and over for March supplement data and for CPS labor force data. Each household and person has a weight that we use in producing population-level statistics. The weight reflects the probability sampling process and estimation procedures designed to account for nonresponse and undercoverage.

We use the CPI for all urban consumer (with base year 1992) to deflate the CPS earnings data and drop all observations that have missing or zero earnings.²² Since the earning data are top-coded for confidentiality issues, we have extrapolated the average of the top-coded values by using a tail approximations based on a Pareto distribution.²³

Figure (5) reports the number of people working in each year by education group, as reported by the CPS. It is clear that some strong and persistent trends towards higher levels of education have characterized the sample period.

Figure (6) plots both the average earnings by year and total wage bills in billions of dollars. Since CPS earning data until 1996 are top coded we report both the censored mean and a mean adjusted by using a method suggested by the BLS (*West (1985)*) which is based on the original Hill's estimator to approximate exponential tails. The difference between the two averages is larger for the most educated people who tend to be more affected by top-coding. We include also self-employed people in the computation of these

²¹ Now note that we have one degree of freedom. We can set the initial relative price of high school and of college graduate labour and we can then choose the utility costs of education to match the proportions going into each of the educational categories. In other words with unobserved costs the data can be rationalised either with high returns and high costs or low returns and low costs. The particular normalisation we choose will not affect the simulation of the policy changes.

²²Eliminating all zero-earnings observations rules out the possibility to incorporate employment risk, which is possibly an important source of risk.

²³This procedure is based on a general approach to inference about the tail of a distribution originally developed by Hill (1975). This approach has been proposed as an effective way to approximate the mean of top-coded CPS earning data by West (1985); Polivka (2000) provides evidence that this method closely approximates the average of the top-coded tails by validating the fitted data through undisclosed and confidential non top-coded data available only at the BLS.

aggregates; however, their exclusion has almost no effect on the value of the wage bills and human capital aggregate, as they never represent more than 5% of the working population in a given education group (and most of the time much less than that).

Finally, dividing the wage bills by the exponentiated value of the time effects estimated through the wage equations using PSID data we finally obtain point estimates of the value of efficiency weighted total labor supply (human capital aggregates) by education and year. These are plotted in Figure (7).

Notice that the evolution of human capital over time is non-monotonic, unlike the wage bills for the two highest education groups. This is due to the large increase in the level of estimated marginal product of these two factors in the early 1990s, which has grown proportionally more than the total remuneration of these factors.

4.7 Aggregate technology

In estimating technology parameters, we start from the relatively easier case of Cobb-Douglas technology. Let aggregate output Y be produced through the following technology

$$Y = \left(H_3^A H_2^{(1-A)B} H_1^{(1-A)(1-B)} \right)^{1-\alpha} K^\alpha$$

Using NIPA data we find the share of capital α to be between 0.3 and 0.35, depending on whether we correct for housing stocks. The share parameters A and B can be easily expressed as a function of the aggregate wage bills. If we apply this procedure separately for each year we can pinpoint the evolution of these functions over the sample period.

Figure (8) reports the value of the share parameters (with bounds equal to 2 standard errors) for the shares associated to each human capital variety. In figure (8) the line that is increasing over the sample periods represents A , whereas the downward sloping one represents $(1 - A)(1 - B)$. The almost flat line on top is $(1 - A)B$.

The time average of such shares is $A = 0.33$, $(1 - A)B = 0.54$ and $(1 - A)(1 - B) = 0.14$. The evolution of the college graduates labor share over time more than doubles (from 0.2 to 0.4) whereas the share of less-than-high-school labor falls dramatically from over 0.30 to roughly 0.06. These findings confirm what we found in terms of marginal products of labor using PSID data: major shifts in technology have taken place between the late 1960s and the end of the century.

Table 3: Point estimates of labor shares in technology

	First Step Weighting: Identity Matrix	First Step Weighting: Optimal Matrix
A	0.260 (0.200)	0.284 (0.207)
B	0.783 (0.115)	0.790 (0.123)

We follow up our initial findings by performing some additional inference on the technology parameters. In order to do this, we first approximate the total human capital factor $H = F \{H_1, H_2, H_3\}$ by combining NIPA and CPS data on wage bills and physical capital and then use a 2-step GMM method which controls for endogeneity and serial correlation of TFP to estimate the parameters. We use lagged shares as instruments.²⁴

The results of the GMM estimation of our favourite specification for the log-linearized C-D technology are reported in the tables above for two alternative moment weighting matrix choices, the identity matrix and the optimal matrix.

We also find that the linear trend included to control for TFP deterministic variation is estimated to be equivalent to an average annual TFP growth rate of roughly 3.5% between 1967 and 1997.

The point estimates for A and B give labor shares very similar to the long-term averages we estimate using the initial Cobb-Douglas computation. The labor shares roughly sum up to one, even though we don't impose this restriction in the estimation procedure.

5 Simulations

5.1 Some tuition experiments

The numerical experiments we report in the rest of this section are compared to a simple benchmark economy in which the discount factor β is set to match a physical capital over output ratio of 3.0. The resulting discount factor is very close to one. The depreciation rate is set to 0.07, which we compute from NIPA data. No negative assets are allowed in the benchmark economy. The deterministic leisure function $f^e(\theta)$ is discretised and then calibrated to match enrolment rates within different ability bins.

²⁴Details of the model can be provided by the authors on request.

The initial wealth distribution is endogenously determined in the simulations: the accidental bequests are distributed to the newborns following the steady state asset density. Thus some people are born with zero assets and others with different, positive amounts, which implies that some will be facing a tight liquidity constraint for college education. In the simulations we are not correlating initial assets and permanent characteristics, although we plan to do it in the future.

The tuition subsidy experiment is implemented by giving agents, *ceteris paribus*, a transfer (same for all) equal to a percentage of the direct cost of schooling. The additional resources needed to finance this policy in equilibrium are obtained by extra proportional income taxation.

The top panel of Table 8 shows the results for the benchmark economy. The bottom panel shows what happens in partial equilibrium, when prices for human capital do not change. However, taxes must change to fund the tuition subsidy and of course the underlying wealth distribution does change as well as the work behaviour. The middle panel shows the general equilibrium results where human capital process and the interest rate are allowed to change.

In partial equilibrium this universal subsidy leads to a substantial increase in college graduates from 20% to 25%. When breaking this down by ability we see that the increase is high for all ability groups, relative to their original position. In addition, this seems to have come for almost “free” since the tax on labour only needs to increase marginally. This is because the policy attracts a number of high ability and previously liquidity constrained individuals into higher education.²⁵ They earn high levels of income which more than compensate the cost of educating them. In fact there is a substantial increase in the college level human capital aggregate from 5.41 to 6.5. This is precisely the logic underlying a number of educational subsidy programmes around the world. Thus in partial equilibrium, the policy pays for itself.

In general equilibrium, though, the situation is quite different, at least as far as the aggregate shares are concerned. Following the policy there is a very small decline in aggregate college attendance. This is due to the decline in the marginal product of college level human capital. However, the aggregate figures hide important differences

²⁵Admittedly, this is also due to the tight zero borrowing limit that has been imposed for all agents. In this setup people who are born with zero assets are kept out of education.

within ability groups. These show a decline in College attendance *vis a vis* the baseline for ability levels two and three and an increase in College attendance for the highest ability level 4. In addition there is an increase in the rates of high school graduation for the lowest level of ability in response to an increase in the relative price for high school graduates. Finally there is a decline in college for the second ability group. All this adds up to an increase in the supply of human capital for the lowest and highest education groups: The subsidy has in fact led to an increase in inequality.

Similar results have been obtained when we use a production function with a higher elasticity of substitution, as can be seen in Table 9.

6 Conclusions

We combine estimation and calibration to obtain an overlapping generations general equilibrium model with heterogeneous agents and idiosyncratic uncertainty. Individuals choose education levels, labour supply and consumption within an incomplete markets set-up. We use this model to evaluate alternative educational interventions.

In the current version we experiment with tuition subsidies. It becomes apparent that while in partial equilibrium such policies can be very effective in increasing education levels and reducing inequality in general equilibrium the results are much less encouraging: The main effect of a subsidy there is to increase the supply of human capital as one would expect. However, it is the more able but liquidity constrained individuals who take up extra education, while the education levels of the less able can actually decrease (they are crowded out). Thus the subsidy acts on the composition of those in education.

In many respects this is very much in line with results found by Heckman, Lochner, and Taber (1998a). The inclusion of risky returns on labor earnings and the fact that labor supply is endogenous lend additional credibility to the result. The distributional changes in this economy under different interventions will be the focus of additional analysis. Moreover, future work includes assessing the relevance of liquidity constraints in the model economy and the equilibrium effects of artificially removing (insuring against) some of the risk components. The importance of risk in the partial equilibrium individual decision about schooling will also be the object of future extensions.

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A PSID Data

The Panel Study of Income Dynamics provides information on a variety of dimensions. Since the beginning, it was decided that those eligible for the 1969 and following waves of interviewing would include only persons present in the prior year, including those who moved out of the original family and set up their own households.²⁶ Until recently, there used to be two different releases of PSID data, Release I (also known as Early Release) and Release II (also known as Final Release). Early release data were available for all years; final release data are available (at time of writing) only between 1968 and 1993. The variables needed for our study are available in both releases. The difference is that Release II data tend to be more polished and contain additional constructed variables. We use Release II data for the period 1968-1993 and Release I data for the period 1994-2001²⁷.

Because of successive improvements in Computer Assisted Telephone Interviewing (CATI) software, the quality of the Public Release I files improved dramatically in recent waves, allowing the use of these data with confidence. The differentiation between Public Release I and Public Release II has recently been dropped altogether.

A.1 Sample selection

Unequal probabilities of selection were introduced at the beginning of the PSID (1968) when the original Survey of Economic Opportunity (SEO) sample of poor families was combined with a new equal probability national sample of households selected from the Survey Research Center 1960 National Sample. Compensatory weights were developed in 1968 to account for the different sampling rates used to select the SEO and SRC components of the PSID.

The probability sample of individuals defined by the original 1968 sample of PSID families was then followed in subsequent years. A distinction between original sample individuals, including their offspring if born into a responding panel family during the course of the study (i.e., both those born to or adopted by a sample individual), and

²⁶A distinction between original sample individuals, including their offspring if born into a responding panel family during the course of the study (i.e., both those born to or adopted by a sample individual), and nonsample individuals must be made. Details about the observations on non-sample persons and their associated weights and relevance are included in the appendix.

²⁷We also have results obtained from a reduced sample using only Release I data for 1968-1993: estimates of the parameters of interest don't substantially differ from the full sample estimates.

Table 4: Distribution of observations for the 1967-1992 sample, by year

year	Number of Observations	year	Number of Observations
1967	783	1980	1575
1968	853	1981	1551
1969	906	1982	1551
1970	965	1983	1586
1971	1090	1984	1636
1972	1192	1985	1656
1973	1280	1986	1610
1974	1328	1987	1535
1975	1382	1988	1484
1976	1428	1989	1415
1977	1489	1990	1349
1978	1513	1991	1285
1979	1550	1992	1201

nonsample individuals was also made. Only original sample persons and their offspring have been followed. These individuals are referred to as sample persons and assigned person numbers in a unique range. If other individuals resided with the sample individuals, either in original family units or in newly created family units, data were collected about them as heads, spouses/long term cohabitators or other family unit members, in order to obtain a complete picture of the economic unit represented by the family. However, these nonsample individuals were not followed if they left a PSID family.

Sample persons who are living members of a 1968 PSID family have a sample selection factor equal to the reciprocal of the selection probability for their 1968 PSID family unit. The computation of the sample selection weight factor for sample persons who are “born into” a PSID family after 1968 uses a formula that is conditional on the “sample status” of their parents. However, data for nonsample persons present a problem for longitudinal analysis since the time series for these individuals is left censored at the date at which they entered the PSID family. Furthermore, it is not likely that this left censoring is random with respect to the types of variables that might be considered in longitudinal analysis. Because of the left censoring of their data series, nonsample persons in PSID families have historically been assigned a zero value selection weight factor and a zero-value for

Table 5: Distribution of observations for the 1967-1992 sample, by education group

years of education	Number of Individuals	Number of Observations
less than 12	330	4,804
12 to 15	1,354	19,902
16 or more	687	10,487

the PSID longitudinal analysis weight.²⁸ This is of course a problem when using the core SRC: non sample people can be tracked through their Person 1968 number (that assumes values between 170 and 228) and whenever we use individual weights we control for the presence of non-sample individuals.

An additional dimension that is included in the core longitudinal weights are adjustments for panel attrition due to nonresponse and mortality. Attrition adjustments were performed in 1969 and every five years thereafter.

In general individual longitudinal weight values for PSID core sample persons are the product of three distinct sets of factors, that can be summarized as follows:

1. a single factor that represents the reciprocal of the probability by which the sample person was “selected” to the PSID panel;
2. a compound product of attrition adjustment factors developed in 1969 and every 5 years thereafter,
3. mortality adjustment factors also developed and applied in 1969 and every 5 years thereafter.

A general formula that reflects the composite nature of the individual weights is:

$$W_{i,1993} = W_{i,sel} \times \prod_{j=1969}^T [W_{i,NR(j)} \times W_{i,M(j)}] \quad (13)$$

where: $W_{i,sel}$ is the selection weight factor – the reciprocal of probability that individual i is selected to the PSID panel by membership in a 1968 PSID sample family or by birth

²⁸Beginning with the 1993 wave, PSID is providing users with a file that includes special weights that will enable analysts to include all 1993 sample and nonsample person respondents in cross sectional analysis of the 1993 PSID data set. These weights are called cross-sectional weights (as opposed to the standard longitudinal weights that have been produced from 1969 onwards).

Table 6: Distribution of observations for the 1967-2000 sample, by year

year	Number of Observations	year	Number of Observations
1967	776	1983	1546
1968	842	1984	1582
1969	891	1985	1609
1970	952	1986	1632
1971	1069	1987	1624
1972	1168	1988	1631
1973	1250	1989	1639
1974	1290	1990	1600
1975	1342	1991	1628
1976	1385	1992	1564
1977	1442	1993	1551
1978	1466	1994	1486
1979	1502	1995	1437
1980	1535	1996	1363
1981	1512	1998	1293
1982	1505	2000	1191

to a PSID sample parent; $W_{i,NR(j)}$ is the attrition adjustment factor applied to the i^{th} individual weight at time period j ; $W_{i,M(j)}$ is the age, sex and race-specific mortality adjustment applied to the i^{th} individual weight at time period j ²⁹.

The 1967-1992 Final Release Sample. The 1968-1993 PSID individual file contains records on 53,013 individuals (that is, all who were ever present in the sample at least on one year) We drop members from the Latino sample added in 1990 (10,022 individuals) and keep a sample of 42,991 individuals. We then drop those who are never heads of their household and we are left with a sample of 16,028 individuals. We then drop all individuals who are younger than 25 and older than 60, which leaves us with a sample of 13,399 individuals. Dropping observations for self-employed people reduces the sample to 11,574 individuals.

We keep in our sample only people with at least 8 (possibly non continuous) observations, which leaves us with 4,529 individuals. Dropping individuals with missing, zero or top-coded earnings reduces the sample to 4,300 individuals, and dropping individuals with total hours of work that are missing, zero or larger than 5840 further reduces our sample

²⁹Of course, non sample people have a zero weight because $W_{i,sel} = 0$ for them.

Table 7: Distribution of observations for the 1967-2000 sample, by education group

<u>years of education</u>	<u>Number of Individuals</u>	<u>Number of Observations</u>
less than 12	364	5,358
12 to 15	1,621	25,358
16 or more	806	13,587

to 4,295 individuals. We eliminate individuals with outlying earning records, defined as changes in log-earnings larger than 4 or less than -2, which leaves 4,211 individuals in the sample.

Finally, dropping people who are connected with the original SEO low-income sample leaves us with a sample of 2,371 individuals.

The composition of the sample by year and by education group is reported in the tables in this Appendix.

The 1967-2000 Mixed (Final and Early Release) Sample. After dropping 10,607 individuals belonging to the Latino sample and 2263 individuals belonging to the new immigrant families added in 1997 and 1999, the joint 1967-2001 sample contains 50,625 individuals. After selecting only the observations on household heads we are left with 19,583 individuals. Dropping people younger than 25 or older than 60 leaves us with 16,733 people. Dropping the self employment observations leaves 13,740 persons in the sample. We then select only the individuals with at least 8 (possibly non continuous) observations, which further reduces the people in the sample to 5559. Dropping individuals with unclear education records leaves 5,544 people in sample. Disposing of individuals with missing, top-coded or zero earnings reduces the sample to 5,112 individuals and dropping those with zero, missing or more than 5840 annual work hours brings the sample size to 5,102 individuals. We eliminate individuals with outlying earning records, defined as changes in log-earnings larger than 4 or less than -2, which leaves 4,891 individuals in the sample. Finally, dropping people connected with the SEO sample reduces the number of individuals to 2,791.

The composition of the sample by year and by education group is reported in the tables in this Appendix.

Table 8: Technology 1: Cobb-Douglas

GROUPS	Edu. Participation (aggr.shares)			Human Capital Aggregates		
	Less than HS	HS	College	Less than HS	HS	College
Benchmark (Tuition \$3105 - 30% of median income)						
All	0.34	0.46	0.20	3.99	9.30	5.41
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.94	0.055	0.004	0.56	1.0	0.95
Ability 2	0.36	0.53	0.11	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.23	0.52	0.26	668	1753	2122
Ability 4 (highest)	0.19	0.43	0.38			
% with wealth=0	0.082	r	0.0252	Tax lab	0.27	
General Equilibrium 50% (Subsidy \$1552)						
	Less than HS	HS	College	Less than HS	HS	College
	0.34	0.47	0.19	4.54	8.67	5.43
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.92	0.075	0.005	0.53	1.0	0.94
Ability 2	0.36	0.55	0.092	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.24	0.52	0.24	652	1710	2155
Ability 4 (highest)	0.20	0.38	0.42			
% with wealth=0	0.082	r	0.02519	Tax lab	0.28	
Partial Equilibrium 50% (Subsidy \$1552)						
	Less than HS	HS	College	Less than HS	HS	College
	0.34	0.42	0.25	4.29	8.01	6.50
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.94	0.050	0.011	0.5575	1.0	0.95
Ability 2	0.36	0.47	0.17	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.23	0.47	0.30	668	1767	2075
Ability 4 (highest)	0.19	0.38	0.43			
% with wealth=0	0.086	r	0.0252	Tax lab	0.272	

Table 9: Technology 2: E.of.S.=1.54, $\rho = 0.35$

GROUPS	Edu. Participation (aggr.shares)			Human Capital Aggregates		
	Less than HS	HS	College	Less than HS	HS	College
Benchmark (Tuition \$2929 - 30% of median income)						
All	0.34	0.50	0.16	4.48	9.71	4.46
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.89	0.10	0.011	0.44	1.0	0.94
Ability 2	0.38	0.56	0.058	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.24	0.55	0.21	563	1816	2310
Ability 4 (highest)	0.19	0.45	0.36			
% with wealth=0	0.082	r	0.025	Tax lab	.27	
General Equilibrium (50% Subsidy)						
	Less than HS	HS	College	Less than HS	HS	College
	0.35	0.50	0.15	4.88	9.20	4.61
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.88	0.11	0.011	0.43	1.0	0.93
Ability 2	0.37	0.58	0.048	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.25	0.56	0.19	556	1777	2361
Ability 4 (highest)	0.21	0.39	0.40			
% with wealth=0	0.081	r	0.025	Tax lab	.2734	
Partial Equilibrium (50% Subsidy)						
	Less than HS	HS	College	Less than HS	HS	College
	0.37	0.44	0.19306	4.99	8.4020	5.42
	Edu. Shares by ability			Marg. Products after Tax. and Depr.		
Ability 1 (lowest)	0.89	0.095	0.016	0.44	1.0	0.94
Ability 2	0.40	0.51	0.09753	Aver. Post-Tax Labor Earn.-1990 US\$		
Ability 3	0.27	0.49	0.24	589	1807	2257
group 4 (highest)	0.23	0.37	0.40			
% with wealth=0	0.084	r	0.025	Tax lab	.2750	

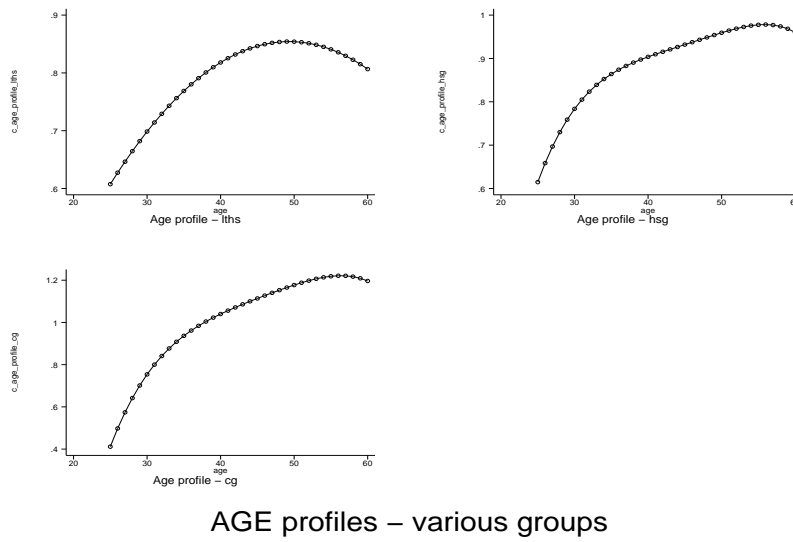


Figure 1: Age profiles of labor efficiency by education group - age on the horizontal axis

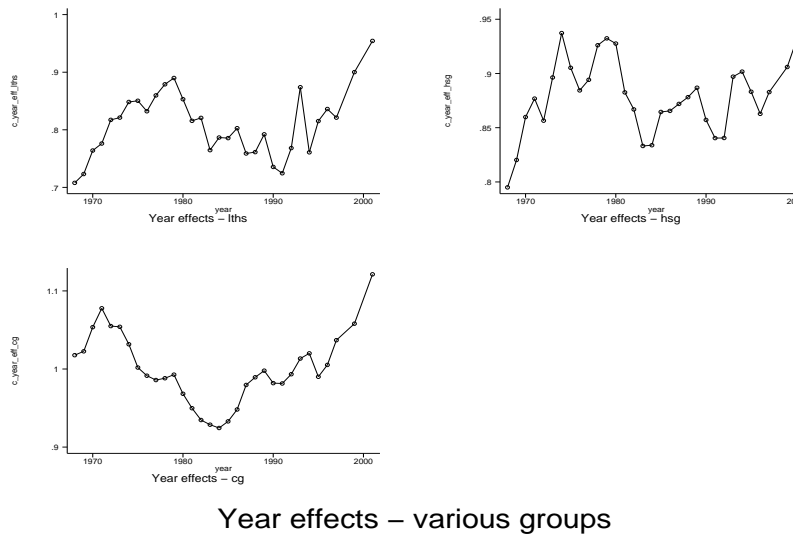


Figure 2: Estimated log of marginal labor productivity, by education and year

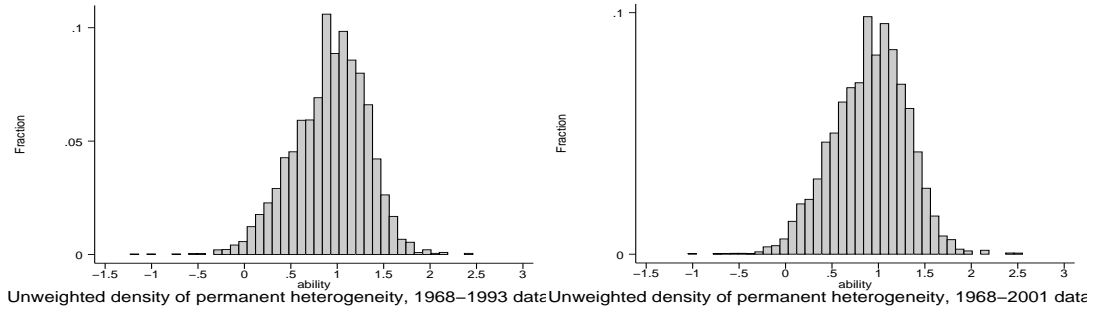


Figure 3: Estimated density of log fixed effects for small (67-93) and large (67-00) samples

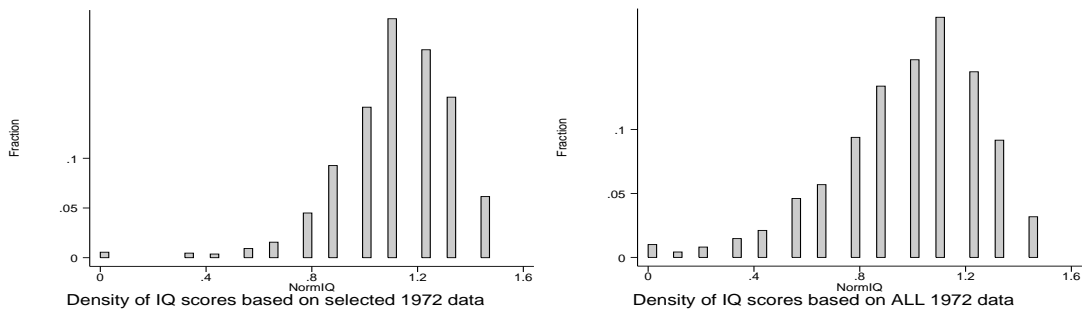


Figure 4: Density of IQ measurement from 1972 PSID wave, for the whole sample and a comparable sub-sample

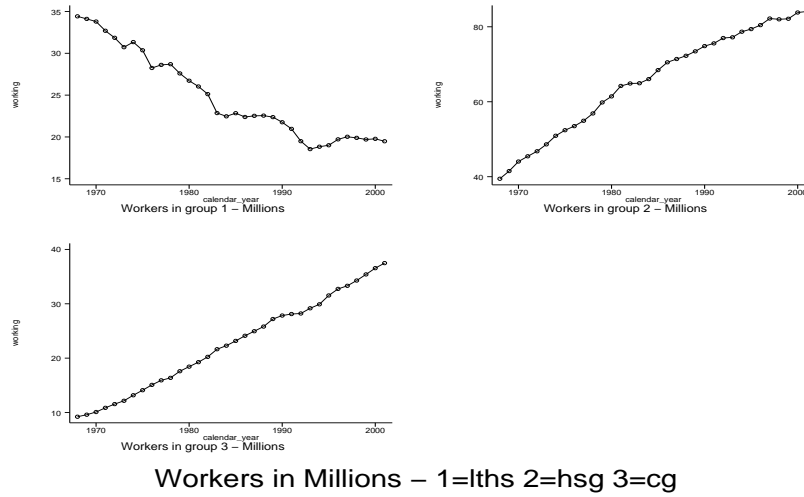


Figure 5: Employed workers in millions, by education and year

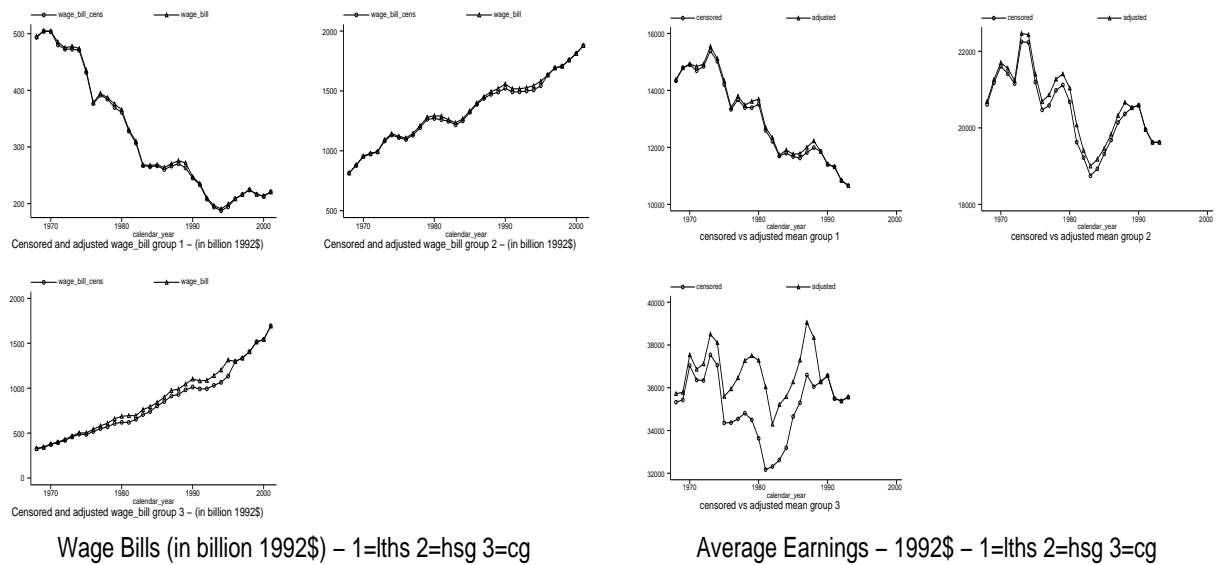


Figure 6: Total and average earned labor income, by education and year. Total in billions of 1992 dollars, average in units of 1992 dollars.

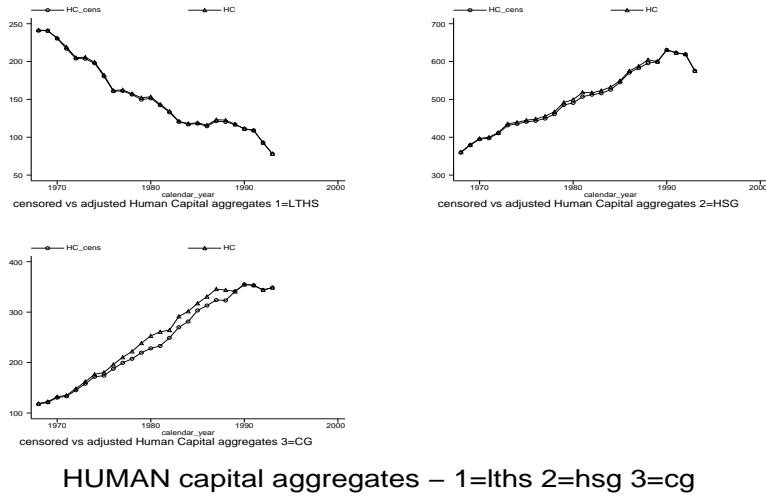


Figure 7: Value of efficiency weighted labor supply (HC) in billions of 1992 dollars, by education and year

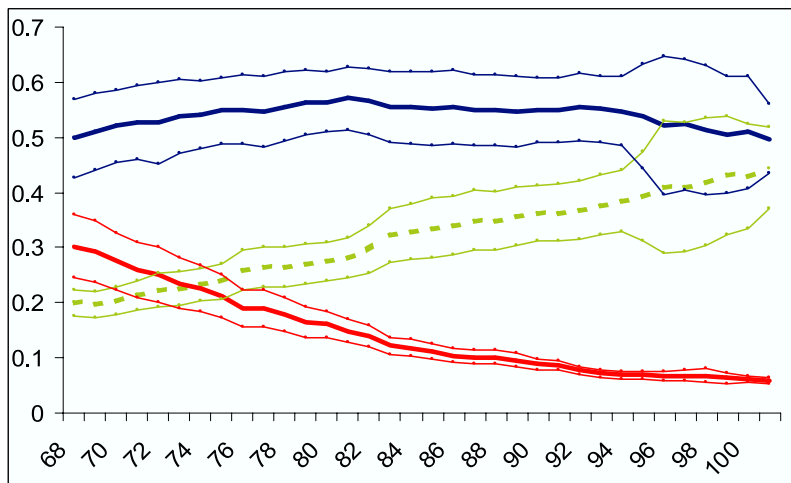


Figure 8: Labor shares in human capital input of technology, computed using Cobb-Douglas specification (with bounds equal to ± 2 standard errors). Period: 1968-2000. Larger bounds after 1996 are due to changes in top-coding of income in the CPS.