# Accounting for Changing Returns to Experience*

Lutz Hendricks†

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Preliminary and incomplete.

**Abstract**

To be written.
JEL: E24, J24 (human capital), I21 (analysis of education).
Key words: Education. College wage premium.

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†University of North Carolina, Chapel Hill; lutz@lhendricks.org

# 1 Introduction

**Related Literature:** Large literature documenting changes in U.S. wage distribution. Recent surveys include Eckstein and Nagypal (2004) and Heathcote, Perri, and Violante (2010).

Two previous approaches that study the evolution of U.S. wages through the lens of human capital theory

Heckman, Lochner, and Taber (1998) - need to say clearly how this is different

Guvenen and Kuruscu (2010)

One innovation: show that the model accounts for cohort specific age wage profiles. More comprehensive comparison with data.

Jeong, Kim, and Manovskii (2012) account for changing experience wage profiles based on changing relative prices of experience and raw labor.

# 2 The Model

## 2.1 The Environment

I study a general equilibrium overlapping generations model. The model abstracts from physical capital. Agents can borrow and lend at an exogenous interest rate (as in a small open economy).

**Demographics:** In each period $c$, $N_c$ households are born. Each lives for $T$ periods. Denote the year in which a person of cohort $c$ is aged $a$ by $t(c, a) = c + a - 1$. Denote the cohort aged $a$ in year $t$ by $c(a, t)$.

**Endowments:** At birth, agents draw two random endowments: $x$, $h_1$. Learning ability $x$ determines how efficiently the agent produces human capital in school or on the job. $h_1$ denotes the age 1 endowment of human capital, which I think of as produced during childhood prior to age 1. $x$ and $\ln(h_1)$ are drawn from a joint Normal distribution

$$\begin{bmatrix} a \\ \ln(h_1) \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{a,h1} \\ \rho_{a,h1} & \sigma^2_{h1} \end{bmatrix}\right) \tag{1}$$

I normalize $\mathbb{E}(a) = \mathbb{E}\ln(h_1) = 0$ and $Var(a) = 1$.

In each period, a person supplies $\ell_{s,c,t}$ market hours. They can be used for work or study.

**Preferences:** Upon entering the labor market, individuals maximize the discounted present value of lifetime earnings. Equivalently, individuals maximize the present value of utility derived from consumption subject to a lifetime budget constraint with perfect credit markets. There is no need to specify the utility function. School choice is also affected by the psychic costs $p_s$ (details below).

**Human capital production:** Human capital is produced in school and on the job. Agents choose from $S$ discrete school levels. Level $s$ lasts $T_s$ years and results in $h_{T_s+1} = F(h_1, x, s)$ units of type $s$ human capital at the start of work (at age $1 + T_s$). On the job, human capital is produced from human capital and study time $l_t$ according to

$$h_{t+1} = (1 - \delta_s)h_t + A(x, s)(h_t l_t)^{\alpha_s} \tag{2}$$

where learning ability affects productivity according to $A(a, s) = e^{A_s + \theta x}$. Each worker's effective labor supply is given by

$$e_{i,s,c,t} = h_{i,s,c,t}(\ell_{s,c,t} - l_{i,s,c,t}) \tag{3}$$

**Aggregate output and skill prices:** Output is produced from human capital augmented labor according to

$$Q_\tau = A_t \left[G_\tau^{\rho_{CG}} + (\omega_{CG,\tau} L_{CG,\tau})^{\rho_{CG}}\right]^{1/\rho_{CG}} \tag{4}$$

where

$$G_\tau = \left[\sum_{s=HSD}^{CD} (\omega_{s,\tau} L_{s,\tau})^{\rho_{HS}}\right]^{1/\rho_{HS}} \tag{5}$$

is a CES aggregator for unskilled labor (with less than a college degree).

Normalize $\omega_{s,t} = 1$.

Skill prices equal marginal products: $w(s,t) = \partial Q_\tau / \partial L_{s,\tau}$. $L_{s,\tau}$ denotes aggregate labor supply in efficiency units ($e$) of school group $s$ in year $\tau$.

## 2.2 Household Problem

The household is born at age 1 with endowments $x, h_1$ .

He first chooses a school level $s$ and then spends $T_s$ years in school, where he produces human capital $h_{T_s+1}$. Upon graduation, he begins work at age $T_s + 1$. In each working period, he divides his time endowment between job-training and work. He retires at age $T$.

### 2.2.1 Work phase:

At the start of work, the agent is endowed with $h_{T_s+1}$ units of type $s$ human capital and with ability $x$. He maximizes the discounted present value of lifetime earnings

$$V(h_{T_s+1}, x, s, c) = \max_{\{l_t\}} \sum_{a=T_s+1}^{T} R^{-a} y(l_a, h_a, a, s, c) \tag{6}$$

subject to the law of motion for $h$ (2) and the time constraint $0 \leq l \leq \ell_{a,s,c}$. $R$ denotes the exogenous gross interest rate. Period earnings are given by

$$y(l, h, a, s, c) = w_{s,\tau(c,t)} h(\ell_{t,s,c} - l) \tag{7}$$

This problem can be solved analytically using a minor extension of the solution given in Huggett, Ventura, and Yaron (2006). Assuming that study time is interior, optimal human capital investment is given by (suppressing schooling and cohort subscripts for ease of notation)

$$(l_t h_t)^{1-\alpha_s} = A d_t \tag{8}$$

where

$$d_t = \frac{\alpha_s}{R w_t} \sum_{j=1}^{T-t} w_{t+j} \ell_{t+j} \left( \frac{1 - \delta_s}{R} \right)^{j-1} \tag{9}$$

with $d_T = 0$. Then

$$\begin{aligned} A(l_t h_t)^{\alpha} &= A(A d_t)^{\alpha/(1-\alpha)} && (10) \\ &= A^{1/(1-\alpha)} d_t^{\alpha/(1-\alpha)} && (11) \end{aligned}$$

so that human capital is given by

$$h_t = h_1(1-\delta_s)^{t-1} + A^{1/(1-\alpha)}x_t \tag{12}$$

where

$$x_t = \sum_{j=1}^{t-1} d_j^{\alpha/(1-\alpha)}(1-\delta_s)^{t-1-j} \tag{13}$$

with $x_1 = 0$.

The fact that $x_t$ is common to all agents dramatically simplifies the numerical solution of the model.

Corner solutions need not be considered, given that the model will be calibrated to match observed age-wage profiles. Setting $l = \ell$ would imply a wage rate of zero and an infinite deviation from the calibration targets.

### 2.2.2 School phase:

School choice is sequential.

Individuals start their lives as high school students.

While in school, human capital accumulation is described by the function $h_s(h_1, x, c)$.

They graduate with probability $\pi(x)$.

Then they decide whether or not to enter college.

$$\max\left\{V\left(h_{HSG}\left(h_1, x, c\right), x, HSG, c\right) + \bar{\eta} - \gamma\eta, V_{coll}\left(h_1, x, c\right) - \gamma\eta\right\} \tag{14}$$

$\eta$ are independent type I extreme value shocks.

$\bar{\eta}$ is a constant that governs college entry rates.

In college: stay for 2 years. Then a dropout shock is realized. With probability $\phi(x)$, a student remains in college for another 2 years and then graduates. With complementary probability, the student must drop out and work as college dropout.

The value of college entry is therefore given by

$$V_{coll}\left(h_1, x, c\right) = \phi\left(x\right) R^{-4} V\left(h_{CG}\left(h_1, x, c\right), x, c\right) + \left(1-\phi\left[x\right]\right) R^{-2} V\left(h_{CD}\left(h_1, x, c\right), x, c\right) \tag{15}$$

## 2.3 Equilibrium

A competitive equilibrium consists of an allocation and a price system $\{w_{s,\tau}\}_{s=1}^{S}$ for all $\tau$ that satisfy:

1. Skill prices equal marginal products.
2. Given skill prices, households optimally choose schooling and on-the-job training.
3. Labor markets clear [improve this +++]

# 3 Data and Calibration [old +++]

## 3.1 Target Moments

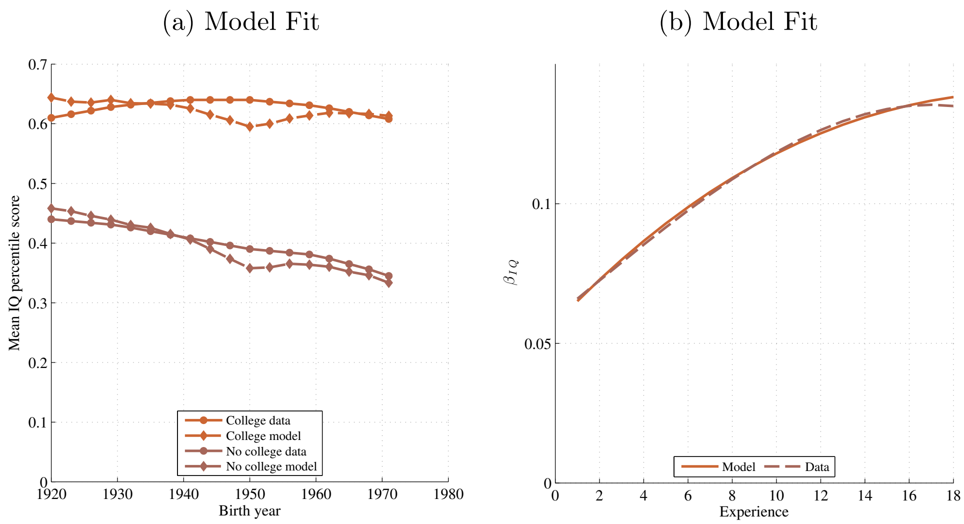
The main calibration targets are constructed from the March CPS files for 1965 − 2011 (King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick, 2010). They characterize men born between 1935 and 1969. To increase sample sizes, I divide the population into 35 equally spaced birth cohorts. For each cohort, I calculate

1. the fraction of persons that attains each of 4 school levels (high school dropouts, high school graduates, college dropouts, college graduates and more);
2. log median wages by age and school group.

Details of the CPS data are described in Appendix A. Additional moments that characterize the relationship between cognitive test scores, schooling, and wages are needed to identify the dispersion of ability $\theta$ and school sorting by ability:

1. The mean cognitive test scores of college educated and non-college educated workers for each cohort, taken from Hendricks and Schoellman (2014) (see Figure 1a). These are informative about the ability gaps between school groups and their evolution over time.

Figure 1: Model fit: IQ targets




2. The coefficients obtained by regressing log wages on standard normal AFQT scores and their interaction with a quadratic experience polynomial. The regression also contain school dummies as controls. This is based on NLSY79 data which are described in **??**. These are shown in Figure 1b. How the association between wages and AFQT scores changes with experience contains information about the effective dispersion of abilities $\theta$ and the correlation of abilities and human capital. For example, if $a$ and $\ln h_1$ were uncorrelated, then the correlation between wages and AFQT would be negative at the start of work and rise thereafter.

In the model, I assume that cognitive test scores (labeled $IQ$) are a noisy signal of ability:

$$IQ = a + \sigma_{IQ}\varepsilon_{IQ} \tag{16}$$

Figure 1 shows that the calibrated model matches both sets of moments reasonably well.

Table 1: Fixed parameters

## 3.2 Assumptions

**Functional forms:** The production function for schooling is the same as that for job-training. That is, $F(h_1, a, s, \tau)$ is found by iterating over 2 with $l_t = 1$.

with CG parameters – highly arbitrary.

Probability of high school graduation: logistic

Probability of college graduation: logistic

**Demographics:** The size of each cohort, $N_\tau$, is calculated from CPS data (see Appendix A). Students enter the model at physical age 18 (model age 1). They work until physical age 65 ($T = 65 - 18$).

**Endowments:** An easy way of drawing joint Normal random variables is as follows. First, I draw $a, \eta$ from independent standard Normal distributions. Then I define

$$\ln h_1 = \sigma_{h1} \frac{\gamma_{ah} a + \eta}{(1 + \gamma_{ah}^2)^{1/2}} \tag{17}$$

Varying $\gamma_{ah} \geq 0$ controls the correlation of $\ln h_1$ and $a$. $\sigma_{h1}$ is the standard deviation of $\ln h_1$ in each cohort.

**Fixed parameters:** Wages are expressed in year 2010 prices. The gross interest rate is set to $R = 1.04$.

Average market hours $\ell_{s,t,\tau}$ are measured from CPS data (see Appendix A).

School durations $T_s$ are set such that high school graduates start working at age $i$ and college graduates start working at age $i$. Table Table 1 summarizes these parameter values.

**Aggregation:** The algorithm computes equilibrium prices and quantities for all years during which one of the model cohorts works ($1952 - 2033$).

In a given year, cohorts that are not modeled contribute to aggregate labor supply. Notably, in 1964 the oldest model cohort is +++ years old.

Assumptions:

1. skill weights:
   (a) during the lifetimes of the model agents, $1952 - 2033$, relative skill weights grow at a constant rate (constant SBTC)
   (b) outside of the period $1964 - 2010$, skill weights grow at a constant rate
   (c) these rates are set to the model implied average skill weight growth rates over the period $1964 - 2010$
2. workers born before 1935 or after 1969:
   (a) have the same schooling as the nearest model cohort (by setting school costs)
   (b) face constant skill prices
   (c) relative skill prices are set at the levels 1952 and 2033.

## 3.3 Calibration Algorithm

The following parameters are calibrated jointly:

- endowment distributions: $\sigma_{h1}$, $\sigma_{IQ}$, $\pi_1, g_\pi$, and the correlation parameters $(\gamma_{ap}, \gamma_{ah})$.
- human capital technologies: $\alpha_s, \delta_s, \theta, A_s$.
- school costs $\mu_{s,\tau}$, where $\mu_{1,\tau}$ may be normalized to 0.
- skill weights: $\omega_{s,1}$ and growth rates +++.

These parameters are jointly calibrated using a simulated method of moments. I search over the parameter space. For each parameter guess, I solve the model and simulate 1000 individuals. The values of $\mu_{s,\tau}$ are chosen so that the model exactly matches the school choices of each cohort.

Rather than directly iterating over the parameters governing skill weights, the algorithm iterates over skill prices, which are approximated by a cubic spline with 82 nodes for each school group. The algorithm ensures that skill prices are consistent with constant skill-biased technical change through a penalty function. This approach is more efficient than iterating over skill bias parameters, in which case it would be necessary to solve a fixed point problem during each iteration (finding the skill prices that are consistent with market clearing and household optimization).

The algorithm minimizes a weighted sum of squared deviations between the model and data moments described above. Deviations from log median wages are weighted by the square root of the number of observations in each data cell.

Table 2 shows the values of the calibrated parameters. The curvature of the human capital production function is unusually low. Common estimates place $\alpha$ near 0.8 (Browning, Hansen, and Heckman, 1999). The calibrated values are between 0.3 and 0.7. This may reflect a difference in the way $\alpha$ is estimated here. Earlier work, such as Heckman (1976) treats the cross-sectional age profile of earnings as representing the longitudinal profile for a hypothetical cohort. The resulting earnings profile is strongly hump-shaped (see Figure 13 in Heckman 1976), which contrasts with the longitudinal profiles observed in CPS data. More recent work, such as Heckman, Lochner, and Taber (1998), uses longitudinal data for a single cohort; in this case the cohort born in 1960 and observed until age 35. My estimate uses longitudinal wage profiles for several cohorts, most of which are observed until age 60.

The depreciation rate of human capital range from 3.0% to 6.8%. These are higher than common estimates found in the literature. Notably, Heckman, Lochner, and Taber (1998) set $\delta = 0$ based on the observation that age-wage profiles seem roughly flat at older ages when theory suggests that training investment should be zero. Due to the lower value of $\alpha$, training investment remains positive until the agent approaches retirement (see Section **??**). Accounting for roughly flat wages then requires positive depreciation.

Table 2: Calibrated parameters

# 4 Results

## 4.1 Accounting for Cohort Wage Profiles

Show that model does a good job replicating age wage profiles for all cohorts and school groups.

Measure fit by $R^2 = 1 - RSS/TSS$ where $RSS$ is the weighted sum of squared model residuals (model log median wage - data log median wage) and $TSS$ is the weighted total sum of squared residuals in the data. Weights are square root of number of observations in each (age, school, cohort) cell.

Overall fit is 0.95 +++

Std dev of residuals = 0.05

By school group $R^2$ ranges from 0.84+++ for HSG to 0.92+++ for CG (cal_fit_so1).

std dev of residuals ranges from 0.05+++ for CG to 0.08 for HSG. [make a table]

could ask: how good is that fit relative to stat models: fixed exper effects; no cohort effects +++

Visual assessment of fit is provided in Figure 2, which compares the model generated age wage profiles with their data counterparts for HSG. 9 of the 35 model cohorts. The same for CG in Figure 3.

plots for other groups in Appendix.

Key data feature for both groups: shape of wage profiles changes over time. Model replicates these changes.

It is apparent that some of the profiles are not consistent with human capital theory and constant skill prices. The age profiles for those not college educated are essentially flat. Those for college graduates are not concave. Note also that the longitudinal wage profiles look very different from cross-sectional profiles that are sometimes used in their stead. They also look very

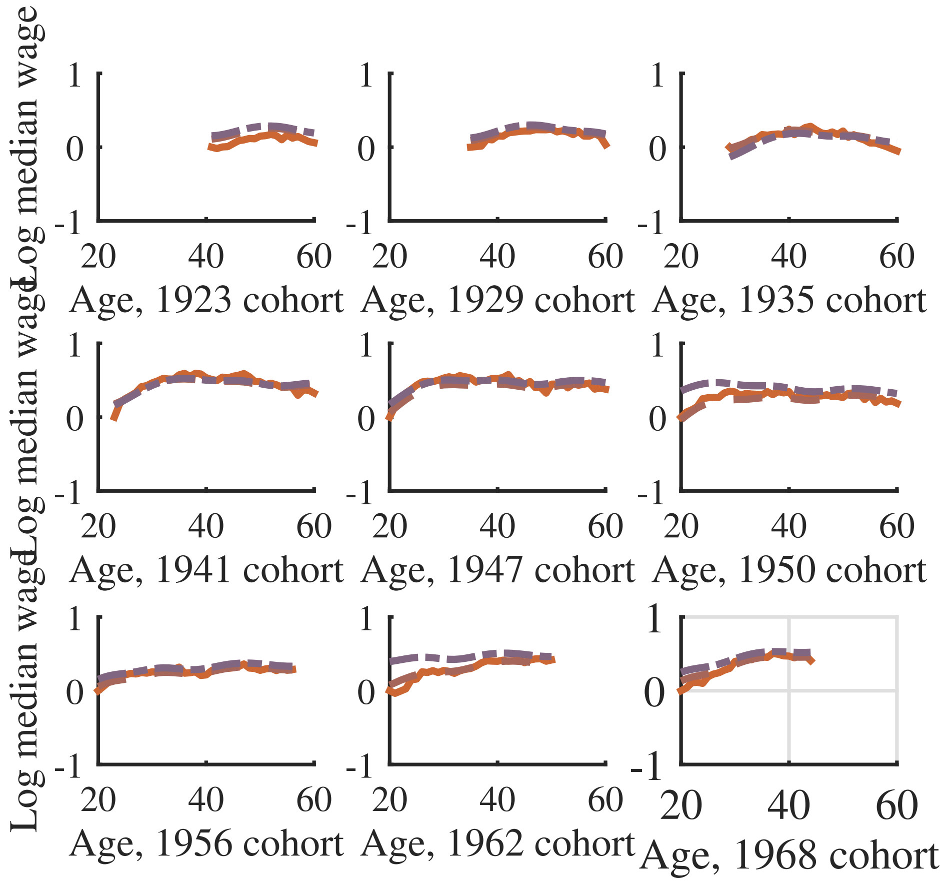



Figure 2: Model Fit HSG

different from the age wage profiles that sometimes estimated using panel data and imposing that a fixed age profile, combined with either year effects or cohort effects, characterizes all cohorts (e.g., Figure 3 in Huggett, Ventura, and Yaron 2006).

To see changes in shapes more clearly, Figure 4 show intercepts and slopes of cohort specific profiles. For all school groups, slopes have a U shape with min near 1950 birth cohort. Intercepts decline over most of the period.

Intercepts and slopes are inversely related. During the expansion of U.S. education up to the cohorts born in the early 1950s, all wage profiles became flatter over time, while their intercepts increased. After the early 1950s birth

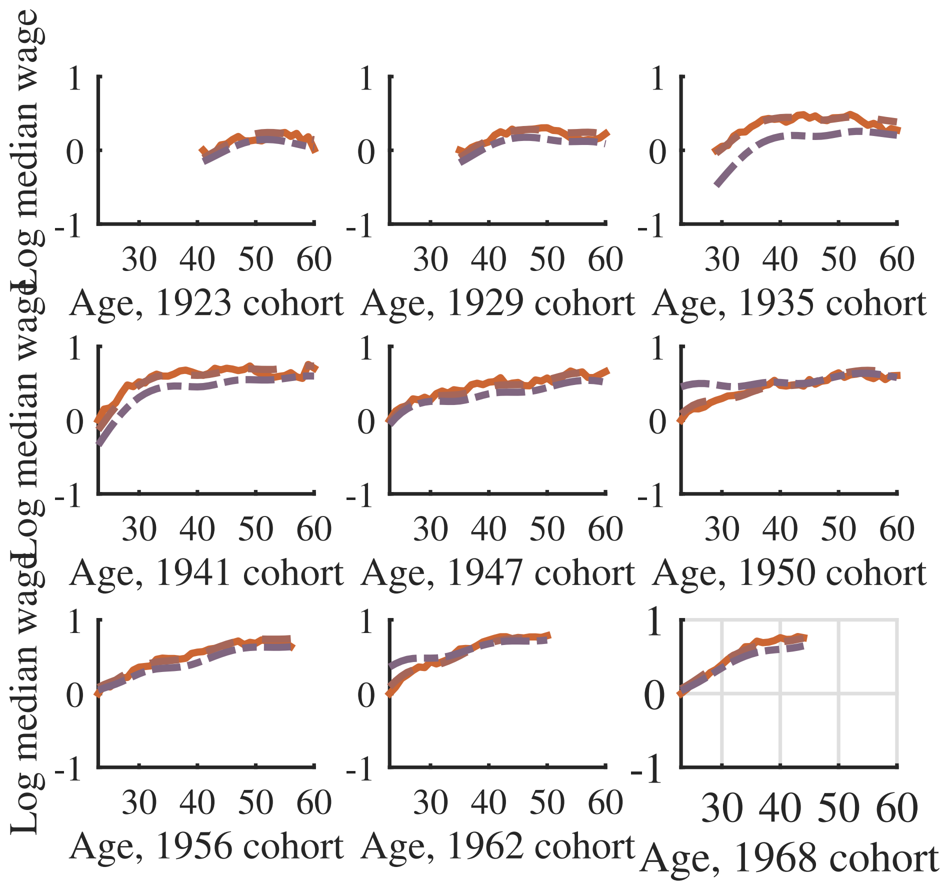



Figure 3: Model Fit HSG

cohorts, U.S. education growth essentially stopped. During this period, wage profiles became steeper with lower intercepts.

Model replicates without cohort effects.

Explain later how this works. Roughly: cohorts born in periods of fast skill price growth invest a lot in human capital. Their wage profiles have low intercepts and high slopes.

## 4.2 Accounting for Aggregate Wages

Show fixed weight skill prices, wages, model/data. Figure 5

Model replicates low frequency movements

How?

Skill prices look like smoothed wages. Reason: h provides amplification. Weak for less skilled where $\alpha_s$ is low. Stronger for college where $\alpha_s$ is higher.

### 4.2.1 The College Wage Premium

Model not only replicates aggregate college premium, but also evolution by age.

Card and Lemieux (2001) document differential evolution for young workers (ages $25-34$) versus older workers (ages $45-54$).

explain how model gets this

without imperfect substitution or changing relative prices of different labor types supplied by each worker in different proportions.

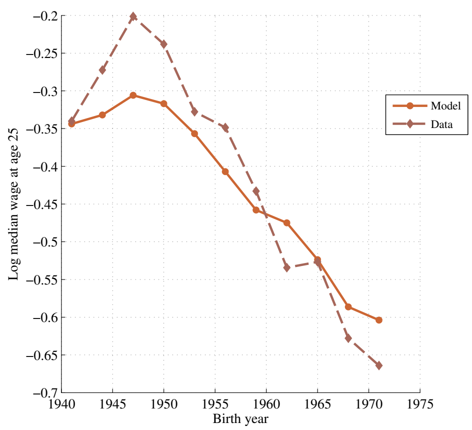
## 4.3 Selection and the College Wage Premium

The second question I address is:

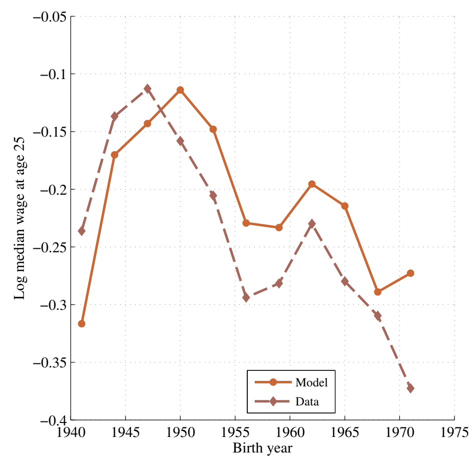
> What part of the college wage premium in a given year reflects differences in the human capital of college graduates relative to high school graduates?

Figure 4: Cohort Intercepts and Slopes

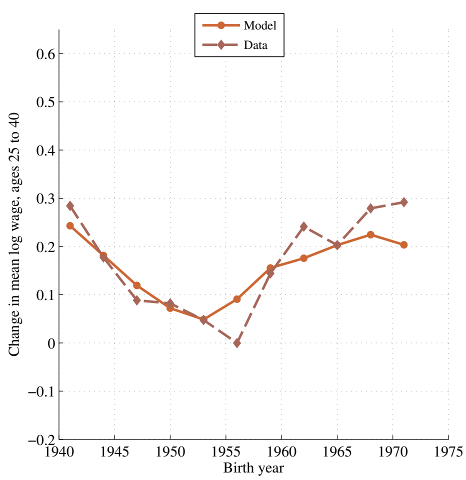
(a) Intercepts, HSG




(b) Intercepts, CG




(c) Slopes, HSG




(d) Slopes, CG

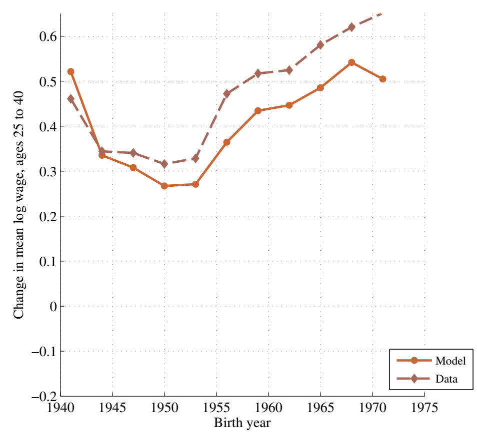


Figure 5: Aggregate Wages

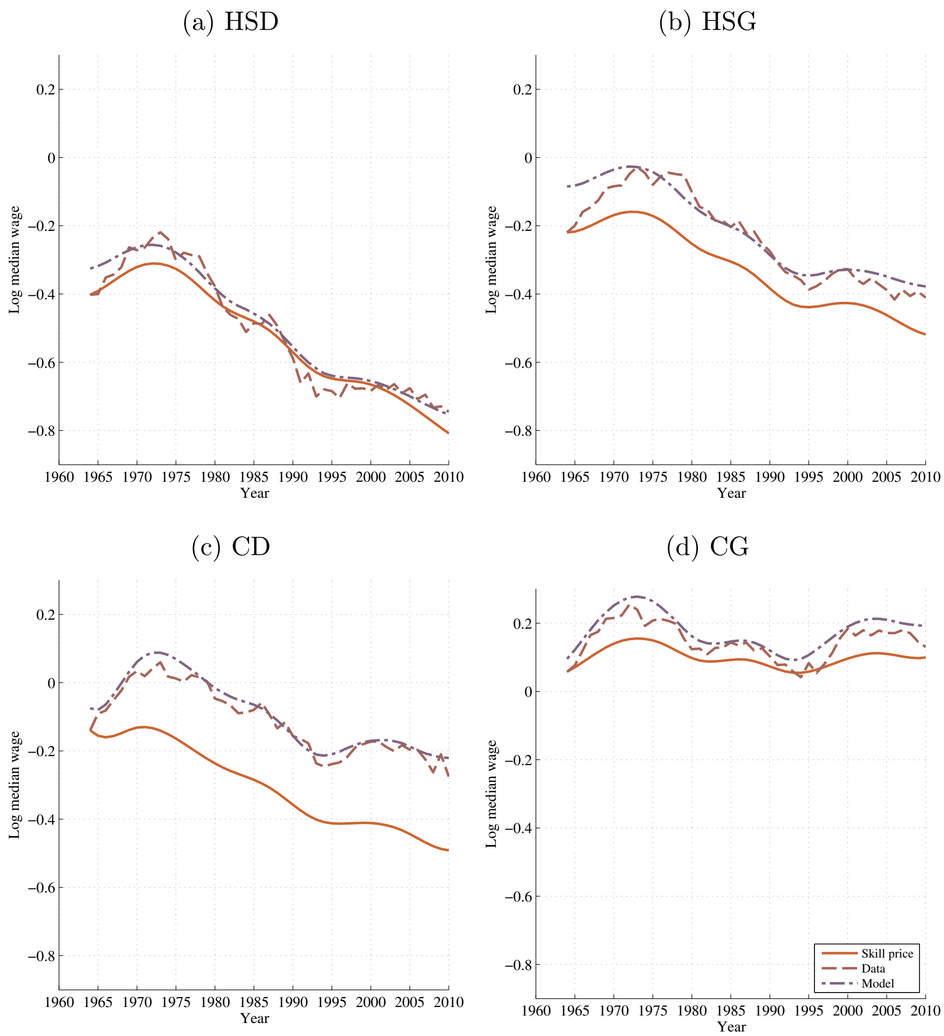
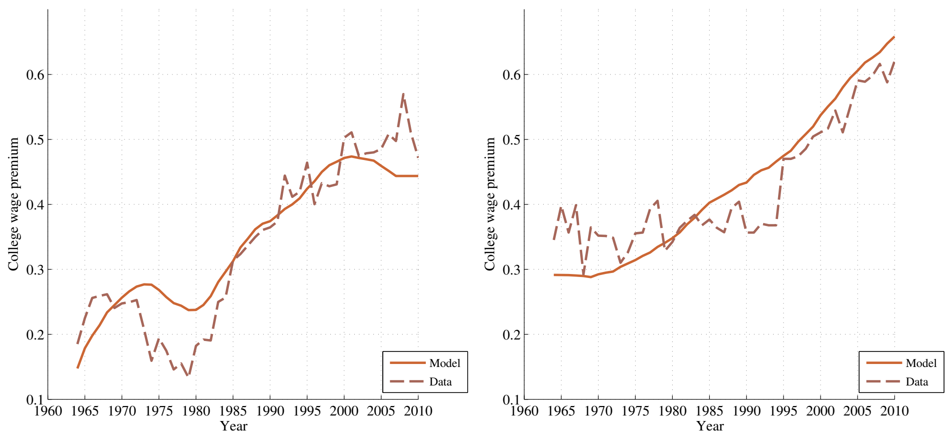


Figure 6: College Wage Premium

(a) Young workers (b) Older workers




This question is closely related to the much studied return to education. The data show a large wage gap between college graduates and high school graduates, especially in recent years. Heckman, Lochner, and Todd (2008) argue that the implied returns to schooling are considerably larger than the returns of common financial assets. One potential resolution of this tension is that part of the college wage premium is an ability premium.

It would be tempting to ask: How much would a person with given human capital earn as a high school graduate and as a college graduate? However, if high school human capital is a different good than college human capital, this is not a meaningful question. I therefore address the question by comparing the college wage premium at age 40 for the following three cases:

1. the baseline model

2. no selection: each person chooses each school level with the same probability

3. equal investment: each person chooses $l_{s,t}$ equal to the optimal $l_{HSG,t}$. [not implemented +++]

Figure Figure 7 shows that selection accounts for around 20 log points of the college wage premium. This leads to the second main finding:

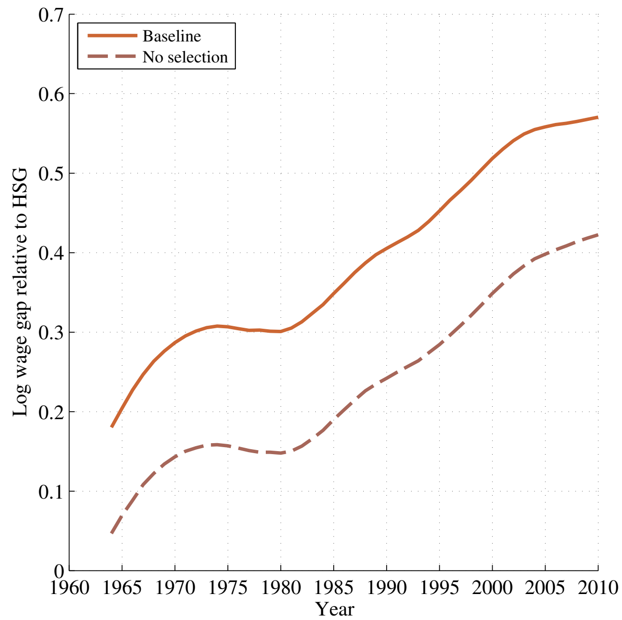



Figure 7: Cohort-specific college wage premiums

> About 40% of the college wage premium in 2005 is due to differences in endowments between college graduates and high school graduates. For earlier years, the fraction is larger.

Why is this so big and roughly time-invariant?

Big, roughly time invariant differences in E(a|s). Ask later how robust.

#### 4.3.1 Selection and lifetime earnings. [not updated +++]

The third question I ask is:

> What fraction of the lifetime earnings gap between college graduates and high school graduates is due to selection?

To address this question, I consider the same experiment as before. For each school group, I compute mean log lifetime earnings for the baseline model

$$Y(s,\tau) = \mathbb{E}\left\{\ln \sum_{t=1}^{T} y(l_{t,s,\tau}, h_{t,s,\tau}, t, s, \tau) R^{1-t} | s, \tau\right\} \tag{18}$$

Figure 8: Lifetime Earnings

The figure shows mean log lifetime earnings relative to high school graduates. Dashed lines represent random school assignment.

and for a group of individuals with mean endowments, $\hat{Y}(s,\tau)$. The contribution of selection to the lifetime earnings of group $(s,\tau)$ is then given by $Y(s,\tau) - \hat{Y}(s,\tau)$.

Figure Figure 8 shows the results. Each solid line represents mean log lifetime earnings relative to high school graduates, $Y(s,\tau) - Y(HSG,\tau)$. Each dashed line shows the same without selection, i.e., $\hat{Y}(s,\tau) - \hat{Y}(HSG,\tau)$. Selection accounts for 10 to 15 log points of the college lifetime earnings premium. For the early cohorts, this amounts to about half of the measured premium. For the later cohorts, where the lifetime college premium is around 0.5, selection accounts for only about one-quarter.

# 5 Conclusion

This paper decomposes changes in measured wages into the contributions of skill prices and human capital stocks. The model implies that unskilled skill prices declined at a far slower rate than measured wages. One reason is the decline in the mean abilities of unskilled workers that results from the expansion of education. The model attributes about one-third of the rise in the college wage premium to changing worker abilities and human capital investments. It attributes about half of the college wage premium in the period around 2005 to ability selection.

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# A Appendix: CPS Data

Refer to general appendix for construction of individual variables.

## A.1 Sample

CPS data are obtained from King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010). Summary information is provided in Table Table 3. The sample contains men between the ages of 18 and 65 observed in the $1965 - 2011$ waves of the March Current Population Survey. Persons are dropped if at least one of the following conditions are true:

1. weeks worked per year $< +++$
2. hours worked per week $< +++$
3. employment is either unpaid or in the armed forces
4. no valid wage information is provided (see below for details).

## A.2 Individual Variables

The construction of individual variables is based on Bowlus and Robinson (2012).

**Schooling:** As discussed in Jaeger (1997), the coding of schooling changes in 1991. I use the coding scheme proposed in his tables 2 and 7 to recode HIGRADE and EDUC99 into the highest degree completed and the highest grade completed.

Hours worked per year are defined as the product of hours worked last week and weeks worked last year. Weeks worked per year are intervalled until 1975. Each interval is assigned the average of weeks worked in years after 1975 in the same interval. Until 1975, hours worked per week are only available for the previous week (HRSWORK). I regress hours worked on years of schooling and a quadratic in experience to impute hours worked. After 1975, I use usual hours worked per week (UHRSWRK).

Table 3: Summary statistics for CPS data

| Year | $N$ | Avg $N$ per cell | $N$ range |
|---|---|---|---|
| 1965 | 20106 | 162 | 24 - 372 |
| 1970 | 18600 | 150 | 34 - 279 |
| 1975 | 16702 | 135 | 40 - 264 |
| 1980 | 22892 | 185 | 55 - 378 |
| 1985 | 20703 | 167 | 48 - 371 |
| 1990 | 21896 | 177 | 47 - 466 |
| 1995 | 19770 | 159 | 42 - 318 |
| 2000 | 34568 | 279 | 51 - 528 |
| 2005 | 32528 | 262 | 39 - 439 |
| 2010 | 30235 | 244 | 38 - 473 |

Notes: $N$ is the number of observations. Avg $N$ per cell refers to the average number of observations in each (age, school) cell. $N$ range shows the minimum and maximum number of observations in each cell. Cells cover age range 30-60.

**Income variables:** Labor earnings are defined as the sum of wage and salary incomes (INCWAGE). Wages are defined as labor earnings divided by hours worked. Wages are set to missing if weeks worked are below +++ or hours worked per week are below +++. Outliers with less than +++% or more than +++ times the median wage are dropped.

Income variables are top-coded. As discussed in Bowlus and Robinson (2012), the frequency of top-coding and the top-coded amounts vary substantially over time. In addition, top-coding flags contain obvious errors. In most years, fewer than 2% of labor earnings observations appear to be top-coded. Following Bowlus and Robinson (2012), I use median rather than mean log wages to avoid this problem. Dollar values are deflated using the Consumer Price Index (all items, U.S. city average, series Id: CUUR0000SA0; see bls.gov).

## A.3 Aggregate Variables

**Schooling:** The fraction of persons in cohort $\tau$ that achieves school level $s$ is calculated by averaging over ages 30 through 50 (not all ages are observed for all cohorts). Figure Figure 9 shows these fractions. Each point represents

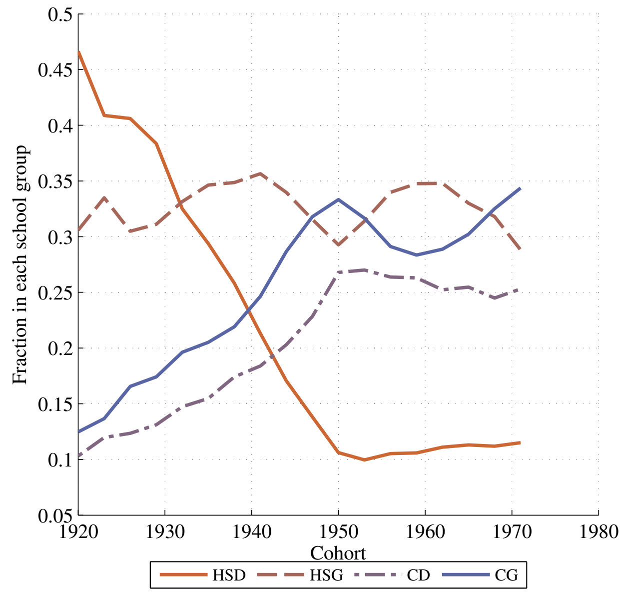


Figure 9: Educational Attainment By Birth Cohort

one cohort. Educational attainment grows until the 1950 cohort and then levels off (see Goldin and Katz 2008 for an extensive discussion of these trends).

Out of sample: assumed constant (for now +++).

**Age hours profiles:** I construct the age profile of annual hours worked, $\ell_{s,t,\tau}$, as follows:

1. For combinations of $s, t, \tau$ that are observed, I set $\ell_{s,t,\tau}$ to the average hours worked of all persons in the cell.

2. For each school group, I regress average hours worked in each $s, t, \tau$ cell on a quartic in age and on cohort dummies. Call the resulting hours values $\hat{\ell}_{s,t}$.

3. For combinations of $s, t, \tau$ that are not observed, I set $\ell_{s,t,\tau}$ equal to $\hat{\ell}_{s,t}$ which is scaled to match the level of $\ell_{s,t,\tau}$ for the nearest observed age.

4. Finally, the hours profile of each cohort is smoothed using an HP filter with parameter 20. Figure Figure 10 shows the smoothed hours profiles.

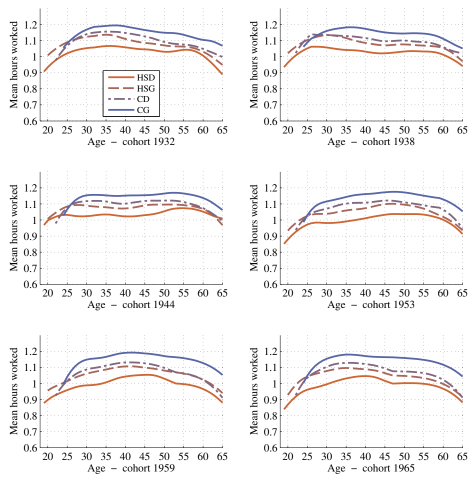


Figure 10: Age Hours Profiles

Since there is generally not much variation: feed a common fitted profile into the model +++

**Age wage profiles:** Construct median earnings per week for each $(s, a, c)$ cell. This drops outliers, but retains workers who report zero hours and thus zero earnings. This is the target.

Shows a very large decline after age 60. Hard to interpret because hours worked decline as well (retirement). For this reason, exclude observations past age 60 from the targets.

Figure +++