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 human capital stocks. 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.

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1 Introduction

The question: The purpose of this paper is to measure the evolution of average human capital and skill prices in the U.S. since the 1960s. This period was characterized by a large expansion in education and by sluggish wage growth, especially for workers without a college degree. Figure 1 illustrates these developments.[1]

Panel (a) shows that the fraction of men with at least some college education rose from 30% to nearly 60% over a 25 year period before levelling off. This raises the possibility that rising schooling has contributed to wage growth. One objective of this paper is to quantify this contribution. Panel (b) shows that mean log real wages of 40 year old men have declined since the 1960s, except among college graduates. One implication is that the college wage premium, defined as mean log wages of college graduates relative to high school graduates, has increased from 0.3 to 0.6.[2] One objective of this paper is to assess to what extent the sluggish wage growth among the less skilled and the rise in the college wage premium reflect movements in skill prices as opposed to human capital stocks.

The problems of measuring human capital and wages have been studied extensively in separate strands of the literature. The most common approach in both strands relies on constant quality indices to measure labor inputs. In the context of measuring human capital and its growth rate, this approach was pioneered by Jorgenson and Griliches (1967).[3] It was introduced to the cross-country context by Klenow and Rodriguez-Clare (1997).

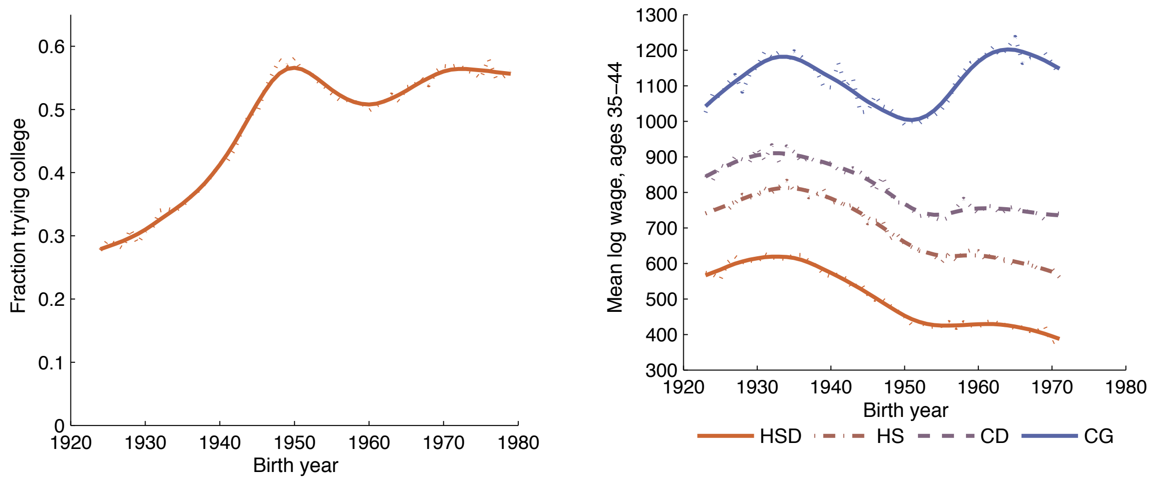
The approach assumes that human capital is a time-invariant function of observable characteristics, such as education and age. In a reference period, the relative human capital stocks of all education/age cells can be measured by their relative wages. Human capital grows over time, if the fraction of persons in high wage cells increases.

A similar approach has been used to measure the growth of wages. A prominent application is the rise in the college wage premium during the 1980s. The observation that the mean wages of college graduates have increased relative to high school graduates, holding

[1]Both panels are based on CPS data for men. Appendix A provides data details. These are well-known developments and discussed at length in the literature (see Levy and Murnane 1992; Goldin and Katz 2008). The main difference is that the literature typically averages across all persons observed in a given year, whereas I consider each birth cohort separately.

[2]See Goldin and Katz (2008) for an extensive discussion and additional references.

[3]See Jorgenson and Yip (2001) for a recent application to growth accounting.



(a) Fraction of persons attempting college

(b) Mean log wage, ages 35-44

Figure 1: Schooling and wages

experience fixed, is commonly interpreted as evidence of skill biased technical change.[4]

Even though they have been studied in separate literatures, the problems of measuring human capital and skill prices are inextricably linked. Assuming that workers are paid their marginal products, the measured wage is the product of human capital and skill price. Thus, measuring one implies the other (see Bowlus and Robinson 2010).

There are reasons to question the assumption that the human capital of a worker with given characteristics is constant over time:

1. The expansion of education may reduce the cognitive abilities or human capital endowments of workers in each school group (Hendricks and Schoellman, 2011). To see this, consider a world where schooling and abilities are perfectly related. In the 1925 cohort, about 30% of students attempted college, so that the median college students would be drawn from the 85th ability percentile. By the 1950 cohort, nearly 60% of students attempted college, so that the median college student's ability would have declined to the 70th percentile.

[4]See, for example, Berman, Bound, and Griliches (1994); Berman, Bound, and Machin (1998); Goldin and Katz (2008). Heckman, Lochner, and Taber (1998), Guvenen and Kuruscu (2010),Bowlus and Robinson (2010), and Hendricks and Schoellman (2011) study the possibility that changes in relative wage reflect movements in human capital.

2. As schooling expands, the abilities of students in different education groups may decline at different rates. Taubman and Wales (1972) show that the mean IQ scores of college students have increased relative to high school students (see Section 3 for details). Hendricks and Schoellman (2011) suggest that this may account for a large part of the rise in the measured college wage premium.

3. As documented in Section 3, the age wage profiles of workers without college degrees flatten over time, suggesting that on-the-job human capital investment may trend down.

4. A large psychometric literature shows that cognitive skills drift up over time at a rate of about one standard deviation every 50 years (Flynn, 1984, 2009). Similarly, the average scores on normed tests, such as ITED and ITBS have trended up over time until the 1950 cohort (Bishop, 1989). Both developments suggest that the ability or human capital endowments, measured during middle school or high school, may change over time.

Motivated by these considerations, the objective of this paper is to jointly measure the evolution of human capital and skill prices, allowing for the possibility that human capital, conditional on schooling and age, changes over time.

The approach: The fact that human capital and skill prices are observable only as their product, the measured wage, poses a difficult identification problem (see Bowlus and Robinson 2010). 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

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. This result supports the notion that viewing returns to experience through the lens of human capital theory is a useful approach.[5] 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.

[5] Huggett, Ventura, and Yaron (2006, 2010) and Guvenen and Kuruscu (2010) apply this idea to wage dispersion.

In spite of a large expansion in education, the model implies that average human capital *declined* slightly between the cohorts born in 1930 and 1964. In part, this is due to a decline in mean abilities and human capital endowments of marginal students in the higher education groups. In part, it is due to a decline in on-the-job human capital investment, which is reflected in a flattening of the age-wage profiles observed in the data (except for college graduates).

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 documented by Taubman and Wales (1972). While my model does not target cognitive test scores, it is consistent with that evidence.

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). Rather than deriving identification from a small subset of the ages observed, my approach considers a wider age range.

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.

Heckman, Lochner, and Taber (1998) and Guvenen and Kuruscu (2010) study the evolution of wage dispersion using human capital models. My focus is instead on the evolution of skill prices.

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. Individuals 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

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

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

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

In addition to the discounted value of working V the agent enjoys an idiosyncratic "psychic" utility $\pi_\tau pT_s$ 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, Schroeder, Trampe, 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 2 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. 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 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).

Figure 3 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

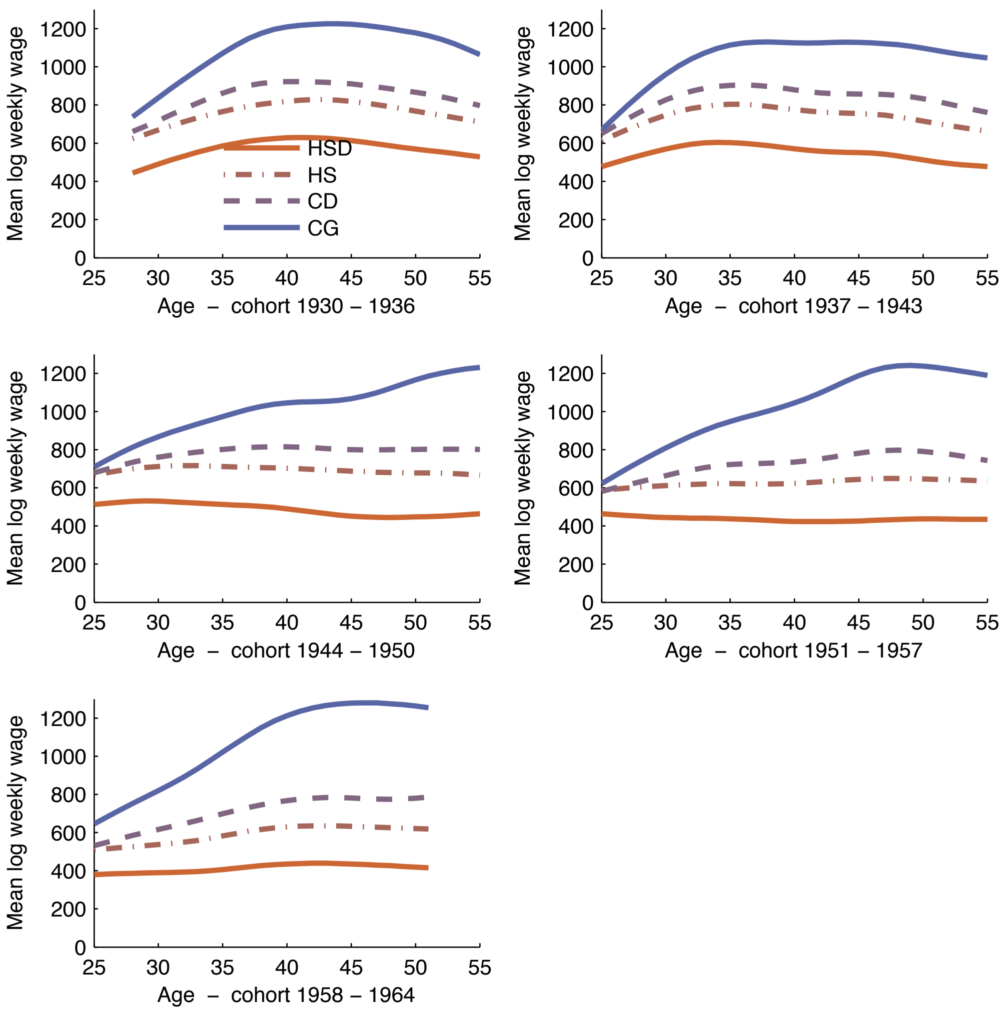


Figure 2: Cohort Age-wage Profiles

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

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 4 and 5. 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.[6]

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.

3.1 IQ Scores

A key feature of the data, highlighted by Hendricks and Schoellman (2011), is the association between cognitive test scores and wages and school choices. Following Hendricks and Schoellman (2011), I think of IQ as a noisy measure of learning ability a. However, I also allow for the possibility that IQ measures human capital. Specifically, I define

$$IQ = \frac{\gamma_{IQ,a} a + (1 - \gamma_{IQ,a})(\ln h_1 - \mathbb{E} \ln h_1)/\sigma_{h1}}{(\gamma_{IQ,a}^2 + (1 - \gamma_{IQ,a})^2)^{1/2}} + \sigma_{IQ} \varepsilon_{IQ} \tag{7}$$

where $\varepsilon_{IQ} \sim N(0,1)$ reflects measurement error. Note that IQ does not have units, so that its standard deviation is meaningless. The numerator in (7) scales the signal to be standard Normal, so that $1/\sigma_{IQ}$ is the signal-to-noise ratio. The correlation of repeated IQ tests imply a lower bound of $\sigma_{IQ} \geq 0.5$ (see Hendricks and Schoellman 2011 for details).

The IQ related data points are taken from Hendricks and Schoellman (2011). The first data point measures the association between IQ and wages. It is constructed by regressing log wages at age 40 on standard Normal IQ scores and school group dummies using white men in the NLSY79 dataset. The resulting regression coefficient is $\beta_{IQ} = 0.104$ (s.e. 0.017).

The second data point measures the association between IQ scores and schooling. Taubman and Wales (1972) collect mean IQ percentile scores for persons who attempt college and

[6] Both are constructed by fitting a quartic to each cohort's age profile of mean log wages. The figures show the fitted value for age 25 and the difference between the fitted values for ages 40 and 25.

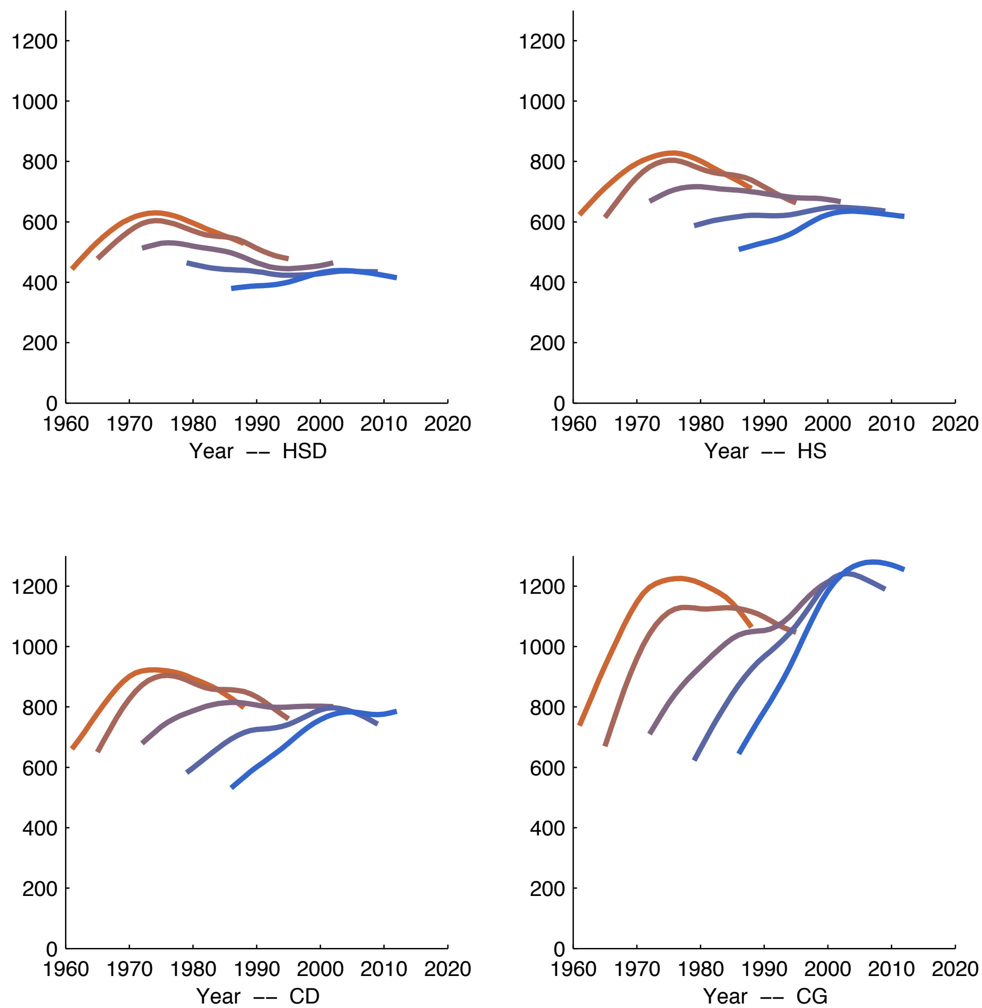


Figure 3: Cohort Age-wage Profiles

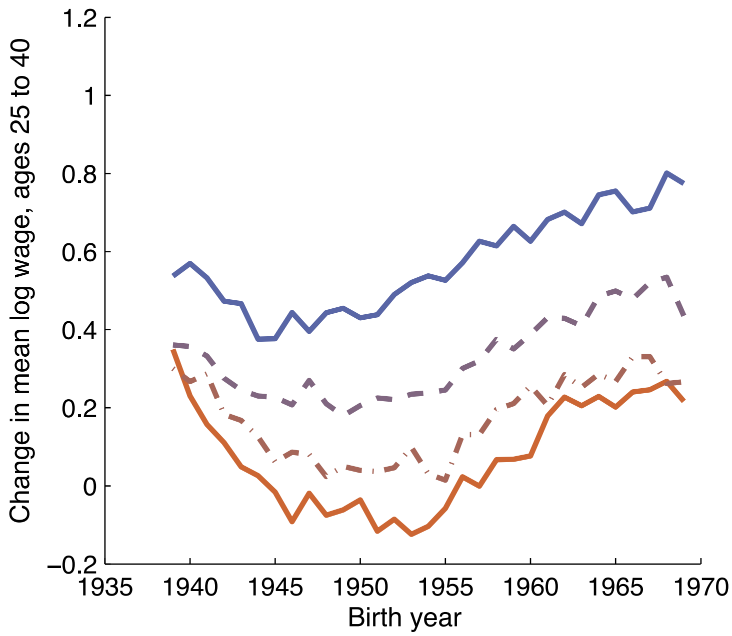


Figure 4: Wage growth by cohort

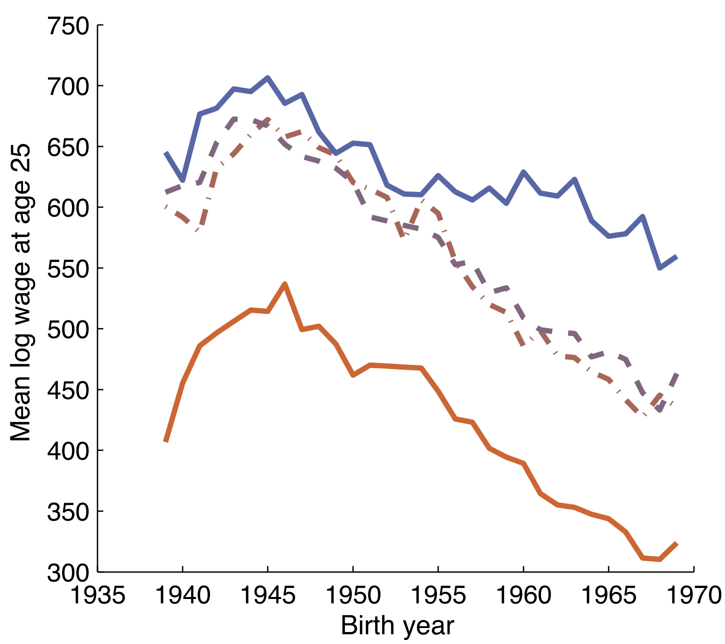


Figure 5: Mean log wage at age 25

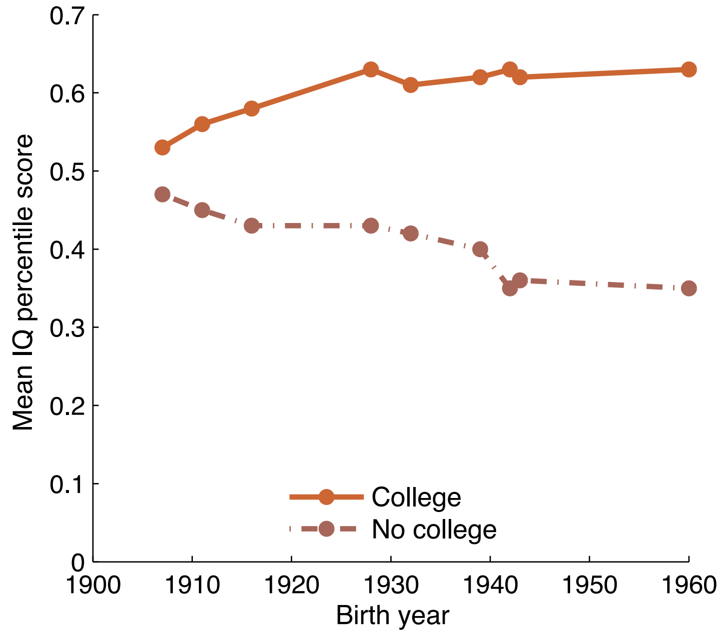


Figure 6: Cognitive Test Scores

who do not. Their data cover various cohorts born between 1907 and 1943. Hendricks and Schoellman (2011) extend the data to the 1960 birth cohort using AFQT scores and NLSY79 data. Figure 6 shows that IQ gaps are small for early cohorts, but rise substantially over time, suggesting that school selection became more strongly related to IQ scores.

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

$$h_{t+1} = (1-\delta)h_t + e^{\theta a} B(s, \tau + t - 1)^{1-\phi} h_t^{\phi} \tag{8}$$

  Iterating over this law of motion yields $F(h_1, a, s, \tau)$.

- On the job, human capital is produced according to

$$G(l, h, a, \tau + t - 1) = e^{\theta a} A(s, \tau + t - 1)^{1-\alpha} h_t^{\alpha} l_t^{\beta} \tag{9}$$

  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 $a, \ln h_1, p$. I restrict all γ_{ij} to be nonnegative.

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:

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	$(1, 3, 5, 7)$
$\ell_{t,s,\tau}$	Market hours	CPS data
R	Gross interest rate	1.04

- endowment parameters: (σ_{h1}, g_{h1}), (π_1, g_π), and the correlation parameters $(\gamma_{pa}, \gamma_{ha}, \gamma_{hp})$.
- IQ parameters: $\gamma_{IQ,a}, \sigma_{IQ}$.
- 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 the following model and data moments:

1. Mean log wages in each s, t, τ cell, weighted by the square root of the number of observations in each data cell.
2. β_{IQ}.
3. Mean IQ percentile scores for workers with at most a high school diploma and workers with at least some college.

Table 2 shows the values of the calibrated parameters. The curvature of the human capital production function is unusually low. Common estimates place α near 0.8 (Browning, Hansen, and Heckman, 1999). The calibrated value is 0.24. This may reflect a difference in the way α 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 55.

The depreciation rate of human capital of $\delta = 4.4\%$ is 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 α, training investment remains positive until the agent approaches retirement (see Section 5.5). Accounting for roughly flat wages then requires positive depreciation.

4.2 Model Fit

Figure 7 compares the model generated age wage profiles with their data counterparts (previously shown in Figure 2). 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 8 shows that the model closely matches the mean IQ scores of workers who did and did not attend college, with the exception of college educated workers in the first cohort.

5 Results

5.1 Skill Prices and Measured Wages

The first question I address is:

Table 2: Calibrated parameters

Parameter	Description	Value
On-the-job training		
$A(s)$	Productivity	0.662 0.768 0.951 0.913
$g(A(s))$	Productivity growth rate	0.0006
α	Curvature	0.267
δ_h	Depreciation rate	0.043
Endowments		
σ_{h1}	Dispersion of h_1	0.032
$g(h_1)$	Growth rate of h_1	-0.0098
θ	Ability scale factor	0.152
π	Psychic cost scale factor	0.186
$g(\pi)$	Growth rate of π	-0.0451
γ_{pa}	Governs correlation of π and a	0.501
γ_{ha}	Governs correlation of $\ln h_1$ and a	0.445
γ_{hp}	Governs correlation of $\ln h_1$ and π	0.204
σ_{IQ}	Noise in IQ	0.876
$\gamma_{IQ,a}$	Governs correlation of a and IQ	0.790

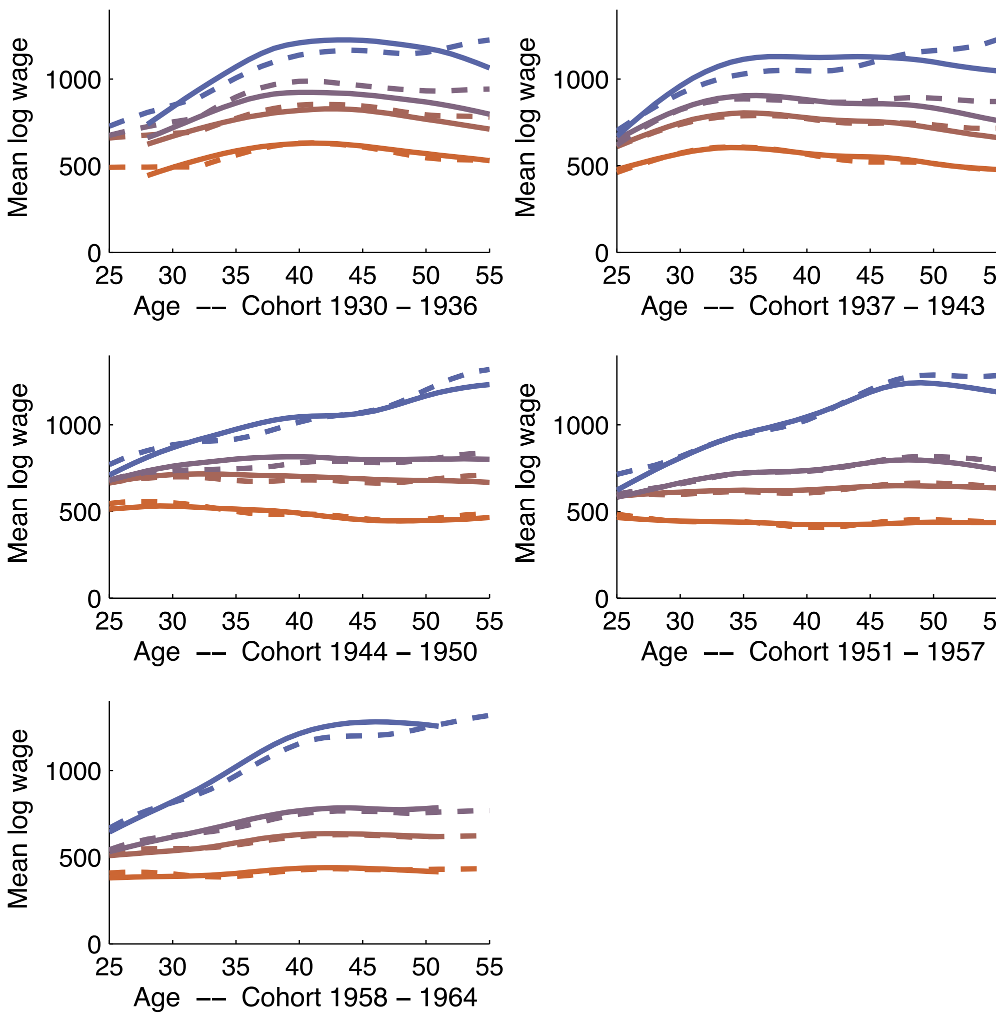


Figure 7: Model Fit

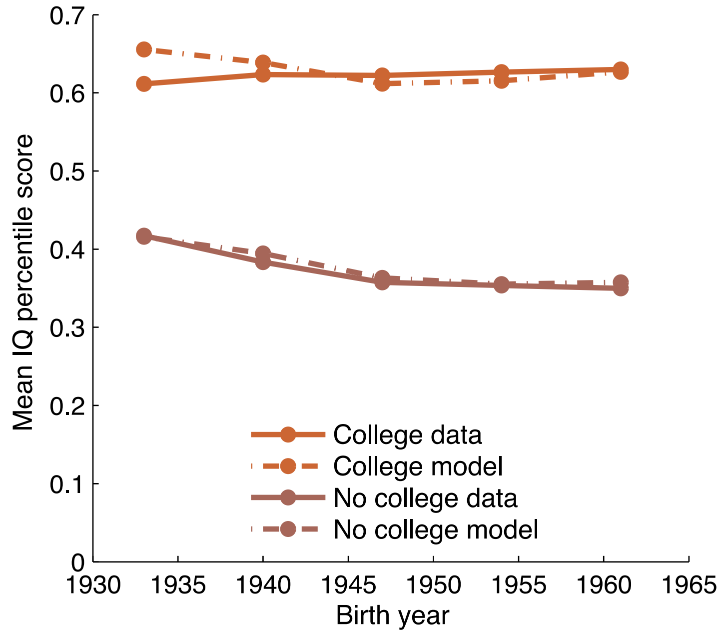


Figure 8: Model Fit

> How much do the growth rates of wages differ from the growth rates of skill prices?

Table 3 compares the average growth rates of measured wages ($z_{s,t}$) and model skill prices ($w_{s,t}$) over the sample period, while Figure 9 shows their entire time paths.

The model implies large upward revisions to unskilled wages. In the data, the wages of high school dropouts decline by more than 30%. The model attributes almost the entire decline to the falling human capital of workers in that category. The revisions to skilled wages are much smaller. Skill prices for CD and CG are essentially smoother versions of measured wages. As a result, the college skill price premium, $\ln w_{CG,t} - \ln w_{HS,t}$, increases one-third less than the college wage premium. This is the first main result:

> About one-third of the change in the college wage premium reflects growth in the human capital of college graduates relative to high school graduates.

5.2 Selection and the College Wage Premium

The second question I address is:

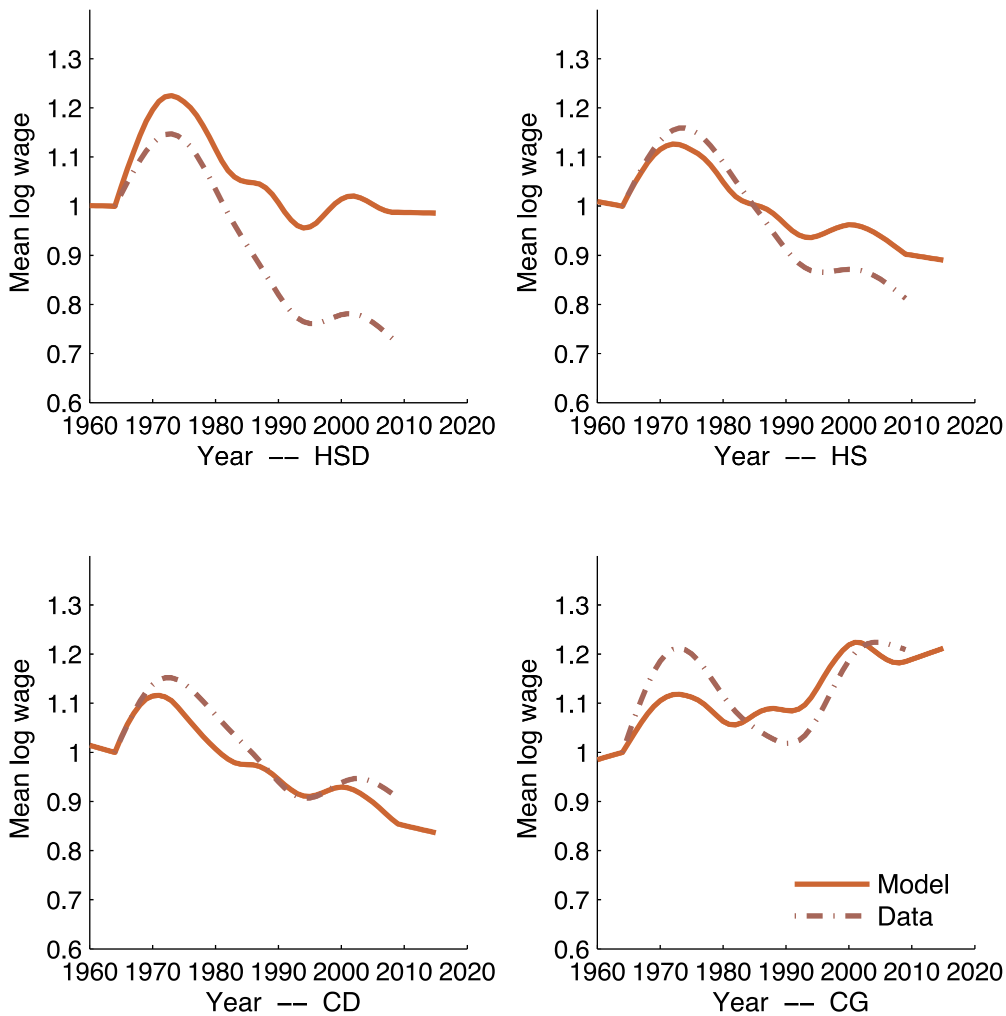


Figure 9: Skill prices and measured wages

Table 3: Changes in Skill Prices

	Skill price growth		Skill premium growth	
School group	Data	Model	Data	Model
HSD	-32.7	-1.3	-12.1	9.0
HS	-20.6	-10.3	0.0	0.0
CD	-9.0	-15.8	11.6	-5.5
CG	20.2	17.0	40.7	27.2

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

> 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?

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: consider a set of individuals with mean endowments: $a = 0$ and $\ln h_1 = g_{h1}\tau$
3. equal investment: consider a set of individuals with mean endowments and human capital investment set to the mean of $l_{t,s,\tau}$ among high school graduates in cohort τ.

Figure 10 shows that selection accounts for around 30 log points of the cohort specific college wage premium. This leads to the second main finding:

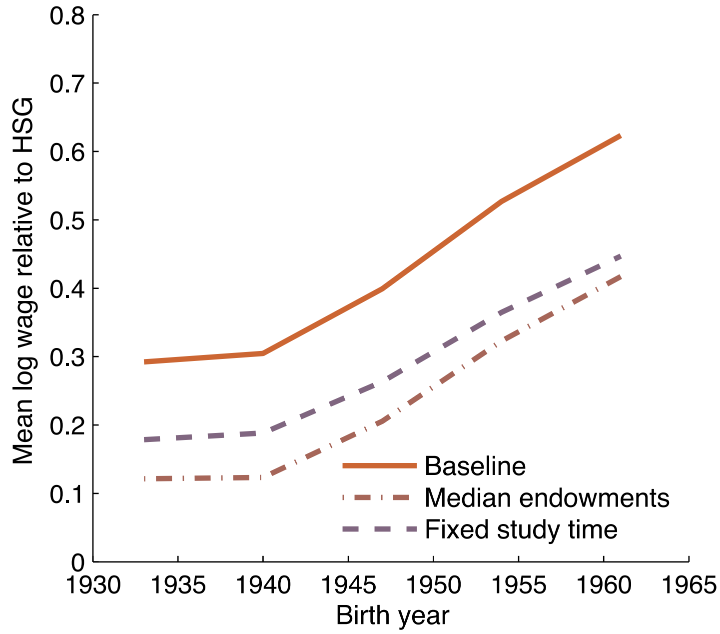


Figure 10: Cohort-specific college wage premiums

> About half of the college wage premium for the cohort born around 1962 is due to differences in endowments between college graduates and high school graduates. For earlier cohorts, the fraction rises to two-thirds.

Almost the entire endowment difference between CG and HSG is due to differences in abilities, not in human capital endowments.

Selection and lifetime earnings. 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

$$Y(s,\tau) = \mathbb{E}\left\{ \ln \sum_{t=1}^{T} y(l_{t,s,\tau}, h_{t,s,\tau}, t, s, \tau) R^{1-t} | s, \tau \right\} \tag{10}$$

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

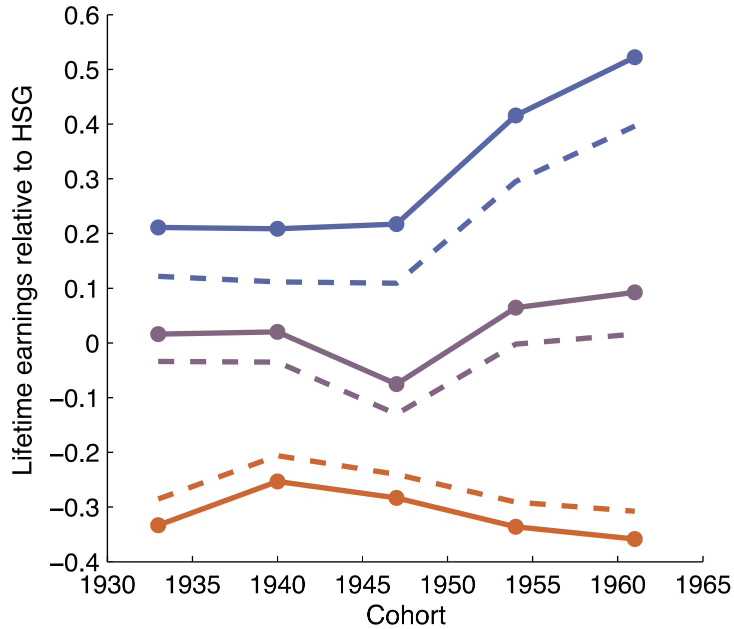


Figure 11: Lifetime Earnings

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

Figure 11 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.

5.3 Changing Selection and Wage Growth

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 Hendricks and Schoellman 2011). Figure 12 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.

Over time, 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

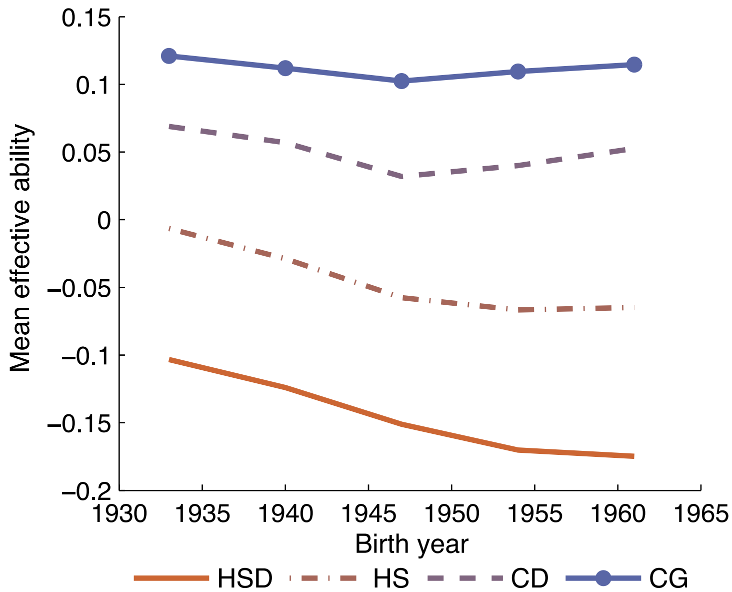


Figure 12: Distribution of Ability, Conditional on Schooling

for those who do. These findings are consistent with Hendricks and Schoellman (2011) and with the evidence presented by Taubman and Wales (1972).

This motivates my fourth question:

> What fraction of the changes in (relative) wages is due to changes in (relative) endowment and human capital investment?

To address this question, I consider the following experiment. I solve the model for three cases:

1. the baseline
2. fixed endowments: for each cohort, I impose the distribution of a, h_1 of cohort 1
3. fixed investment: in addition to fixing endowments, I fix human capital investments at the level of cohort 1.

Table 4 shows the resulting growth rates of wages and wage premiums relative to high school graduates. Similar to Table 3, the model implies large revisions to the growth rates

Table 4: Changing Selection and Wage Growth

School group	Baseline	Fixed a, h_1	Fixed l	Revision
	Wage growth			
HSD	-39.0	-30.6	-19.6	19.4
HS	-31.6	-22.5	-16.2	15.4
CD	-27.6	-21.3	-17.7	9.9
CG	1.5	7.1	8.9	7.4
	Skill premium growth			
	Baseline	Fixed a, h_1	Fixed l	Revision
HSD	-7.4	-8.0	-3.4	4.0
HS	0.0	0.0	0.0	0.0
CD	3.9	1.3	-1.5	-5.5
CG	33.0	29.6	25.1	-7.9

Note: The table shows changes in mean log wages at age 40, 1964-2009.

of unskilled wages.[7] The contributions of changing endowments and changing investments to the revision of wage growth rates are roughly equal. As a result, the same is true for changes in skill premiums.

Note that the revision to measured wage growth equals the negative of the growth rate of human capital. That is,

$$\Delta \mathbb{E} \ln z_{t,s,v} = \Delta \ln w_{s,v} + \Delta \mathbb{E} \ln \left\{ h_{t,s,v} \frac{\ell_{t,sv} - l_{t,s,v}}{\ell_{t,s,v}} \right\} \tag{11}$$

Hence, the model implies that human capital in each school group declines over time by between 7% and 19%. This decline is due, in roughly equal parts, to the worsening ability and human capital endowments that stem from the expansion of education and to a decline in on-the-job training investments.

5.4 Human Capital Growth

The final question I ask is:

[7] The growth rates differ because Table 4 considers average wages in each year across all working cohorts, whereas Table 3 only considers the wages of a single cohort in each year. The latter is easier to analyze because it is not affected by the changing cohort composition of workers in each year.

By how did the stock of human capital grow between the first and the last cohort in my sample?

To address this question, I consider the following experiment. I simulate workers in the first and last cohort and compute mean log wages at age 40:

$$\sum_s f_{s,\tau} \left\{ \ln w_{s,v} + \mathbb{E} \left[\ln h_{t,s,\tau} \frac{\ell_{t,s,\tau} - l_{t,s,\tau}}{\ell_{t,s,\tau}} | s, \tau \right] \right\} \tag{12}$$

where it is understood that $v = \tau + t - 1$. I do this for the following scenarios:

1. Schooling changes, but the distribution of endowments and human capital investment are fixed at their cohort 1 levels. For human capital investments, I fix the policy function that yields l as a function of t, a, s. Skill prices are fixed at their cohort 1 levels.

   This calculation would correctly measure the effect of schooling on human capital in a simple Mincerian model where human capital is a fixed function of schooling.

2. Schooling and the distribution of endowments change over time. Investment is fixed.

3. Schooling, endowments and investment vary by cohort.

4. The baseline: schooling, endowments, investment, and skill prices vary by cohort.

Table 5 shows the change in mean log wages at age 40 for the four scenarios. The expansion of schooling increases average human capital by only 9% over a 30 year period. Roughly speaking, 20% of worker mass is moved from the HSD category into the CD and CG categories, which earn about 45% more than high school dropouts.

The expansion of education leads to a decline in the mean abilities of students at all levels, except for CG. Accounting for the changes in endowments, given s, reduces human capital growth to only 4%. As shown below, on-the-job human capital investment declined over the sample period. This is reflected in the flattening of the unskilled age-wage profiles shown in Figure 7. It further reduces human capital growth to -3.3%. The remaining decline in mean log wages is due to falling skill prices. The model thus implies:

> In spite of a large expansion in schooling, average human capital *declined* slightly between the 1930 and 1960 birth cohort.

Table 5: Change in Mean Log Human Capital

Time varying	Change in mean log wage
Schooling	9.69
Endowments	4.73
Investment	-2.60
Skill prices	-12.54

Note: The table shows changes in mean log human capital at age 40 between the first and the last cohort.

5.5 Human Capital Investment

Figure 13 shows the human capital age profiles of workers in each cohort. Figure 14 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.

5.6 On-the-job Training and Lifetime Earnings

Kuruscu (2006) argues that on-the-job training has little effect on lifetime earnings. His finding does not hold in my model. Figure 15 shows that training increases lifetime earnings by 50% to 90%.

The underlying experiment is as follows. For each school group and cohort, I calculate the present value of lifetime earnings for a person with average endowments, $a = \mathbb{E}(a|s,\tau)$ and $\ln h_1 = \mathbb{E}(\ln h_1|s,\tau)$. I compare these present values for optimally chosen training time and for $l = 0$.

Two central identifying assumptions underly Kuruscu's result. First, he assumes that wage profiles are essentially flat after 20 years of experience. In my data, this is also true, except for college graduates. However, I do not assume that skill prices are constant over time, so that human capital may continue to rise beyond 20 years of experience.

More importantly, Kuruscu assumes that human capital does not depreciate, whereas my calibrated depreciation rate is 4.4%. As a result, training investment falls to near zero in Kuruscu's model after 15 to 20 years of experience, whereas it continues in my model until

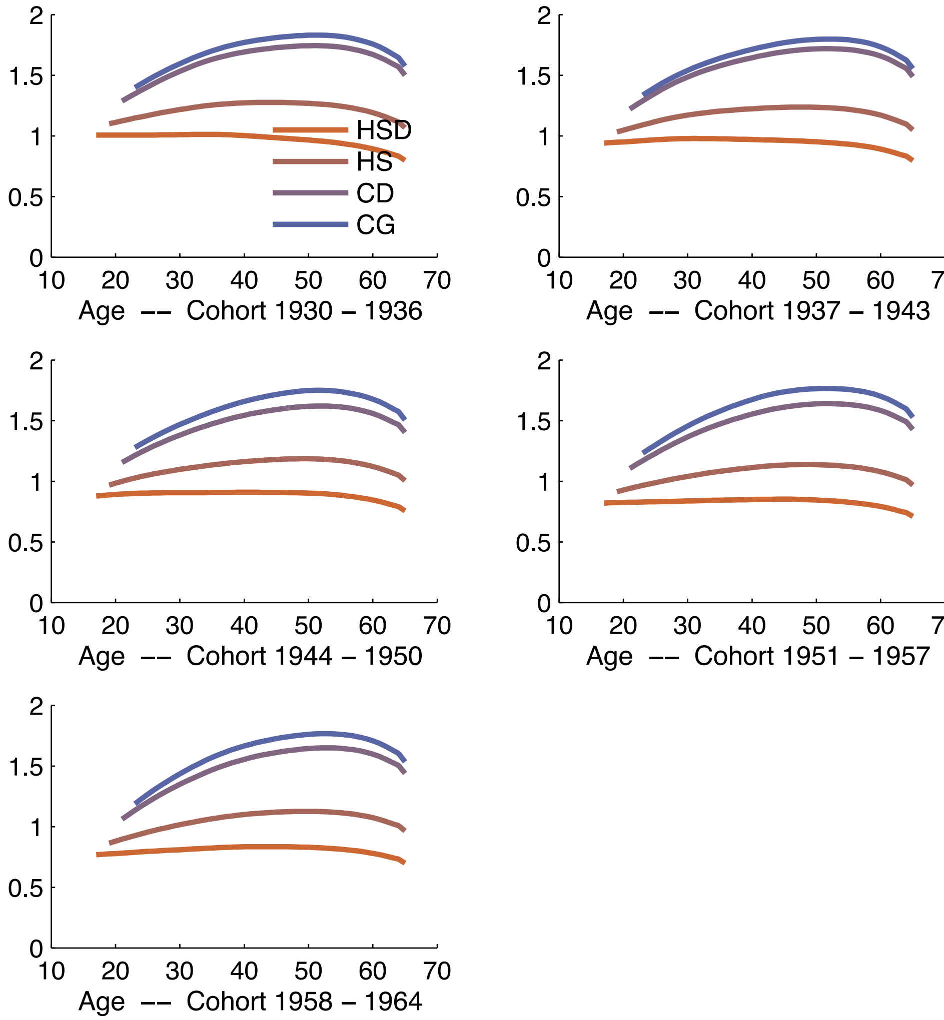


Figure 13: Age Profiles of Median Human Capital

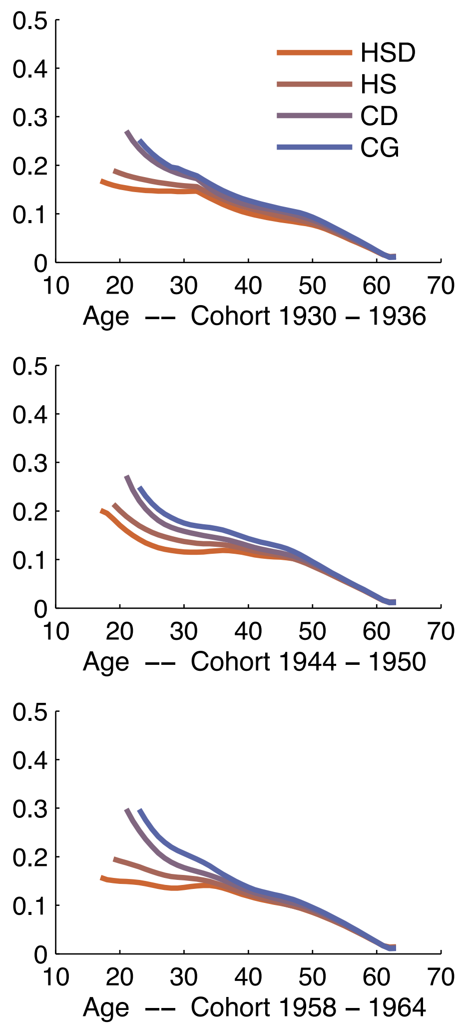


Figure 14: Median Job-training Time

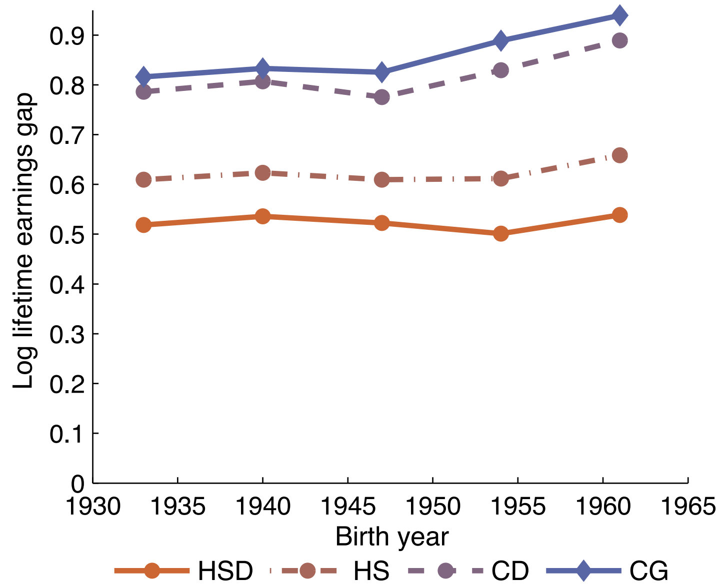


Figure 15: On-the-job training and lifetime earnings

close to retirement. Section 4 discusses why my calibrated depreciation rate differs from the smaller values typically found in the literature.

6 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

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, Schroeder, Trampe, and Vick, 2010). The data are obtained from King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, 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

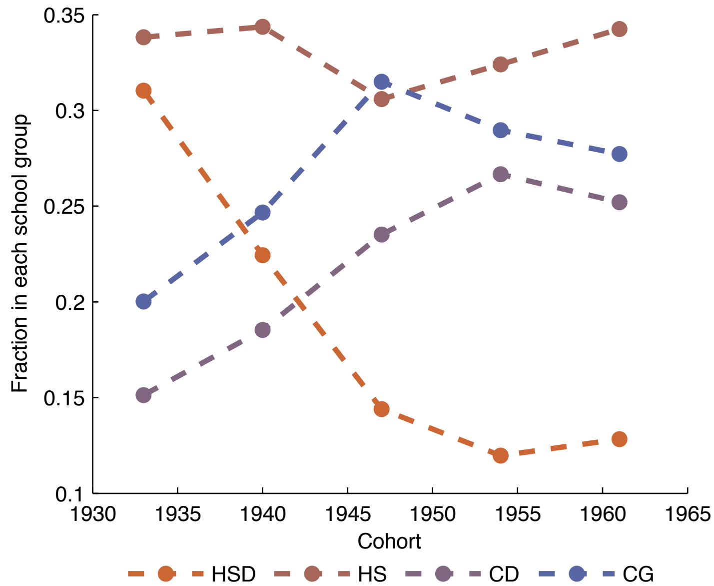

Figure 16: Educational Attainment By Birth Cohort

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

1. For combinations of s, t, τ 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, 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, 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. Figure shows the smoothed hours profiles.

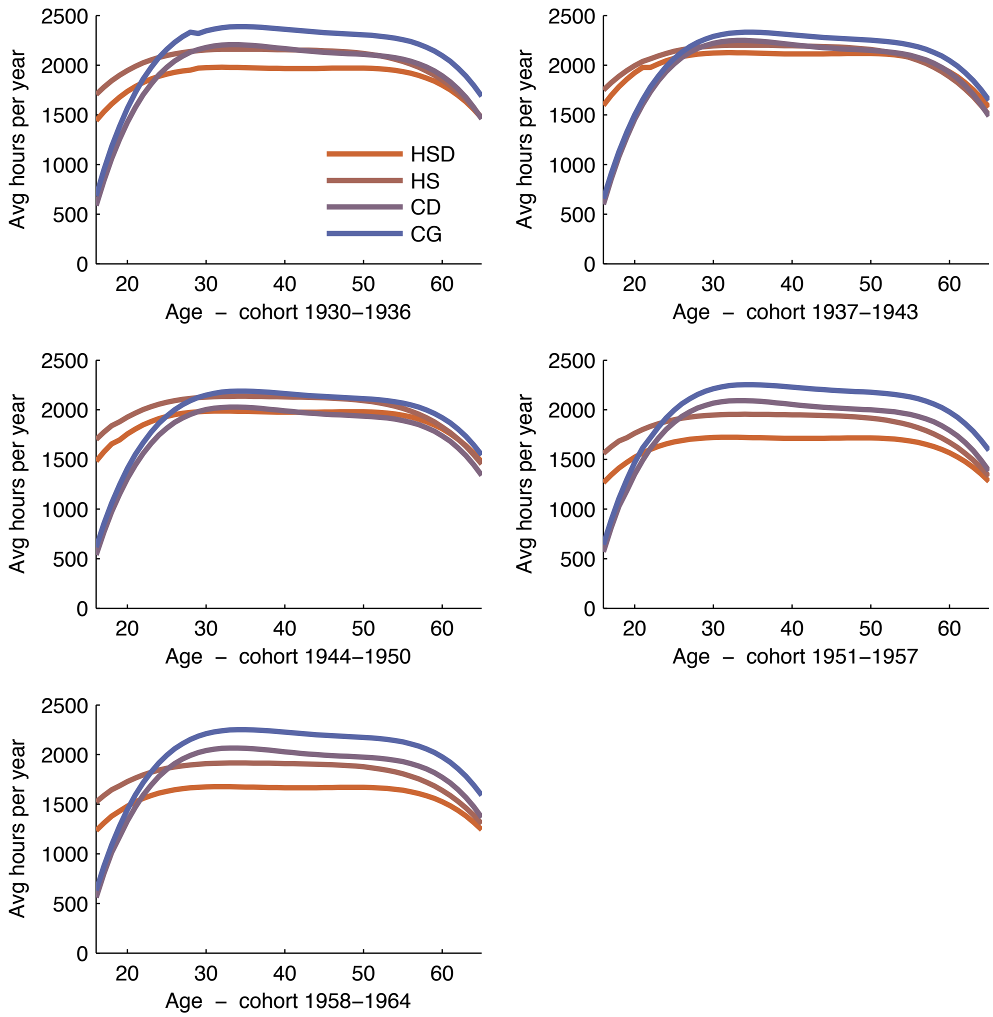

Figure 17: Age Hours Profiles