The Evolution of U.S. Wages: Skill Prices versus Human Capital*

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Preliminary and incomplete.

Abstract

The objective of this paper is to decompose movements in U.S. wages into movements of skill prices and labor qualities. The idea is to interpret the age-wage profiles of various birth cohorts observed in CPS data through the lens of human capital theory. Theory predicts that age-efficiency profiles should be concave (absent large skill price changes) and vary systematically with cohort education. I develop a model of school choice and on-the-job training and calibrate it to post-war U.S. wage data. The model measures the initial endowments (at age 17) and age-human capital profiles of each birth cohort as well as the school-specific skill prices for each year.

JEL: E24, J24 (human capital), I21 (analysis of education).

Key words: Education. College wage premium.

*The usual disclaimer applies.

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1 Introduction

The question: Since 1950, the U.S. has witnessed a substantial increase in educational attainment and, more recently, a widening of the wage gap between skilled and unskilled workers.[1] For recent cohorts, the return to attending college appears large relative to the returns offered by competing assets (Heckman, Lochner, and Todd, 2006).

One interpretation of the data holds that the skill price gap between college educated and high school educated labor has widened over time, perhaps due to skill-biased technical change.[2] A competing interpretation holds that the quality of college educated labor has increased relative to that of high school educated labor.[3] The two views are not mutually exclusive. Quantifying their relative importance for understanding the evolution of U.S. wages is the objective of this paper.

More generally, my purpose is to decompose the wages observed for workers of different school groups in each year into the contributions of skill prices and human capital. This task is challenging because neither skill prices nor human capital are directly observable (see Bowlus and Robinson 2010).

The approach: The idea of this paper is to solve the identification problem by exploiting the restrictions implied by human capital theory. The identification is based on the following ideas:

1. Human capital theory predicts that age-efficiency profiles should be concave for each birth cohort (unless skill prices vary too much over time; see Heckman 1976). When the data exhibit convex sections in a cohort's age-wage profile, this suggests rapid skill price growth during this period. This idea borrows from Bowlus and Robinson (2010) who propose a flat spot method to identify skill prices in part because the resulting age-wage profiles are consistent with human capital theory.

2. When the wages of all birth cohorts move together, it suggests that skill prices have moved. When the wages of different cohorts move against each other, it suggests that

[1] Goldin and Katz (2008) survey these developments.

[2] See, for example, Berman, Bound, and Griliches (1994); Berman, Bound, and Machin (1998); Goldin and Katz (2008).

[3] This idea is pursued, using various methods, by Heckman, Lochner, and Taber (1998), Guvenen and Kuruscu (2010),Bowlus and Robinson (2010), and Hendricks and Schoellman (2011).

labor quality has moved. This idea borrows from Katz and Murphy (1992), Murphy and Welch (1993), and Katz and Autor (1999) who observe that the wages of different cohorts tend to comove and interpret this as evidence that movements in labor quality are not important.

3. As schooling expands, the abilities of different school groups change. This should be reflected in the slopes of the age-wage profiles. This idea borrows from Hendricks and Schoellman (2011) and from Huggett, Ventura, and Yaron (2006) who propose to identify the distribution of endowments in a model of human capital accumulation based on the age variation of wage moments.

To quantify the implications of these ideas, I develop a model of school choice and on-the-job training. At age 17, agents are endowed with a learning ability and some human capital, which I think of as produced prior to age 17. Each agent chooses from 4 school levels, corresponding to high school dropouts, high school graduates, college dropouts, and college graduates or more. After completing their education, workers accumulate human capital on the job in a Ben-Porath fashion.

I calibrate the model to match the age wage profiles of several cohorts born between 1930 and 1964. The model identifies the distribution of ability and human capital endowments for each birth cohort. Further, the model measures how the skill prices and human capital stocks of each school group evolve over time.

Results. Preliminary results show that the model closely fits the observed age-wage profiles of all cohorts and school groups. Consistent with the evidence presented by Taubman and Wales (1972), the model implies that the cognitive skills of college students relative to high school students rise over time.

Partly due to the expansion of education and partly due to a strengthening of the association between schooling and ability, the model implies that the human capital of college graduates rises relative to that of high school graduates. A substantial fraction of the observed increase in the college wage premium is attributed to labor quality changes rather than movements in skill prices.

Related Literature: This paper is most closely related to Hendricks and Schoellman (2011) who study the same questions posed here using a very different identification strategy.

Theirs is based on the divergence of cognitive test scores between college and high school students over the post-war period.

Bowlus and Robinson (2010) also decompose measured wages into skill prices and labor qualities. Identification is based on the assumption that the labor quality of certain groups remains constant over time. This is the flat-spot method proposed by Heckman, Lochner, and Taber (1998).

Katz and Murphy (1992), Murphy and Welch (1993), and Katz and Autor (1999) observe that within-cohort wage changes are closely related to within-age group wage changes. They interpret this as evidence against important changes in cohort quality. However, human capital theory predicts that rising skill prices lead to large human capital investment and steep within-cohort age-wage profiles. Thus, human capital accumulation may amplify skill price movements. Rather than asking whether observed wage changes reflect either skill price movements or quality movements, I attempt to quantify the relative importance of the two.

2 The Model

Demographics: Time v is discrete and continues forever. In each period a cohort of exogenous size N_τ is born. τ denotes the year of birth. Individual live from model ages $t = 1$ (physical age 16) through T (physical age 65). Cohort τ is aged t in period $v = \tau + t - 1$.

Preferences: 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.

Endowments: At birth, agents draw three random endowments. Learning ability a 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 earlier childhood prior to age 1. p is a "psychic cost" that determines how much the individual enjoys schooling.

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

Technologies: Human capital is produced in school and on the job. Agents choose from S discrete school levels. Level s takes up T_s years and results in $h_{T_s+1} = F(h_1, a, s; \tau)$ units of type s human capital at the start of work (at age $1 + T_s$). Human capital production in school depends on learning ability a and the initial endowment h_1. The production function may vary by cohort.

On the job, human capital is produced from human capital and study time $l_{t,\tau}$ according to

$$h_{t+1,\tau} = (1-\delta)h_{t,\tau} + G(h_{t,\tau}, l_{t,\tau}, a, \tau + t - 1) \tag{1}$$

A single consumption good is produced from labor of different school levels according to the constant returns to scale production function

$$Y_v = J\left(L_{1v}, ..., L_{Sv}; \omega_v\right) \tag{2}$$

where ω_v is a vector of parameters and

$$L_{s,v} = \sum_{\tau=v-T}^{v-T_s-1} N_\tau f_{s,\tau}(\ell_{s,t,\tau} - l_{s,t-\tau+1})h_{s,t-\tau+1} \tag{3}$$

is an aggregate of the effective labor supplied by different cohorts who work at date v. $f_{s,\tau}$ denotes the fraction of persons in cohort τ who choose school level s.

2.1 Household Problem

The household is born at age 1 with endowments a, h_1, p. 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. I solve the household problem by backward induction, starting with the work phase.

Work phase: In each work period, the household is endowed with human capital $h_{t,\tau}$, ability a, and school level s. The Bellman equation is given by

$$V(h_{t,\tau}, t, a, s, \tau) = \max_{l_{t,\tau}} y(l_{t,\tau}, h_{t,\tau}, t, s, \tau) + R^{-1}V(h_{t+1,\tau}, t+1, a, s, \tau) \tag{4}$$

subject to the law of motion for h (1), the definition of period earnings

$$y(l_{t,\tau}, h_{t,\tau}, t, s, \tau) = w_{s,t+\tau-1} h_{t,\tau} (\ell_{t,s,\tau} - l_{t,\tau}) \tag{5}$$

and the time constraint $0 \leq l \leq \bar{l} \ell_{t,s,\tau}$, which states that the agent can spend at most fraction $\bar{l}$ of his time endowment on job training. R denotes the exogenous gross interest rate.

School phase: At age 1 the agent chooses one of S school levels. The value of level s is given by

$$W_s(h_1, a, p, \tau) = R^{-T_s+1} V(F[h_1, a, s; \tau], T_s + 1, a, s, \tau) + e^{\pi_\tau p} T_s + \mu_{s,\tau} \tag{6}$$

In addition to the discounted value of working V the agent enjoys an idiosyncratic "psychic" utility $e^{\pi_\tau p} T_s$ and a common, school specific utility $\mu_{s,\tau}$.

The psychic utility plays its usual role as a stand-in friction that generates imperfect school sorting by ability and h_1. $\pi > 0$ is a scale factor that defines the units of p. The specification ensures that, ceteris paribus, persons with higher p choose longer schooling. The common utility $\mu_{s,\tau}$ allows the model to match the fraction of persons choosing each school level in each cohort.

Each person chooses the school level that maximizes lifetime utility: $W(h_1, a, p, \tau) = \max_s W_s(h_1, a, p, \tau)$.

2.2 Equilibrium

A competitive equilibrium consists of an allocation and a price system $\{w_{s,v}\}_{s=1}^{S}$ for all v that satisfy ... (details to be written).

3 Data

The data are taken from the March CPS files for 1964-2010 (King, Ruggles, Alexander, Flood, Genadek, Matthew B Schroeder, and Vick, 2010). The sample contains men born between 1930 and 1964. To increase sample sizes, I divide the population into 5 equally spaced birth cohorts. For each cohort, I construct the fraction of persons that attains each of 4 school levels (high school dropouts, high school graduates, college dropouts, college graduates and more). I also construct age profiles of mean log wages. These are smoothed using an HP filter. To avoid problems with top-coding and measurement error, the 2% highest and lowest wage observations are dropped. The age wage profiles form the calibration targets for the model, as described in Section 4.

Figure 1 displays the cohort age-wage profiles. 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.

Figure 2 displays the same data, but lines up observations by year rather than age. A key observation is that the intercepts of successive wage profiles decline over time. When young, those born later earn less than those born earlier. At the same time, the age profiles for college educated workers become steeper as time goes by.

These points are made more clearly in Figures 3 and 4. The first figure shows the slope of the age-wage profile for each birth cohort, measured by the change in the log median wage between the ages of 25 and 40. The second figure shows the intercept of the wage profiles, measured by the level of the log median wage at age 25.

Cohort schooling expands smoothly until the 1950 birth cohort and then flattens out. During the expansion of cohort schooling, the intercepts of the age-wage profiles rose, while the slopes declined. The reverse pattern characterizes the period of roughly level schooling after the 1950 birth cohort. One idea of this paper is to exploit the comovements between cohort schooling and wage profiles to identify the changing endowments of human capital and abilities.

4 Calibration

At this point, I am working with a partial equilibrium model that treats the skill prices $w_{s,v}$ as exogenous.

Functional forms: I choose the following functional forms.

- In school, human capital is produced according to $h_{t+1} = (1-\delta)h_t + e^{\theta a}B(s, \tau + t - 1)^{1-\phi}h_t^{\phi}$. Iterating over this law of motion yields $F(h_1, a, s, \tau)$.

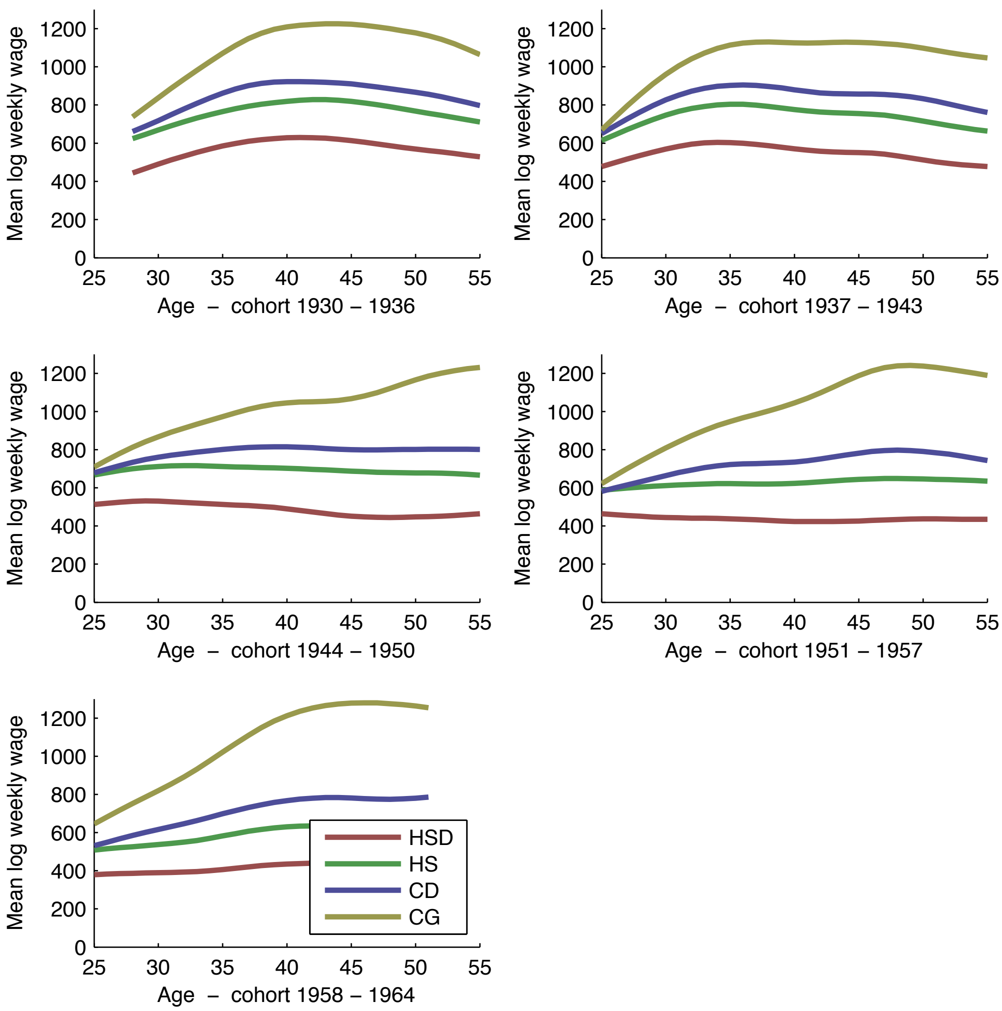

Figure 1: Cohort Age-wage Profiles

Notes: Wages are per week and denominated in year 2000 prices.

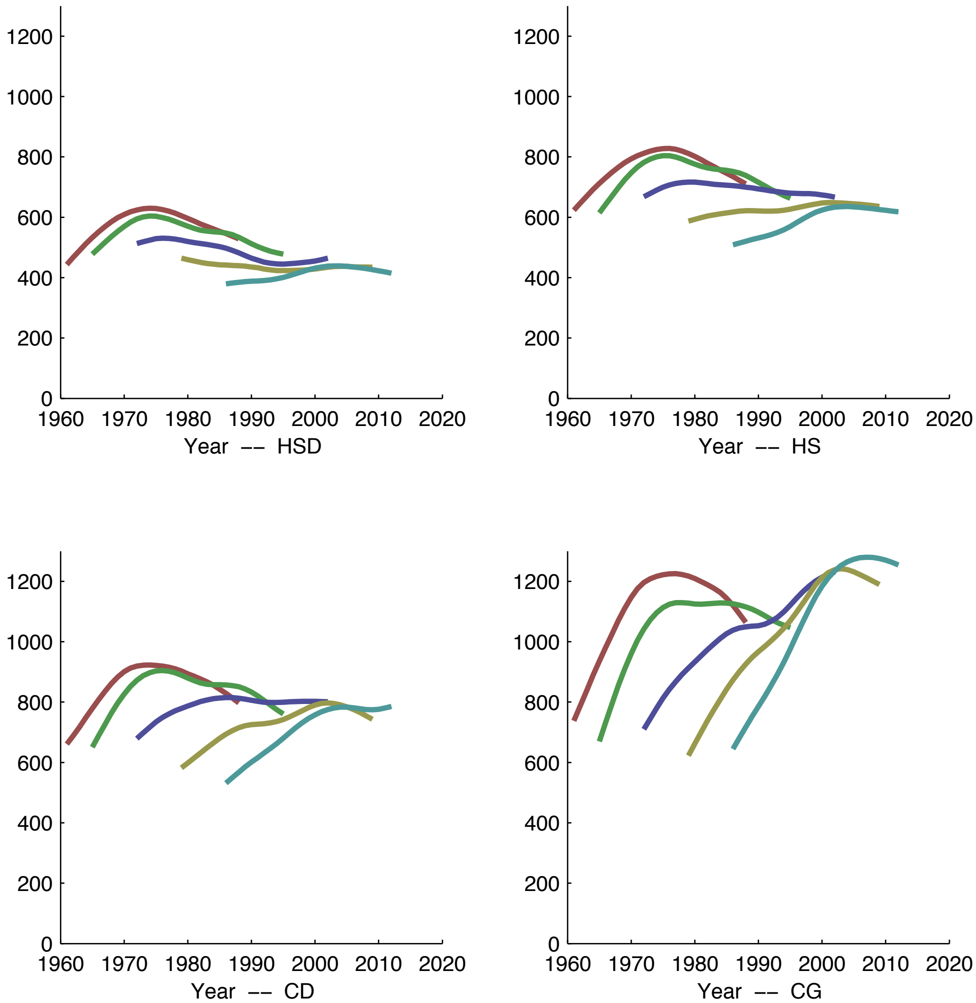

Figure 2: Cohort Age-wage Profiles

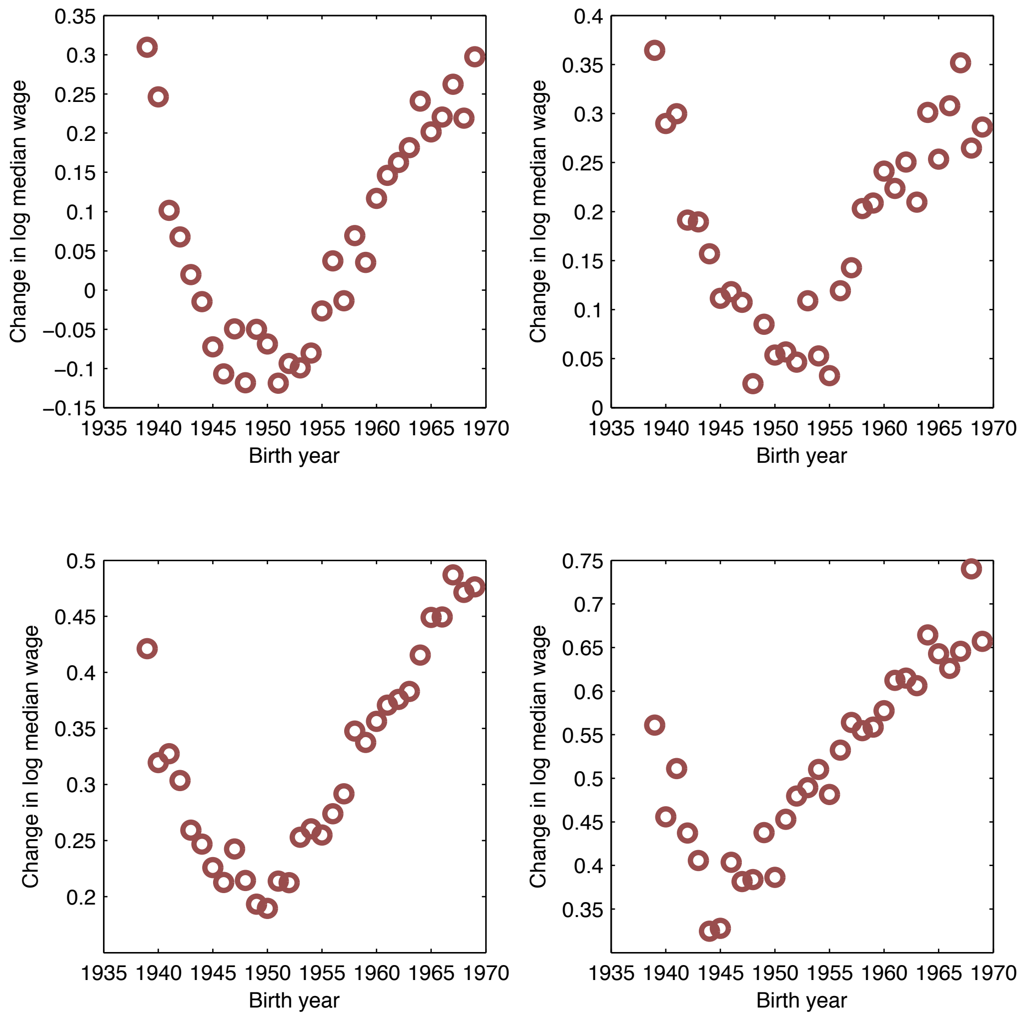

Figure 3: Wage Growth By Cohort

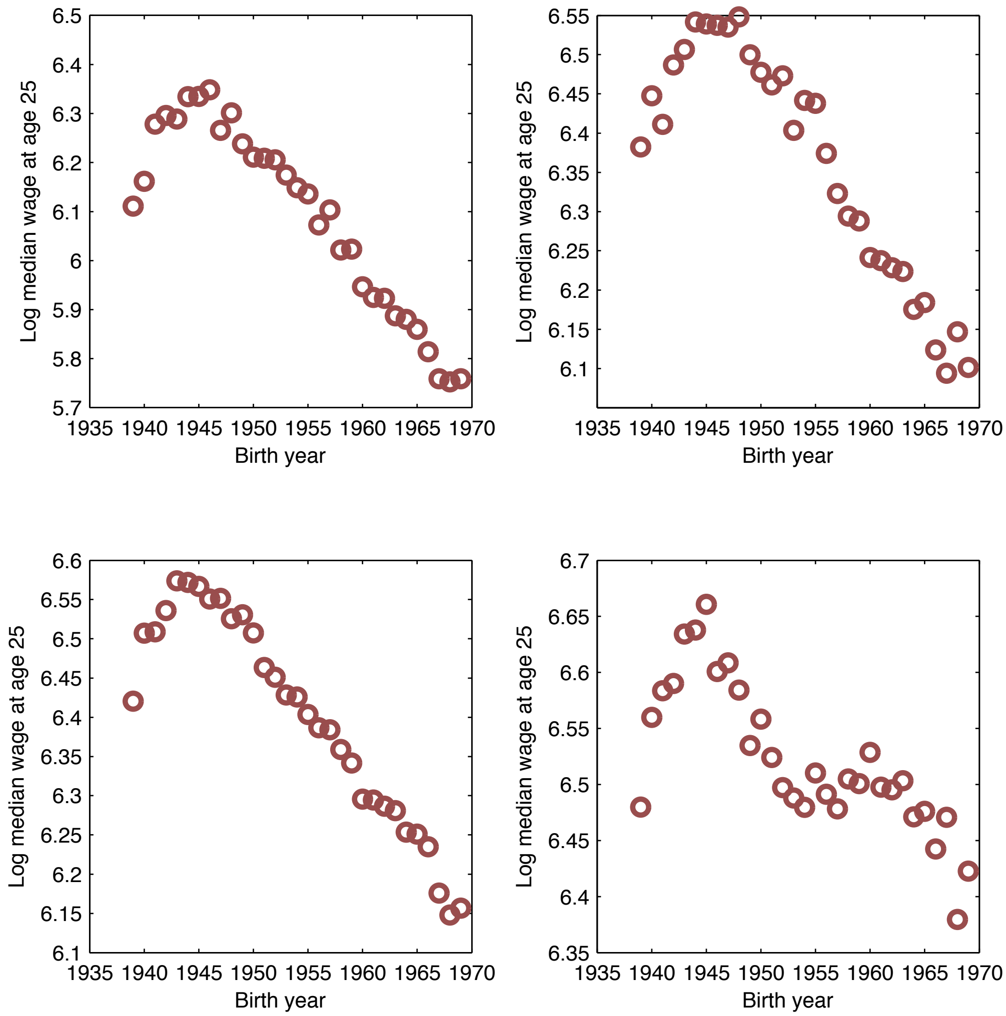

Figure 4: Log Median Wage at Age 25

- On the job, human capital is produced according to $G(l, h, a, \tau+t-1) = e^{\theta a} A(s, \tau+t-1)^{1-\alpha} h_t^{\alpha} l_t{}^{\beta}$. Huggett, Ventura, and Yaron (2006) prove that the job-training problem is concave when $\alpha = \beta$. I impose this assumption.

- I set $A(s, v) = B(s, v)$ and let all productivities grow at a common rate g_A. I also set $\phi = \alpha$.

Endowments: $(a, \ln h_1, p)$ are drawn from a joint Normal distributions. I normalize $\mathbb{E}(a) = 0$ by choosing productivity levels in the human capital production functions and $Var(a) = 1$ by choosing the scale parameter θ. I set $\mathbb{E}(p) = 0$ and normalize $Var(p) = 1$ by choosing π_τ. I assume that π_τ changes by g_π per year. The mean of $\ln h_1$ is normalized to 0 for the first cohort and grows by g_{h1} each year. The standard deviation of $\ln h_1$ is the same for all cohorts and called σ_{h1}.

An easy way of drawing joint Normal random variables is as follows. First, I draw $a, \hat{h}, \hat{p}$ from independent standard Normal distributions. Then I define $p = [\gamma_{pa} a + \hat{p}]/[\gamma_{pa}^2 + 1]^{1/2}$, where the scaling implies that $Var(p) = 1$. I define $\ln h_1 = \sigma_{h1}[\gamma_{ha} a + \gamma_{hp} \hat{p} + \hat{h}]/[\gamma_{ha}^2 + \gamma_{hp}^2 + 1]^{1/2}$. Varying the weights γ_{ij} allows me to adjust the correlations of $a, \ln h_1, p$.

Fixed parameters: Wages are expressed in year 2000 prices. I consider 5 birth cohorts that cover the birth years 1930 through 1964. The gross interest rate is set to $R = 1.04$. The size of each cohort N_τ, the fraction of persons in each school group $f_{s,\tau}$, and average market hours $\ell_{s,t,\tau}$ are measured from CPS data. The Appendix provides details.

Agents may spend at most $\bar{l} = 0.5$ of their time endowment on job training. This fraction is arbitrary. The school groups correspond to high school dropouts (HSD), high school graduates (HSG), college dropouts (CD), and college graduates or more (CG). School durations are set to $T_s = [1, 3, 5, 7]$, so that high school graduates start working at age 19 and college graduates start working at age 23. Table 1 summarizes these parameter values.

4.1 Calibrated Parameters

The following parameters are calibrated jointly:

- endowment parameters: (σ_{h1}, g_{h1}), (π_1, g_π), and the correlation parameters $(\gamma_{pa}, \gamma_{ha}, \gamma_{hp})$.

Table 1: Fixed parameters

Parameter	Description	Value
T	Lifespan	50
Birth cohorts	Cohort 1	1930 - 1936
	Cohort 2	1937 - 1943
	Cohort 3	1944 - 1950
	Cohort 4	1951 - 1957
	Cohort 5	1958 - 1964
T_s	School duration	$(1, 3, 5, 7)$
R	Gross interest rate	1.04

- human capital technologies: $\alpha, \theta, \delta, A(s, 1)$, g_A.
- school costs $\mu_{s,\tau}$, where $\mu_{1,\tau}$ may be normalized to 0.
- skill prices: $w_{s,v}$.

To limit the number of parameters, I calibrate $w_{s,v}$ for 5 years and interpolate by fitting a spline.

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 $100,000$ individuals. The values of $\mu_{s,\tau}$ are chosen so that the model exactly matches the school choices of each cohort. The algorithm minimizes a weighted sum of squared deviations between median wages constructed from the data and the model in each s, t, τ cell. The weights are given by the square root of the number of observations in each data cell.

Table 2 shows the values of the calibrated parameters.

4.2 Model Fit

Figure 5 compares the model generated age wage profiles with their data counterparts (previously shown in Figure 1). The fit is quite close. The only exceptions are college educated workers over the age of 50 in the first 2 cohorts. Their earnings drop off in the data, but not in the model.

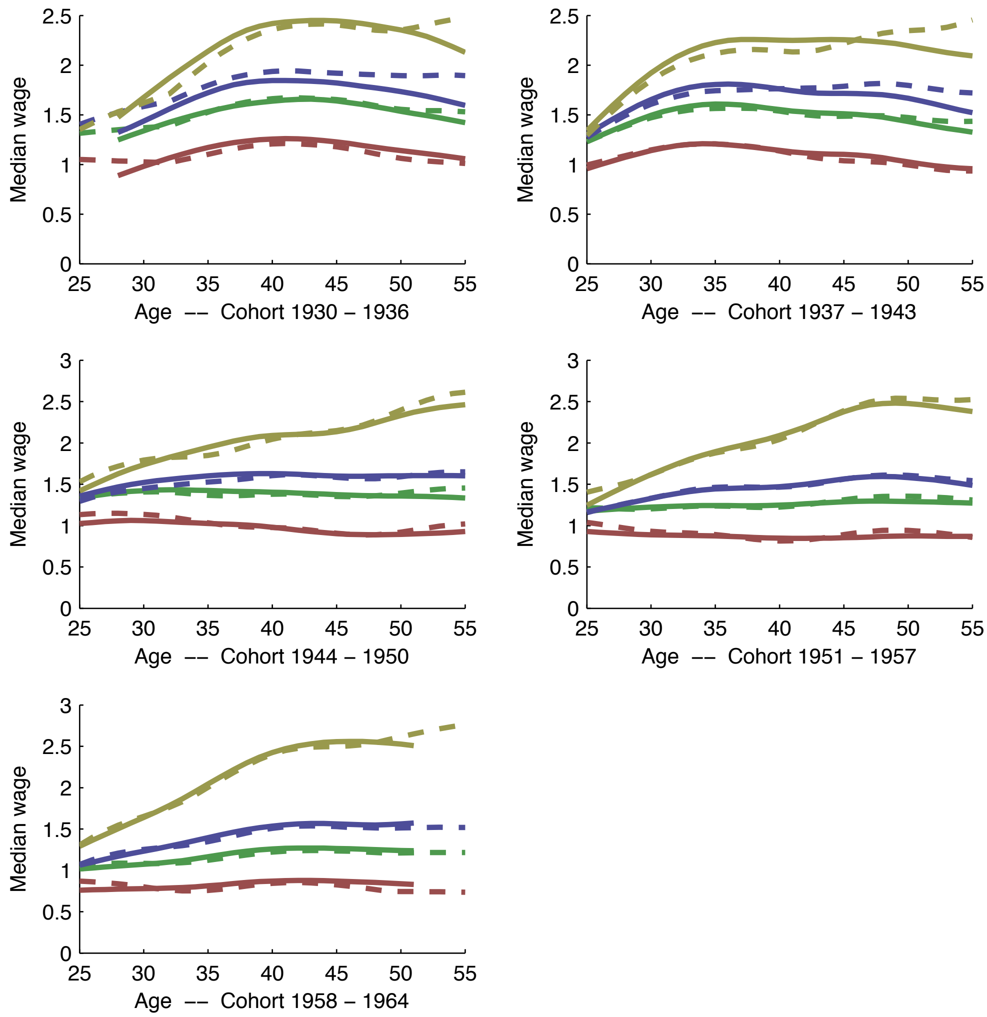

Figure 5: Model Fit

Table 2: Calibrated parameters

Parameter	Description	Value
On-the-job training		
$A(s)$	Productivity	0.540 0.732 1.023 0.982
$g(A(s))$	Productivity growth rate	0.0004
α	Curvature	0.313
δ_h	Depreciation rate	0.042
Endowments		
σ_{h1}	Dispersion of human capital endowment	0.017
$g(h_1)$	Growth rate of human capital endowment	-0.0083
θ	Ability scale factor	0.105
π	Psychic cost scale factor	0.123
$g(\pi)$	Growth rate of π	-0.0042

5 Results

Figure 6 compares the paths of skill prices and measured wages. For the less educated, skill prices decline more slowly than measured wages. This reflects a decline in the human capital of non-college educated workers.

For college educated workers, the trend growth of skill prices and wages is similar. The model attributes part of the rise in the college wage premium to a decline in the human capital of low skilled workers.

Table 3 shows the growth rates of measured wages and model skill prices over the sample period. The model implies large revisions to all wage growth rates. About half of the change in the college wage premium reflects growth in the human capital of college graduates relative to high school graduates.

Figure 7 shows the human capital age profiles of workers in each cohort. Figure 8 shows the fraction of time spent on job-training, $l_{s,t,\tau}/\ell_{s,t,\tau}$. Even at young ages, high-school dropouts invest too little in training to offset depreciation, so that their age profiles of human capital are downward sloping.

A key intuition which motivates this paper is that the expansion of education should lead to a decline in the abilities of students, especially in the lower education categories (see

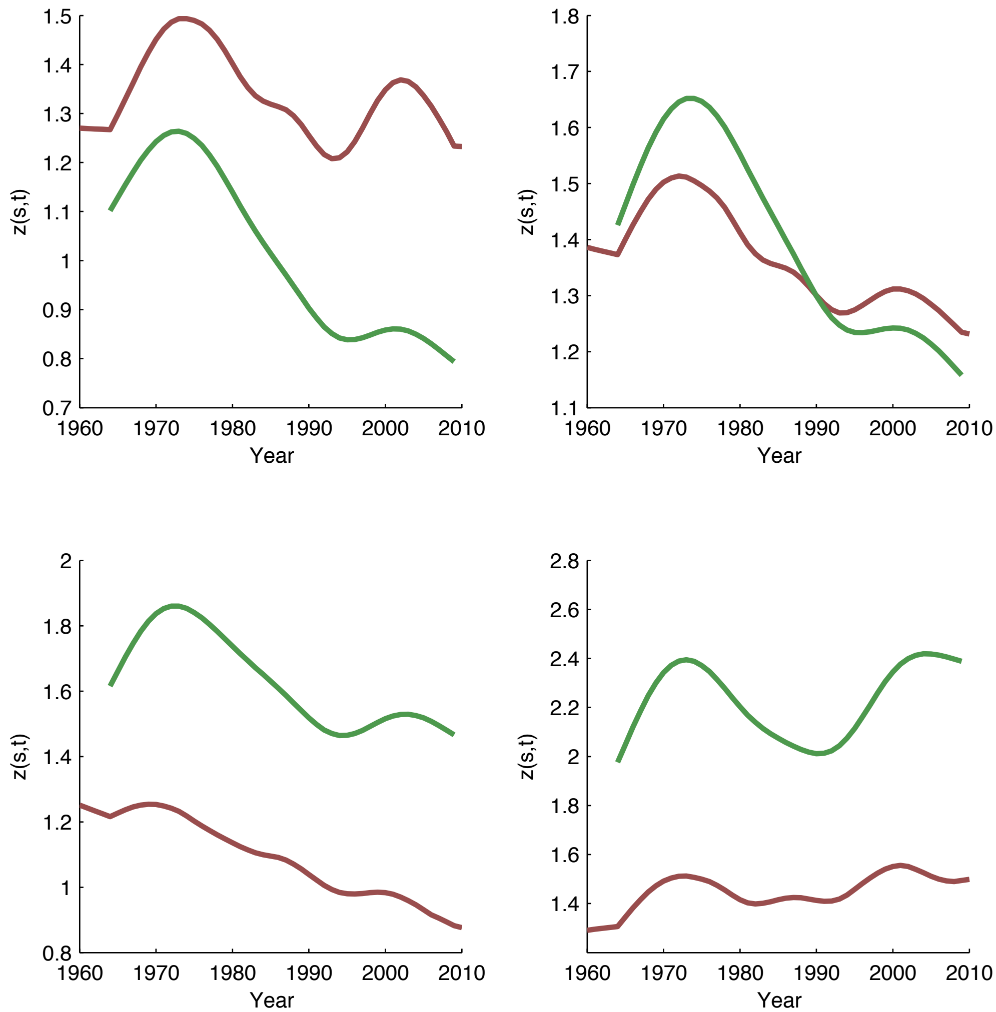

Figure 6: Skill Prices and Measured Wages

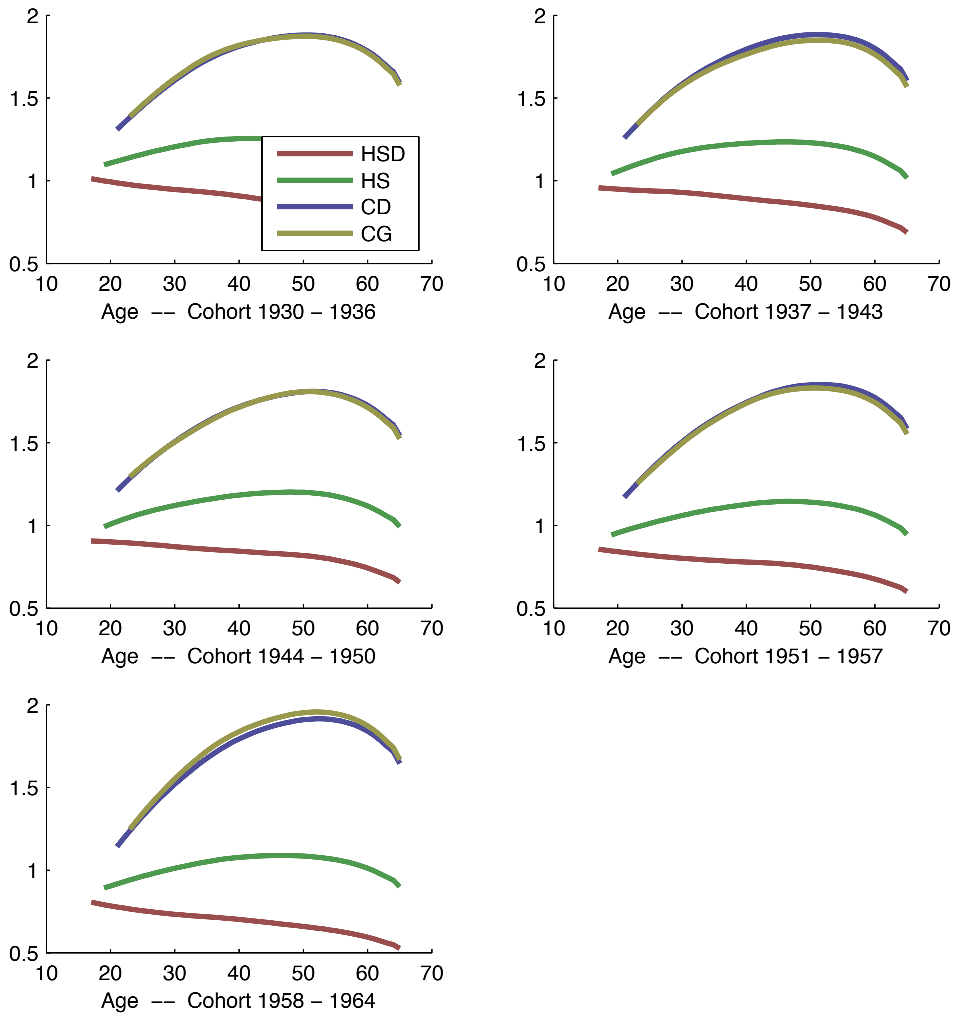

Figure 7: Age Profiles of Median Human Capital

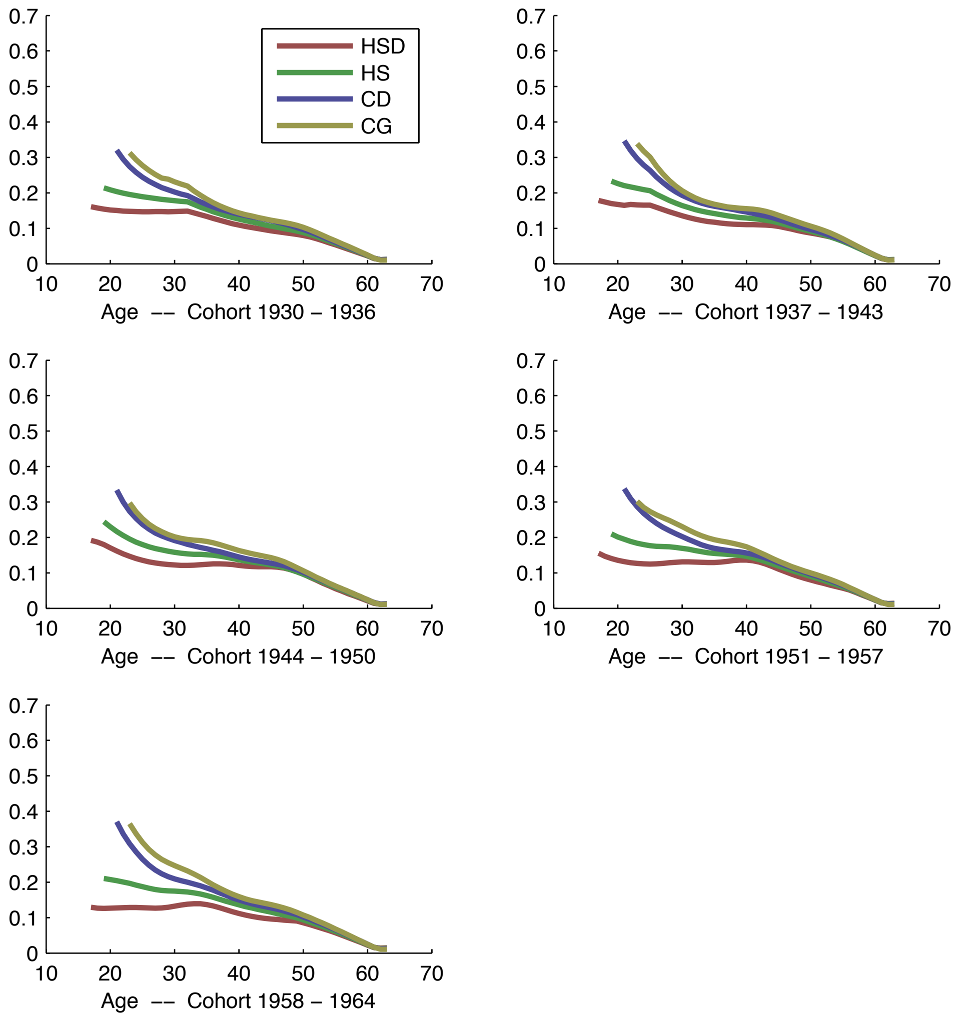

Figure 8: Median Job-training Time

Table 3: Changes in Skill Prices

	Skill price growth		Skill premium growth	
School group	Data	Model	Data	Model
HSD	-32.7	-2.7	-12.1	7.9
HS	-20.6	-10.6	0.0	0.0
CD	-9.0	-32.0	11.6	-21.4
CG	20.2	13.4	40.7	24.0

Note: The table shows changes in measured log wages ("data") and model log skill prices ("model"), 1964-2009.

Hendricks and Schoellman 2011). Figure 9 illustrates this trend in the model. Each panel represents one cohort. Each line shows the density of a for persons who choose a given s.

Schooling is essentially independent of ability for the first 2 cohorts. Then large ability gaps open up between students who attend college and those who do not. As a result, mean abilities decline for those who do not attend college, but rise for those who do. These findings are consistent with Hendricks and Schoellman (2011) and with the evidence presented by Taubman and Wales (1972). The model predicts that ability sorting strengthens over time, even though no ability measures are used in the calibration.

6 Conclusion

To be written.

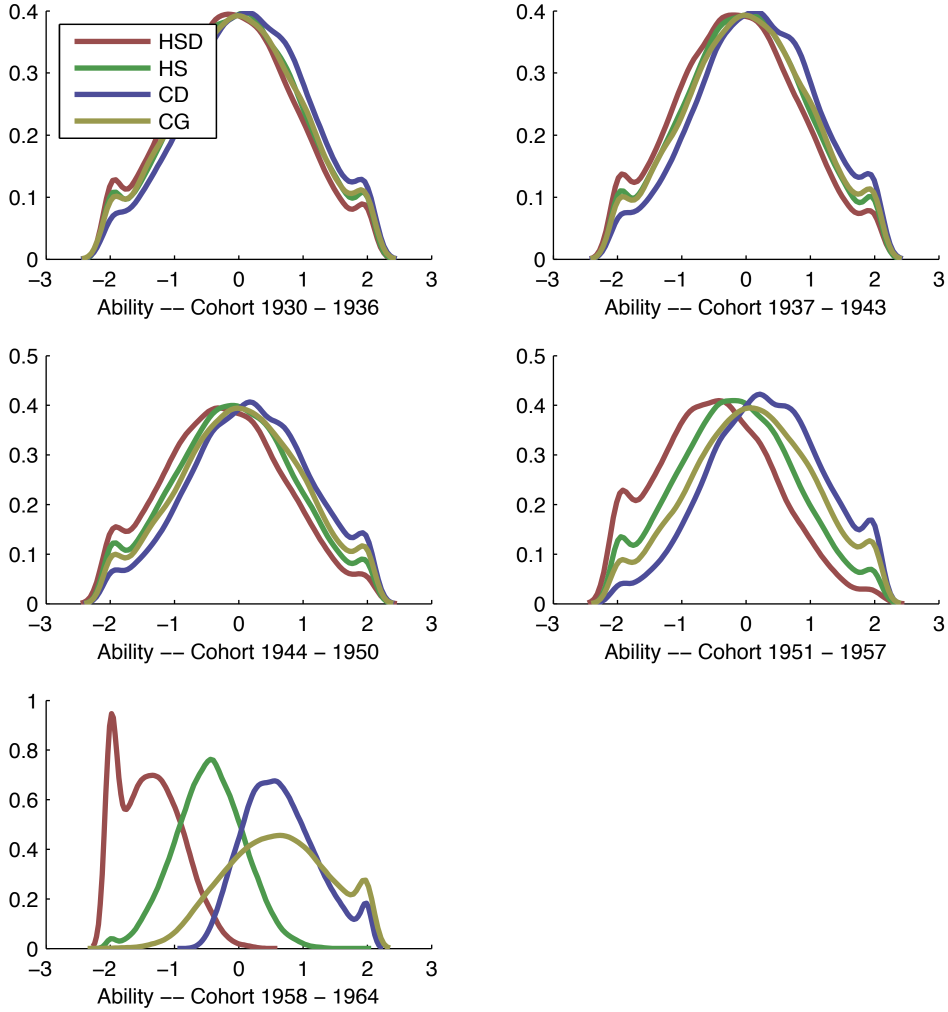

Figure 9: Distribution of Ability, Conditional on Schooling

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A Appendix: CPS Data

A.1 Sample

Our sample contains all men between the ages of 18 and 75 observed in the 1964-2010 waves of the March Current Population Survey (King, Ruggles, Alexander, Flood, Genadek, Matthew B Schroeder, and Vick, 2010). The data are obtained from King, Ruggles, Alexander, Flood, Genadek, Matthew B Schroeder, and Vick (2010). We drop persons who live in group quarters or who fail to report wage or business income.

A.2 Individual Variables

Hours worked per year are defined as the product of hours worked last week (HRSWORK) and weeks worked last year (intervalled, WKSWORK2). Each category of WKSWORK2 is recoded as the interval midpoint.

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.

Income variables: Labor earnings are defined as the sum of wage and salary incomes (INCWAGE) plus two-thirds of non-farm business income (INCBUS). The latter captures the labor portion of income earned from self-employment and professional practice.

Wages are defined as labor earnings divided by weeks worked. Wages are set to missing if weeks worked are below 25. Outliers with less than 5% or more than 100 times the median wage are dropped.

Income variables are top-coded. As discussed in Bowlus and Robinson (2010), 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 Autor, Katz, and Kearney (2008), I multiply top-coded amounts by 1.5 in years before 1988. From 1996 onwards, top-coded amounts are set to the average of all values above to top code. I leave these value unchanged. Between 1988 and 1995 there is no clear way of identifying top-coded values in IPUMS data because

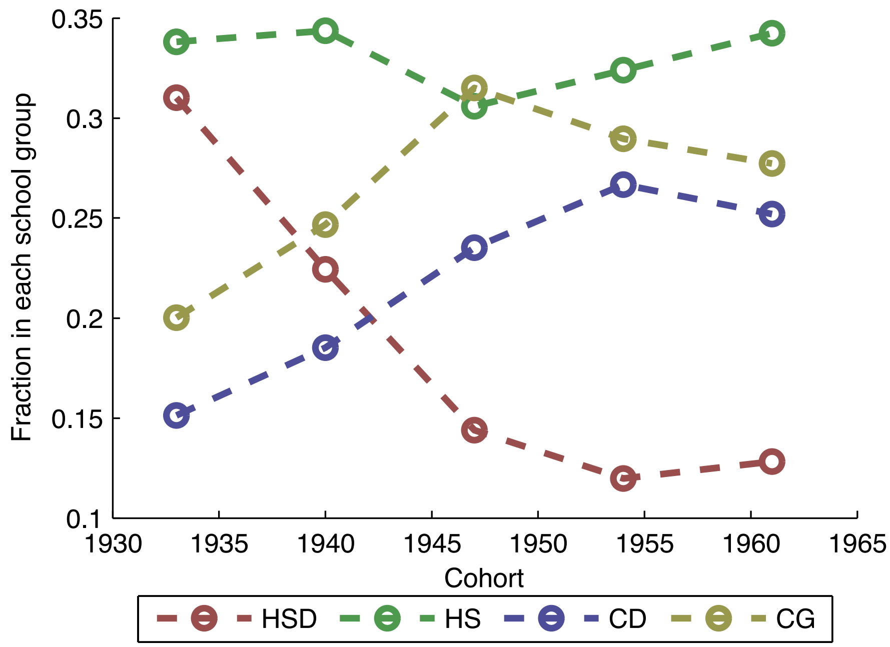

Figure 10: Educational Attainment By Birth Cohort

INCWAGE is the sum of two variables with different top codes. In these years I leave top-coded values unchanged.

To avoid top-coding issues, I drop the top 2% of wage observations from the data and from the simulated model data in each year when computing wage statistics (such as mean log wages).

Since Bowlus and Robinson (2010) find that allocated values have little effect on the constructed wage series, I do not exclude them.

A.3 Aggregate Variables

Schooling: The fraction of persons in cohort τ that achieves school level s is calculated by averaging over ages 35 through 44(not all ages are observed for all cohorts). Figure 10 shows these fractions. Each point represents 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).

Wage statistics: For each (age, school, cohort) cell, I compute the following statistics:

1. Median wage among those reporting a valid wage.
2. Mean log wage among those reporting a valid wage, dropping the top and bottom 2% of observations.

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

1. For combinations of s, t, τ that are observed, we set $\ell_{s,t,\tau}$ to the average hours worked of all persons in the cell.
2. For each school group, we regress average hours worked in each s, t, τ 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, τ that are not observed, we 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.