Accounting for Changing Returns to Experience

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Abstract

Returns to experience for U.S. workers have changed over the post-war period. This paper argues that a simple model goes a long way towards replicating these changes. The model features three well-known ingredients: (i) an aggregate production function with constant skill-biased technical change; (ii) cohort qualities that vary with average years of schooling; and crucially (iii) *time-invariant* age-efficiency profiles. The model quantitatively accounts for changes in longitudinal and cross-sectional returns to experience, as well as the differential evolution of the college wage premium for young and old workers.

JEL: E24 - wages, aggregate human capital; I26 - returns to education; J31 - wage level and structure.

Key words: Returns to experience. College wage premium.

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1 Introduction

A growing literature documents that wage returns to experience have changed for U.S. workers over the post-war period. An early literature showed that cross-sectional wage profiles became steeper over time (see Katz and Murphy (1992) for the period 1963-1987). A more recent literature has focused on longitudinal wage growth as a given cohort accumulates experience. Notably, Kambourov and Manovskii (2009) document a flattening of experience profiles over the birth cohorts 1950-1970, while Kong et al. (2015) document a similar flattening for the cohorts born between 1915 and 1955. Additional evidence suggests that the changes in returns to experience differ across school groups. Notably, Card and Lemieux (2001) show that the cross-sectional college wage premium evolves differently for young and old workers.

These findings have spawned a literature that seeks to explain time-varying returns to experience. There are two main themes in this literature:

1. The *price* of experience has changed over time. According to this view, old and young workers supply different labor inputs. As their relative supplies change over time, so do their relative prices (Katz and Murphy, 1992; Card and Lemieux, 2001; Jeong et al., 2015).

2. The *quantity* of experience has changed over time. According to this view, the rate at which cohorts accumulate human capital varies over time (Guvenen and Kuruscu, 2010; Kong et al., 2015).

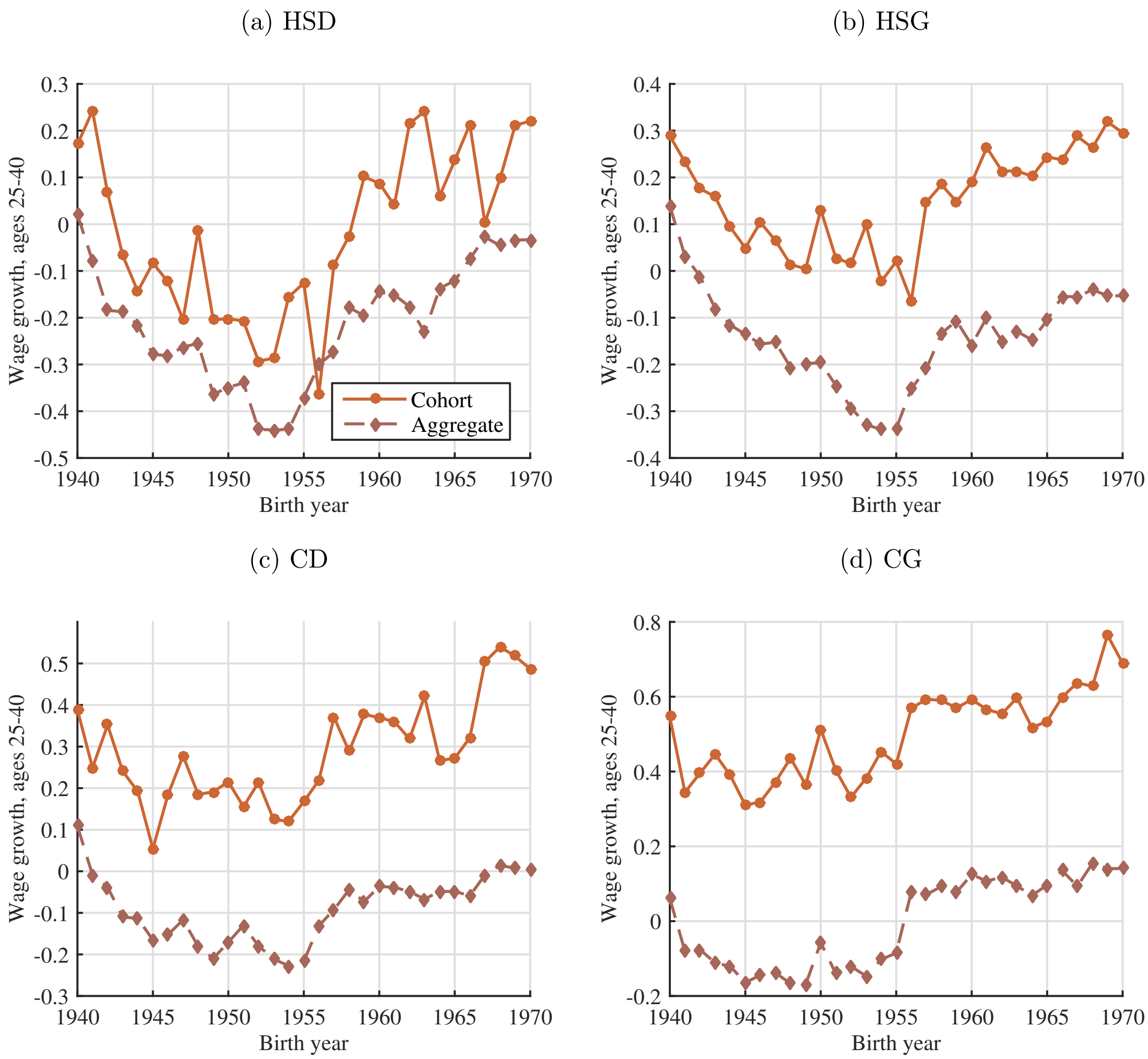
The purpose of this paper is to offer an alternative explanation. The idea is that longitudinal changes in returns to experience reflect time-varying wage growth as cohorts age. Cross-sectional changes in returns to experience reflect time-varying cohort qualities. According to this view, neither the price nor the quantity of experience accumulated by a cohort change over time.

The motivation for this approach is shown in Figure 1. Each panel represents a school group (high school dropouts, high school graduates, college dropouts, college graduates). Two data series are shown. The first is the longitudinal return to experience for each cohort (the change in the log median wage earned by a given birth cohort of male workers between the ages of 25 and 40). The second is the change in the log median wage earned by *all* men in the same school group over the same time period.[1]

The key observation is: for all school groups, the two series are roughly parallel. Both measures of wage growth decline until the early 1950s birth cohorts and rise thereafter. This property suggests that time-varying age-efficiency profiles may not be needed to account for the data.

[1] section 2 explains how these figures are constructed from CPS data.

Figure 1: Wage Growth as Cohorts Age



Notes: The figure shows the change in log wages between the ages of 25 and 40 for a given cohort. "Cohort" denotes the cohort's own change in log wages. "Aggregate" denotes the change in the log median wage across all ages.

To make this statement precise, suppose that the log median wage at age a in school group s and year t is given by $w_{a,s,t} = p_{s,t} h_{a,s} q_{s,c}$. Here, $p_{s,t}$ is the rental price of labor input s, $h_{a,s}$ denotes the amount of labor provided at age a in efficiency units (relative to an arbitrary reference age), and $q_{s,c}$ is a cohort effect. Then cohort c's change in log wages between two ages (a_1 and a_2) is given by

$$\ln w_{a_2,s,t_2} - \ln w_{a_1,s,t_2} = (\ln p_{s,t_2} - \ln p_{s,t_1}) + (\ln h_{a_2,s} - \ln h_{a_1,s}) \tag{1}$$

where $t_j = c + a_j - 1$ is the year in which cohort c is aged a_j. The first term is the change in log skill prices over the period $t_1 - t_2$. The second term reflects efficiency growth as a cohort ages (common to all cohorts).

Assume further that skill prices $p_{s,t}$ are approximately proportional to the median wages plotted in Figure 1. This might be true because changes in the composition of workers within school groups are "small." Then the two lines shown in Figure 1 should be parallel, which is approximately the case.

To rephrase the key point: If skill prices are proportional to median wages, the data shown in Figure 1 imply that the efficiency gaps between older and younger workers do not change across cohorts.

This insight motivates the present paper. It shows that a simple model with *time-invariant age-efficiency profiles* ($h_{a,s}$) goes a long way towards accounting for the observations highlighted in the literature. It also does a decent job fitting the age-wage profiles of all cohorts observed in CPS data.

To make this point, I study a model with three ingredients, all of which are well-known from the literature:

1. An aggregate production function with constant skill-biased technical change, similar to Katz and Murphy (1992).
2. Cohort effects ($q_{s,c}$) that are a function of average years of schooling, similar in spirit to Hendricks and Schoellman (2014).
3. Time-invariant age-efficiency profiles ($h_{a,s}$).

The details of the model are described in section 3. I estimate this model using CPS data for men observed during the period $1964 - 2009$ (see section 4). The model accounts well for the low frequency changes in cohort-specific age-wage profiles over time (subsection 4.2). The main results, presented in section 5, may be summarized as follows:[2]

1. The model replicates the longitudinal returns to experience shown in Figure 1.

[2] The computer code and detailed results are available at https://github.com/hendri54/experience-quartic.

2. The model partly accounts for time variation in the cross-sectional returns to experience. It replicates the low frequency changes in returns, but understates their magnitudes.

3. The model replicates the differential evolution of the college wage premium for young, middle-aged, and older workers (Card and Lemieux, 2001).

2 Data

This section documents the data construction. Individual level data on schooling and earnings are taken from the March CPS files for 1965−2010 (King et al., 2010). Earnings are observed for the previous calendar year. Each person is assigned to one of the following school categories: high school dropouts (HSD), high school graduates (HSG), college dropouts (CD), and college graduates (CG).

The count sample contains men born between 1920 and 1980 who report valid schooling. From this sample, I calculate for each (age, school, year) cell:

1. $N_{a,s,t}$: the mass of persons;

2. $L_{a,s,t}$: total hours worked;

3. $\bar{s}_{a,s,t}$: average years of schooling.

The wage sample contains those who work a positive number of hours and who report non-zero earnings. The wage concept is labor earnings plus 67% of self-employment income divided by weeks worked.[3] From this sample, I calculate the median wage in each cell, $w_{a,s,t}$, deflated to year 2010 prices.[4]

Summary statistics for selected years are shown in Table 1. A more detailed documentation is available in Hendricks (2015).

From the (age, school, year) summary matrices, I construct:

1. Each cohort's average years of schooling, defined as a weighted average of schooling observed between the ages 30 and 50:

$$\bar{s}_c = \frac{\sum_{a=50}^{30} N_{a,s,t}\bar{s}_{a,s,t}}{\sum_{a=30}^{50} N_{a,s,t}} \tag{2}$$

Not all ages are observed for all cohorts.

[3] Restricting the sample to wage earners who work at least 20 hours per week and 20 weeks per year or not counting self-employment income does not change the findings significantly.

[4] As pointed out by Bowlus and Robinson (2012), changes in top-coding over time make it difficult to construct a consistent measure of mean (as opposed to median) wages.

Table 1: CPS Summary Statistics

Year	N	$N_{a,s}$	$\bar{s}$	Median wage
1965	27,231	149	11.2	896
1970	25,637	166	11.7	1,017
1975	23,790	162	12.3	1,033
1980	33,205	210	12.8	983
1985	29,943	172	13.1	952
1990	31,504	188	13.2	906
1995	26,513	190	13.3	918
2000	45,138	332	13.5	998
2005	42,290	321	13.5	979

Notes: N is the number of observations in the year. $N_{a,s}$ is the median number of observations in each (age, school) cell. $\bar{s}$ denotes average years of schooling.

2. Cohort wage profiles, defined as log median wages, $w_{a,s,t}$, collected for each birth cohort. Only partial profiles are observed for most cohorts.

I defer the discussion of salient data features to section 5 where I compare the implications of the model (described next) with the data. Additional descriptive statistics are available in Appendix A.

3 The Model

The paper's objective is to show that a simple model accounts well for the changes in the age-wage profiles observed in CPS data. The model should be parsimonious to avoid "overfitting." It should contain "standard" ingredients that have been found useful in previous research. These considerations motivate the choice of the main model elements:

1. A nested CES aggregate production function with constant skill-biased technical change. This is a minor extension of Katz and Murphy (1992), who consider only two school classes (college, no college).
2. Cohort qualities $q_{s,c}$ that are a function of the cohort's average years of schooling.
3. Time invariant age-efficiency profiles $h_{a,s}$.

Aggregate production function: Output is produced from human capital augmented labor according to the nested CES aggregator

$$Y_t = B_t \left[G_t^{\rho_{CG}} + (\mu_{CG,t} H_{CG,t})^{\rho_{CG}}\right]^{1/\rho_{CG}} \tag{3}$$

where

$$G_{\tau} = \left[\sum_{s=HSD}^{CD} \left(\mu_{s,t} H_{s,t} \right)^{\rho_{HS}} \right]^{1/\rho_{HS}} \tag{4}$$

is a CES aggregator for unskilled labor (with less than a college degree) and H denotes labor input in efficiency units. The parameters ρ_{HS} and ρ_{CG} govern the elasticities of substitution of the labor inputs. B_t is an exogenous neutral productivity sequence.

Following Katz and Murphy (1992), relative skill weights are assumed to grow at constant rates (constant skill-biased technical change): $\ln \mu_{s,t} - \ln \mu_{HSG,t} = \bar{\mu}_s + g(\mu_s)(t - 1964)$. In each year, the skill weights are normalized to sum to 1.

The only departure from Katz and Murphy (1992) is that I consider four school groups instead of two. Treating college graduates as separate from college dropouts allows the model to capture the large rise in the college wage premium since the 1980s (see Katz and Murphy 1992 and more recently Autor et al. 2008). Throughout, I define the college premium as the gap in log median wages between college graduates and high school graduates.

Labor inputs: Labor inputs in efficiency units are given by

$$H_{s,t} = \sum_{a=a_s}^{A} L_{a,s,t} h_{a,s} q_{s,c} \tag{5}$$

Here, it is assumed that persons in school group s work from age a_s to A. Hours worked $L_{a,s,t}$ and age efficiency profiles $h_{a,s}$ are taken as exogenous. (5) defines "cohort quality" as the intercept of the cohort's age-efficiency profile.

Wages: Unobserved skill prices equal marginal products:

$$p_{s,t} = \frac{\partial Y_{s,t}}{\partial H_{s,t}} \tag{6}$$

Observed wages equal skill prices times labor efficiency:

$$w_{a,s,t} = p_{s,t} h_{a,s} q_{s,c} \tag{7}$$

Cohort quality: For simplicity, I assume that cohort quality is a quadratic function of average years of schooling:

$$q_{s,c} = \phi_{s,1} \bar{s}_c + \phi_{s,2} \bar{s}_c^2 \tag{8}$$

This captures the idea that expanding schooling is associated with declining average abilities of workers in all school groups (see Hendricks and Schoellman 2014).

Adding a linear time trend to cohort qualities would not change any of the paper's implications. Adjusting the experience-efficiency profiles and the time paths of skill prices using appropriate linear trends would generate the same cohort wage profiles as reported here. This is the flip side of the well-known problem of identifying cohort, time, and age effects (Schulhofer-Wohl and Yang, 2011). However, the assumption of no trend in cohort qualities is important for decomposing observed growth in wages into the contributions of skill price growth and human capital growth.

4 Estimation

The following parameters are estimated jointly:

- Neutral productivities B_t.
- Relative skill weights and their growth rates: $\bar{\mu}_s$, $g(\mu_s)$.
- Age-efficiency profiles: $h_{a,s}$. For the sake of parsimony, $h_{a,s}$ is modeled as a quartic polynomial in experience $(a - a_s)$.[5]
- Cohort qualities: $\phi_{s,j}$.

The estimation approach is weighted least squares. The objective to be minimized is the weighted sum of squared deviations between log model wages (see (7)) and log median data wages:

$$D = \sum_{s=1}^{S} \sum_{a=a_s}^{60} \sum_{c=1920}^{1980} \omega_{a,s,c} \left[\ln w_{a,s,c} - \ln \hat{w}_{a,s,c}\right]^2 \tag{9}$$

Observations for which data do not exist ($t = c + a - 1 < 1964$ or > 2009) are, of course, dropped. The weight of each cell (ω) is the square root of the number of observations. The estimation uses $\sum_{s=1}^{S} (A - a_s) \times (2009 - 1964 + 1) \approx 4 \times 35 \times 46 = 6,440$ data moments to estimate 80 parameters.[6] Thus, the model does not trivially fit the data.

Estimating the model would be slightly complicated due to the fact that skill prices are not observable. Fortunately, it turns out that a simpler approach is available. This involves the following steps:

[5] Using age dummies instead makes essentially no difference. A quartic polynomial approximates the estimated age-efficiency profiles very well.

[6] For each school group, we have: 1 intercept, 4 experience quartic parameters, 2 cohort quality parameters, 2 skill weight parameters (except for HSG). The total number of parameters is therefore 34 plus 46 for the neutral productivities B_t.

1. Regress log median wages in each (age, school, year) cell on an intercept, a quartic in experience (that estimates $\ln h_{a,s}$), time dummies ($\ln p_{s,t}$), and a quadratic in cohort schooling ($\ln q_{s,c}$). This is done separately for each school group.
2. Construct aggregate labor supplies from (5).
3. Recover the skill weights from (7) and verify that they are consistent with constant skill-biased technical change.

Intuitively, the reason why this approach "works" is that time variation in relative labor supplies is dominated by variation in hours worked in each (age, school) group. Variation in labor efficiency per hour worked is relatively small. Thus, the model yields skill prices that are similar to what would be obtained from the procedure proposed by Katz and Murphy (1992), except that four school groups are used.

Only the last step (recovering the skill weights) depends on substitution elasticities of labor inputs. Since the results of interest do not depend on their values, I simply fix the substitution elasticities at 4.0 for the inner aggregator G and at 3.0 for the outer aggregator of the aggregate production function (3). Changing these values would alter the recovered skill weights, but not the estimated values of $h_{a,s}$, $q_{s,c}$, or $p_{s,t}$.

4.1 Estimation Results

Table 2 shows selected regression results. For the sake of brevity, the table only shows the coefficients that determine age-efficiency profiles and cohort qualities. Year effects are shown in Appendix B. All model parameters are precisely estimated. The R^2 values for all school groups are above 0.9.

Figure 2a shows that the implied age-efficiency profiles exhibit the usual inverse U shape. Figure 2b shows the cohort effects relative to high school graduates. During the expansion of educational attainment, roughly until the birth year 1950, the relative quality of college graduates declines. It levels off thereafter as schooling stabilizes. These patterns are consistent with a narrative where expanding college education reduces the relative quality of college students.[7]

Figure 2c shows the evolution of skill weights relative to high school graduates. As mentioned, their time paths depend on the substitution elasticities in the aggregate production function. These are fixed at arbitrary values. However, for my purposes, it suffices to show that the skill weights can be consistent with constant skill-biased technical change. This is clearly the case, except for high school dropouts, where the trend growth rate increases after 1990.

[7] Here it is important to keep in mind that linear trends in cohort qualities are not identified. The findings therefore do not contradict Hendricks and Schoellman (2014).

Table 2: Regression Results

	HSD	HSG	CD	CG
exper	0.109	0.100	0.130	0.0985
	(0.003)	(0.002)	(0.003)	(0.0025)
$exper^2$	-0.00649	-0.00539	-0.00788	-0.00540
	(0.00028)	(0.00020)	(0.00028)	(0.00028)
$exper^3$	0.000178	0.000145	0.000226	0.000146
	(0.000010)	(0.000007)	(0.000011)	(0.000011)
$exper^4$	-1.76×10^{-6}	-1.49×10^{-6}	-2.43×10^{-6}	-1.59×10^{-6}
	(1.20×10^{-7})	(8.91×10^{-8})	(1.38×10^{-7})	(1.54×10^{-7})
ϕ_1	1.18	0.892	0.845	0.994
	(0.12)	(0.080)	(0.101)	(0.090)
ϕ_2	-0.0469	-0.0327	-0.0312	-0.0404
	(0.0048)	(0.0032)	(0.0041)	(0.0036)
R^2	0.91	0.95	0.92	0.93
N	1780	1746	1675	1600

Notes: Each column shows the coefficients obtained from regressing log median wages on a quartic polynomial in experience, a quadratic polynomial in cohort schooling, and year dummies. Standard errors are in parentheses.

As discussed in subsection 4.2, the model does not do as well for high school dropouts along a number of dimensions. This is perhaps to be expected. Over the sample period, the fraction of workers with less than a high school degree dropped from 45% to 14%. One implication is that the sample sizes underlying the high school dropout wage statistics are small in recent years. Another concern is that labor force participation rates for high school dropouts have declined (Juhn and Potter, 2006). This introduces additional selection effects which may cause age-efficiency profiles or cohort qualities to change over time.

4.2 Model Fit

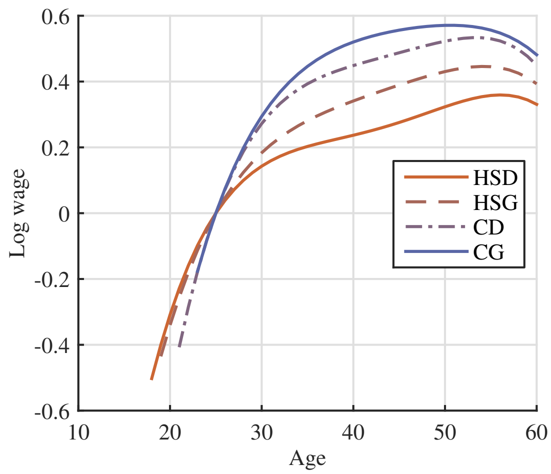
This section assesses the model's ability to fit observed age-wage profiles. One measure of fit is $R^2 = 1 - RSS/TSS$ where RSS is the weighted sum of squared model residuals (model log median wage - data log median wage) and TSS is the weighted total sum of squared residuals in the data. This is calculated for each (school, cohort) cell with at least 15 years of data. The weights are the ones used in the estimation ($\omega_{a,s,c}$).

Table 3 summarizes the model fit. Across school groups, the median R^2 ranges from 0.71 to 0.90. To get an intuitive sense of what this means, Figure 3 plots model and data age-wage profiles for selected cohorts of high school graduates.

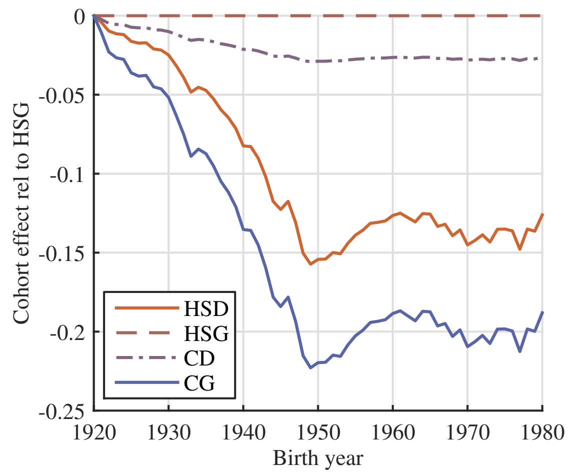
There is substantial variation in the "shape" of the age profile across cohorts. The early cohorts experience substantial declines in wages as they approach retirement. These

Figure 2: Estimation Results

(a) Age-efficiency profiles



(b) Cohort effects



(c) Skill weights relative to HSG

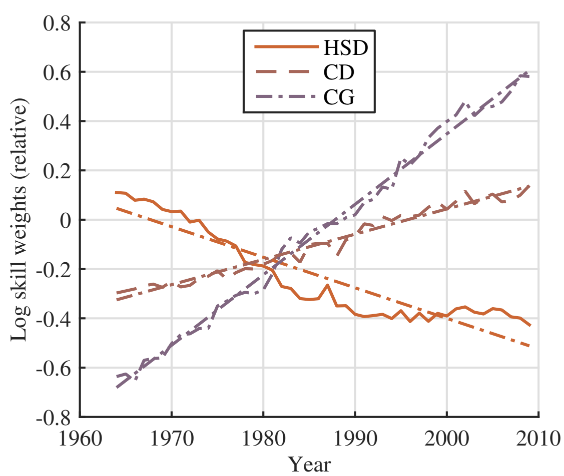
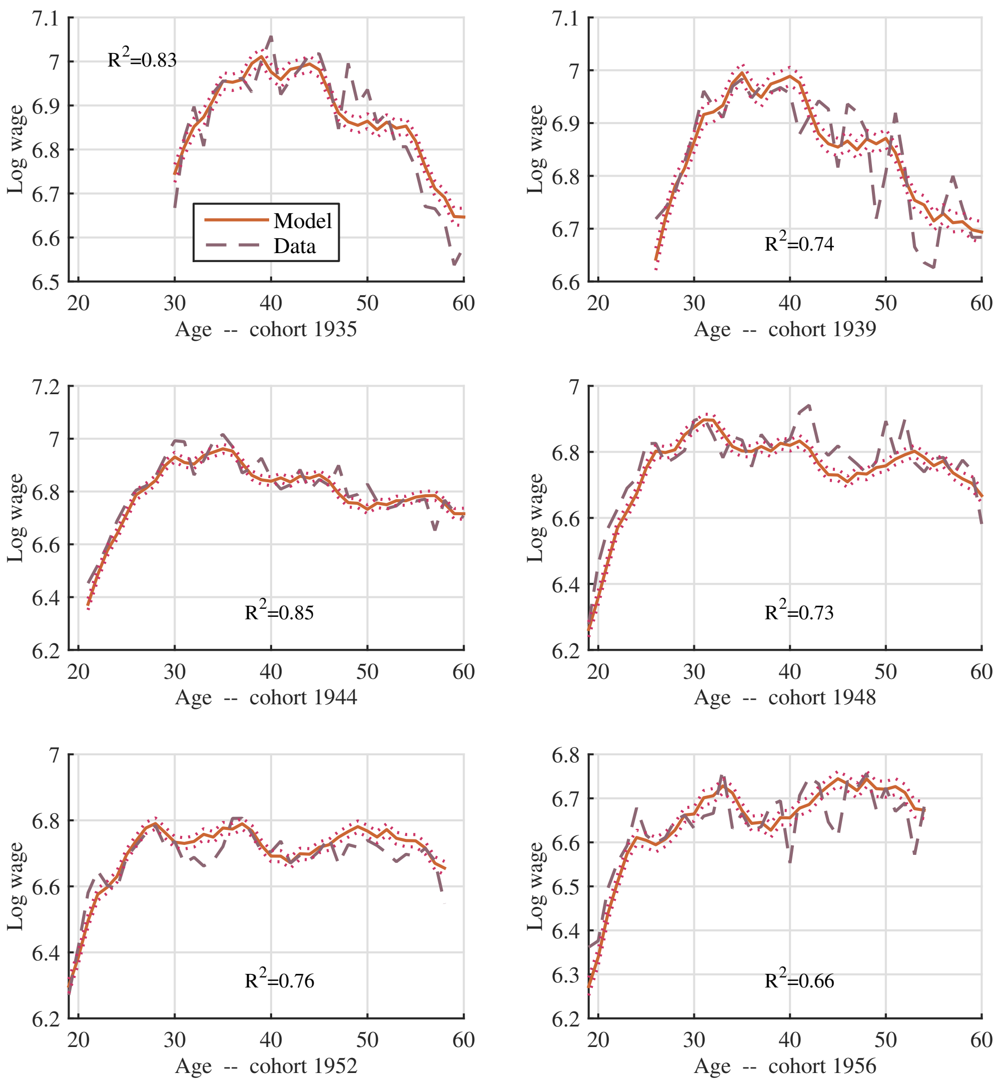


Table 3: Model Fit

	Median	25th	75th	N
HSD	0.71	0.58	0.80	59
HSG	0.81	0.71	0.91	58
CD	0.79	0.62	0.93	56
CG	0.90	0.70	0.95	54

Notes: Each row shows quantiles of the distribution of R^2 across cohorts for one school group. N is the number of cohorts with sufficient data to calculate R^2 (at least 15 years of data).

Figure 3: Model Fit: HSG



Notes: The figures shows age-wage profiles for selected cohorts of high school graduates. The dotted lines represent 95% confidence bands around the model wage profiles.

workers are affected by the productivity slow-down that started in the 1970s. For later cohorts, wages flatten out after an initial steep rise (consistent with Murphy and Welch 1990). There is little evidence of declining wages among older workers (consistent with Rupert and Zanella 2015).

The model replicates these low frequency changes in the shapes of the age profiles (which are precisely estimated). Comparing across cohorts, the fit tends to be worse early on. Appendix C shows that similar conclusions hold for the other school groups, though the fit is less satisfactory for high school dropouts.

5 Results

This section examines to what extent the model accounts for the time variation in returns to experience observed in CPS data. I focus on the summary statistics highlighted in the literature discussed in the Introduction.

5.1 Longitudinal Returns to Experience

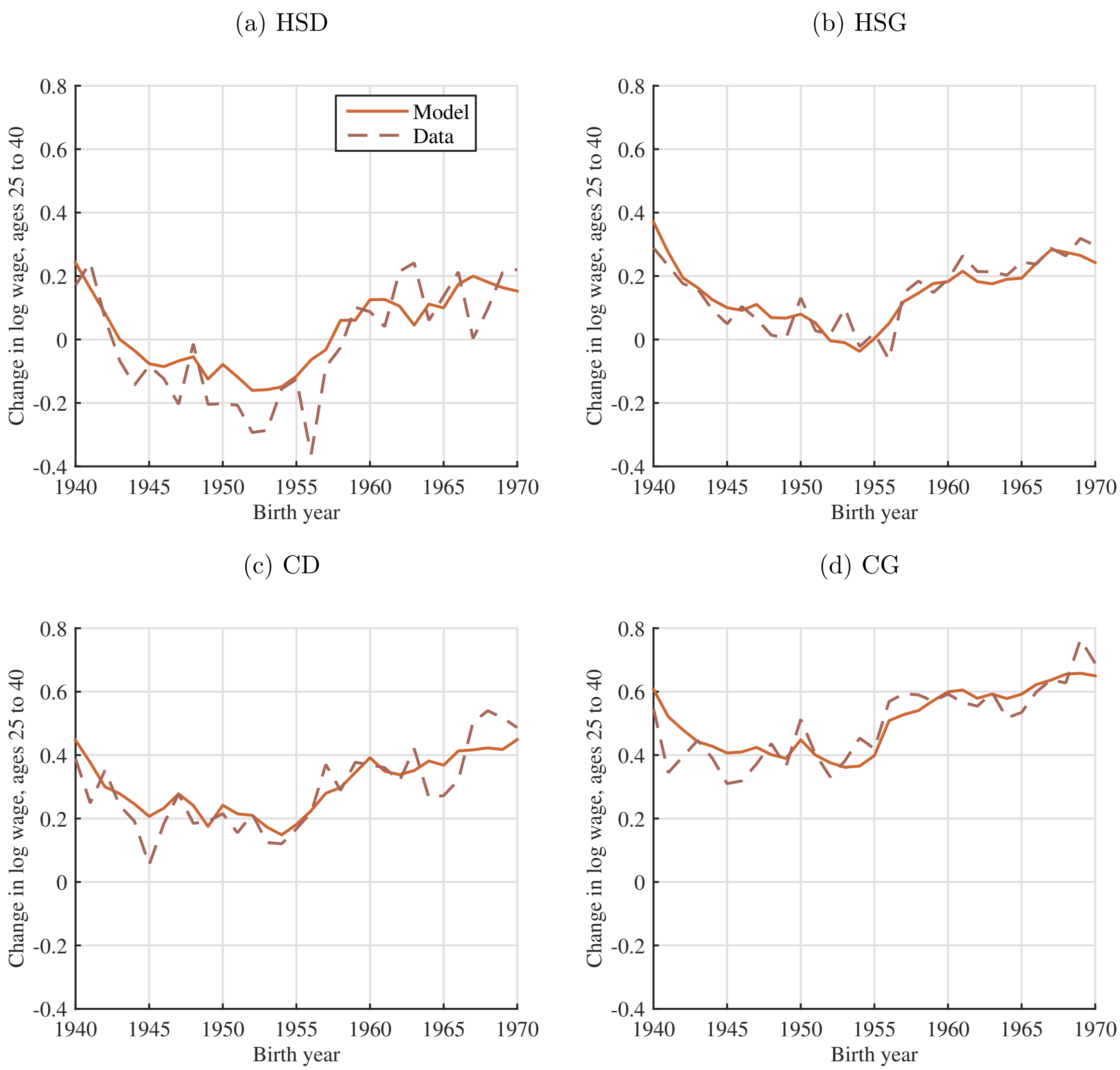
Consider first the longitudinal returns to experience recently emphasized by Kambourov and Manovskii (2009) and Kong et al. (2015). As a summary statistic, I calculate the change in log median wages for a given cohort between the ages of 25 and 40. The first age is chosen so that all school groups have entered the labor market. The second age marks the beginning of the flat portion of the age-wage profiles documented by Murphy and Welch (1990) (between 15 and 20 years of experience).

Figure 4 shows that returns to experience exhibit a clear U shape for all school groups with a minimum around the 1950-55 birth cohorts. The flattening of the wage profiles is quite dramatic. Notably, for high school graduates, the change in log wages declines from around 25 log points for the earliest cohorts to around 5 log points for the cohorts born in the early 1950s.[8] The increase in the return to experience over the later period is equally dramatic.

Figure 5 shows the intercepts of the longitudinal wage profiles (median log wages at age 25). The intercepts exhibit inverted U shapes with peaks in the late 1940s. Roughly speaking, the intercepts rise while the slopes decline and vice versa. In other words, cohorts' wage profiles rotate over time. During the expansion of U.S. education, up to the cohorts born in the early 1950s, all wage profiles became flatter over time,

[8] This does not mean that the cohorts born in the 1950s experienced no wage growth over the life-cycle. However, as Figure 3 reveals, their peak wages occurred before age 40, followed by later declines as the median wage of non-college workers fell over time.

Figure 4: Cohort Returns to Experience



while their intercepts increased.[9] After the early 1950s birth cohorts, U.S. education growth essentially stopped. During this period, wage profiles became steeper with lower intercepts.

Figure 4 and Figure 5 show that the model replicates the timing and, for the most part, the magnitudes of the observed changes. How the model accounts for time-varying returns to experience is clear from the Introduction. The change in log wages over a cohort's life-cycle has two parts:

1. a time invariant efficiency gain with experience: $\ln h_{40,s} - \ln h_{25,s}$ and

2. a time varying change in the log skill price as the cohort ages.

The second part is the only source of variation in longitudinal returns to experience over time. The model therefore implies that returns to experience track skill price growth over a cohort's lifetime. Since, in the model, skill prices evolve very similarly to median log wages (see Figure 9 in Appendix B), the model replicates the key feature observed in Figure 1: returns to experience closely track log median wage growth over a cohort's life-cycle.

The implication is fundamental: *changes in skill price growth rates over time are sufficient to account for time-varying returns to experience*. Viewed from this perspective, time varying longitudinal returns to experience are not a puzzle. In particular, accounting for them does not require time-varying age-efficiency profiles or time-varying relative prices of experience, which is what the literature has emphasized (see the references cited in the Introduction).

To be clear: The evidence presented here does not in any way demonstrate that the models proposed in the literature are invalid or flawed. It does, however, offer an alternative and simpler explanation.

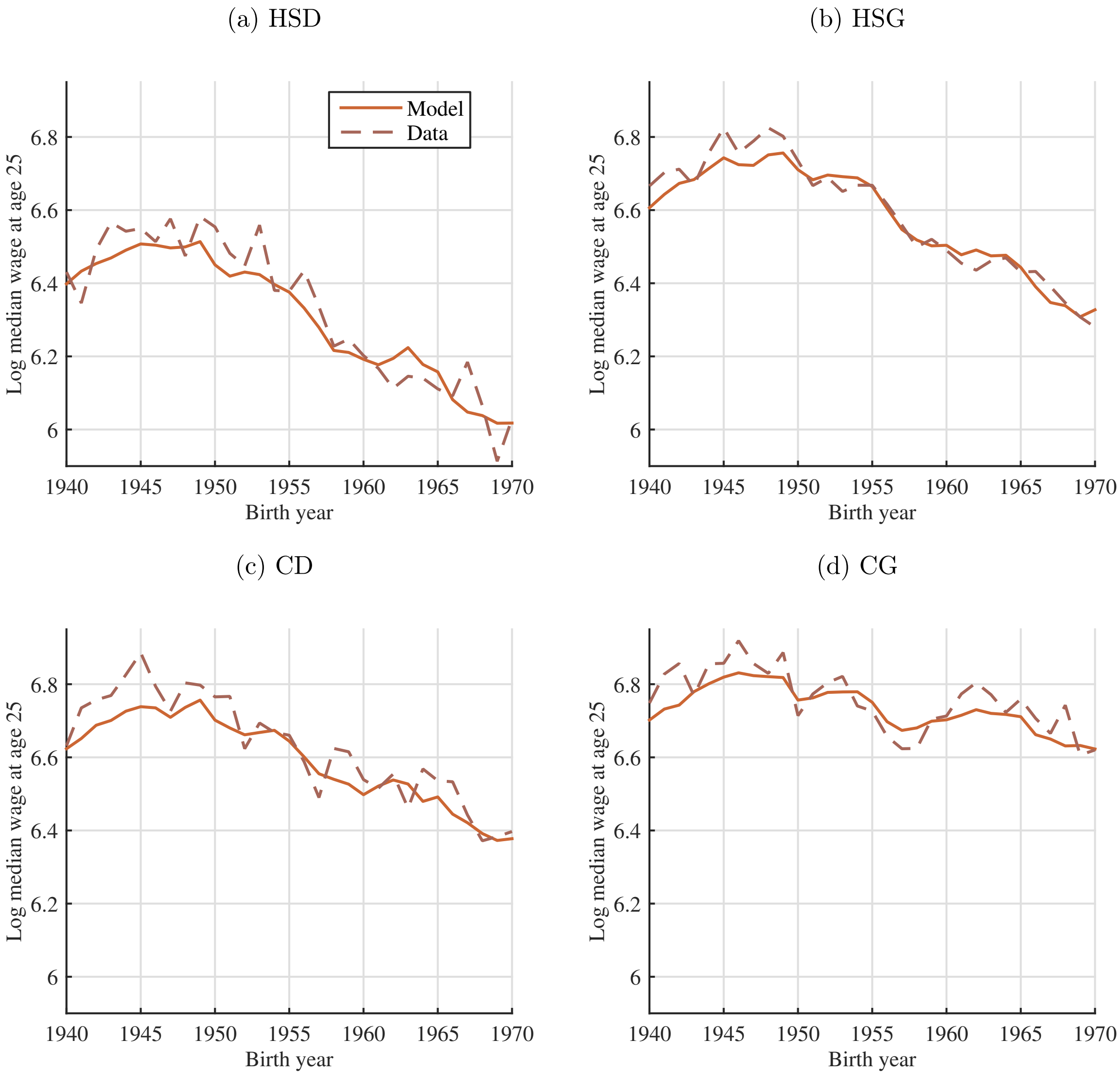
5.2 Cross-sectional Returns to Experience

Figure 6 shows cross-sectional returns to experience, defined as the difference in log median wages between workers aged 40 and 25. Broadly speaking, for workers without a college degree, returns to experience increase until the mid 1980s and then flatten out. For college graduates, the pattern is very different (rising until around 1975; falling until 1985; then rising until the end of the sample period).

The model's ability to replicate the observed time variation in returns is mixed. For high school dropouts, the model is essentially unsuccessful. This reflects the observation,

[9] This observation motivates the model proposed by Kong et al. (2015). According to their theory, an exogenous expansion of schooling increased the human capital endowments of cohorts born until about 1950. Diminishing returns to human capital investment imply that highly educated cohorts have flatter experience wage profiles.

Figure 5: Cohort Wage Intercepts



made earlier, that the model does not fit the observed age wage profiles for this group particularly well (see subsection 4.2). For the other groups, the model replicates the observed low-frequency changes in returns, but the amplitudes are somewhat smaller than in the data.

With constant age-efficiency profiles $h_{a,s}$, the model implies that changes in cross-sectional return to experience are entirely due to cohort qualities. Specifically, the cross-sectional return in the model is given by $(\ln h_{40,s} - \ln h_{25,s}) + \Delta_c \ln q_{s,c}$. The first term is time invariant. The second term is the difference in the qualities of the cohorts aged 40 and 25 in a given year. Given the simple specification of cohort effects, the mixed model fit is perhaps to be expected.

5.3 The College Wage Premium

The final observation highlighted in the literature is the differential evolution of the college wage premium for young workers (ages $26-35$) versus older workers (ages $45-60$) (see Card and Lemieux 2001).

Figure 7 shows the time paths of the college wage premium for these two age groups, defined as the log median wage of college graduates versus high school graduates. For young workers, the college premium declines until 1980 and then rises sharply until the end of the sample period. For old workers, the increase starts earlier and is smaller overall. For completeness, Figure 7 also shows middle aged workers (ages $36-44$).

The literature has suggested two potential explanations for the different evolution of the old versus the young college premium. Card and Lemieux (2001) argue that young and old workers are imperfect substitutes in production. Changes in the relative supplies of the two groups' labor supplies then induce changes in their relative prices. Jeong et al. (2015) propose a related idea. Workers supply raw labor and experience that are imperfect substitutes in production. Older workers supply relatively more experience than younger workers. Over time, changes in the age composition of the population induce changes in the relative price of experience versus raw labor.

The model presented here offers an alternative interpretation. In the model, the cross-sectional log college premium is $(\ln p_{CG,t} - \ln p_{HSG,t}) + (\ln q_{CG,c} - \ln q_{HSG,c})$ where c is the appropriate birth year for the age group considered in year t. The first term is the skill price gap between college graduates and high school graduates. It creates a common trend for all ages: the college premium starts to rise around 1980.

The second term is the gap in cohort qualities between college graduates and high school graduates. It is the only source of the divergence between old and young college premiums in this model. Even so, this mechanism alone is able to account closely for the college premium by age, as shown in Figure 7.

Figure 6: Cross-sectional Returns to Experience

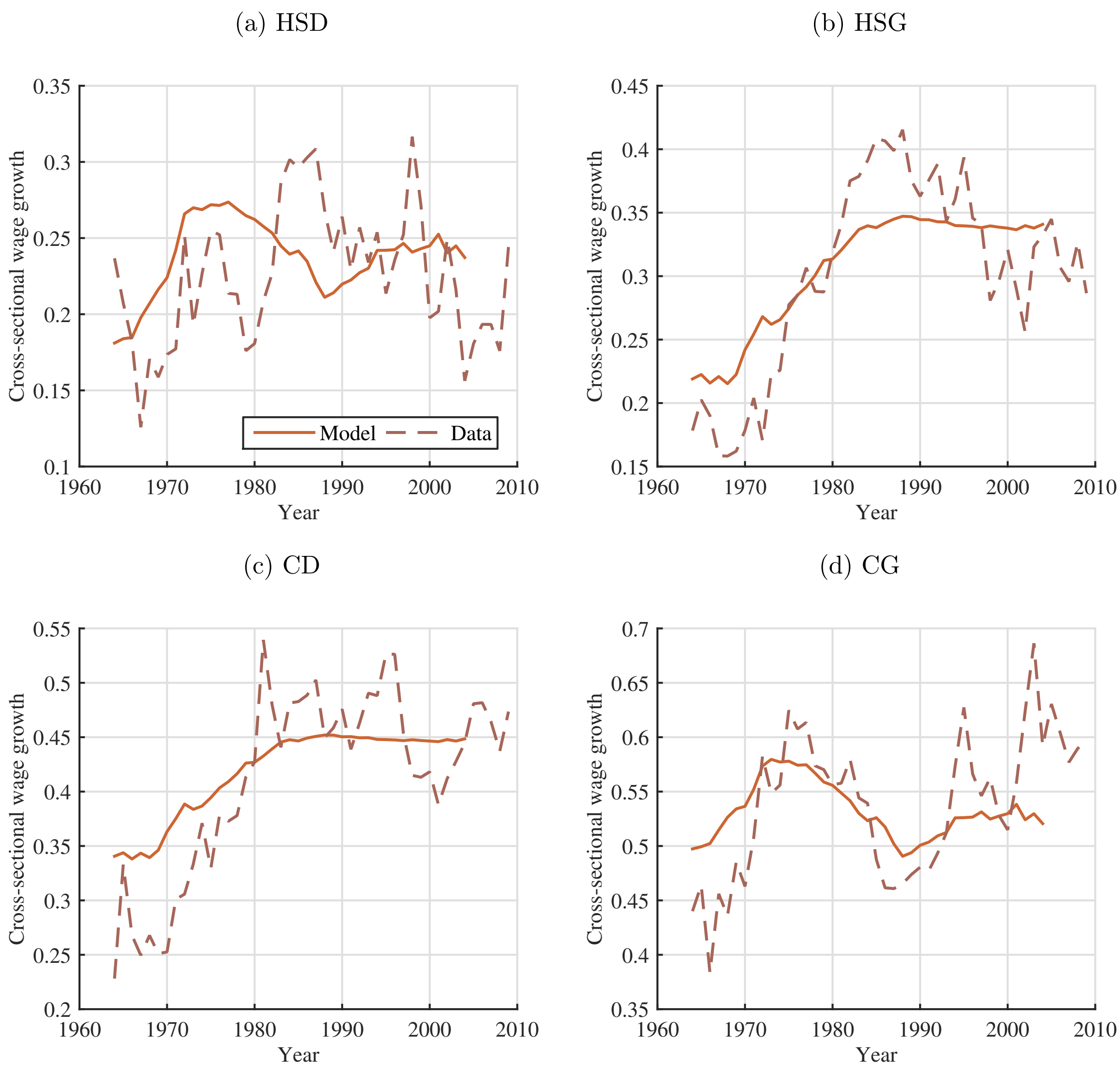
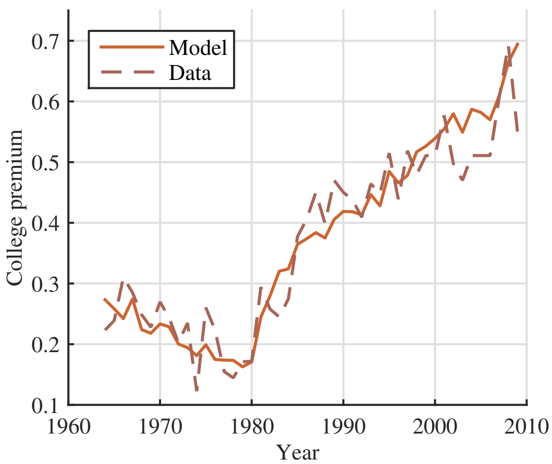
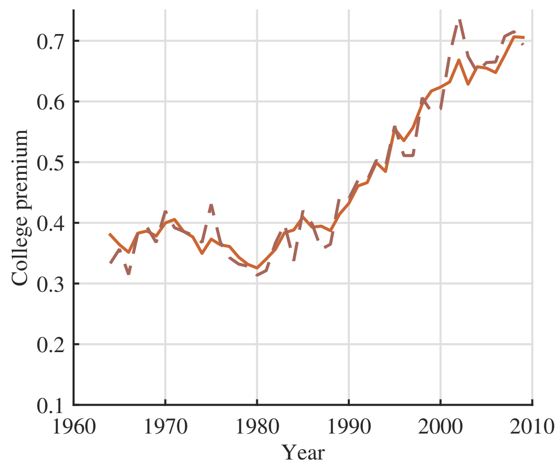


Figure 7: College Wage Premium

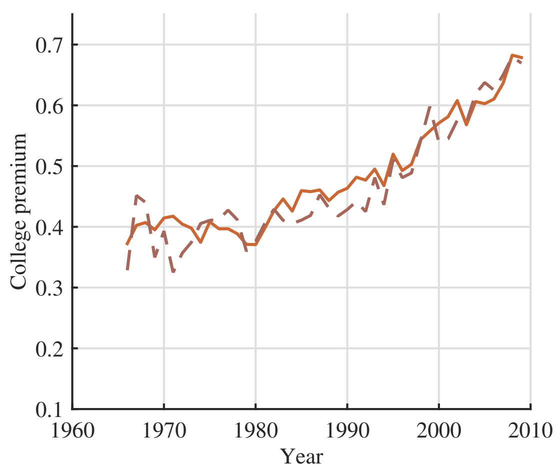
(a) Young workers



(b) Middle-aged workers



(c) Older workers



6 Conclusion

The purpose of this paper is to offer a simple account of time-varying returns to experience that is based entirely on "standard" model ingredients that are familiar from the literature:

1. Skill prices equal marginal products. Workers of different school groups are imperfect substitution in production. There is constant skill-biased technical change. This is a minor extension of Katz and Murphy (1992).

2. Cohort quality is a function of cohort schooling.

3. In contrast to much of the previous literature on this topic, age-efficiency profiles are constant over time.

I show that this simple model provides a good fit for the age-wage profiles of the cohorts observed in CPS data. It also accounts well for time variation in longitudinal returns to experience (as a given cohort ages) and in the college premiums for young and old workers. It partially accounts for time variation in cross-sectional returns to experience.

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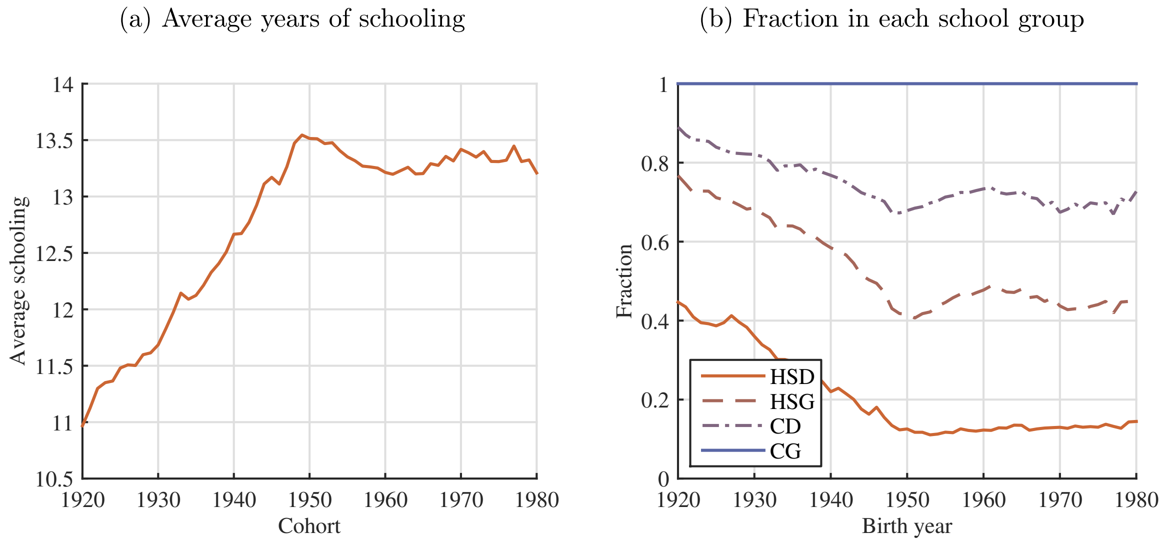
Figure 8: Cohort Schooling



A Data Details

Figure 8a shows estimated average years of schooling by cohort. Figure 8b shows the cumulative fraction of persons in each school group. The key (well-known) data feature is a large expansion of education which strops abruptly around the 1950 birth cohort.

B Estimation Results

Figure 9 shows log median wages estimated from CPS data and log skill prices implied by the model. Aside from linear trends, which are not identified without strong assumptions on cohort qualities, skill prices evolve quite similarly to median wages.

C Model Fit

Figure 10 through Figure 12 compare the observed and model predicted age-wage profiles for selected cohorts.

Figure 9: Skill Prices and Wages

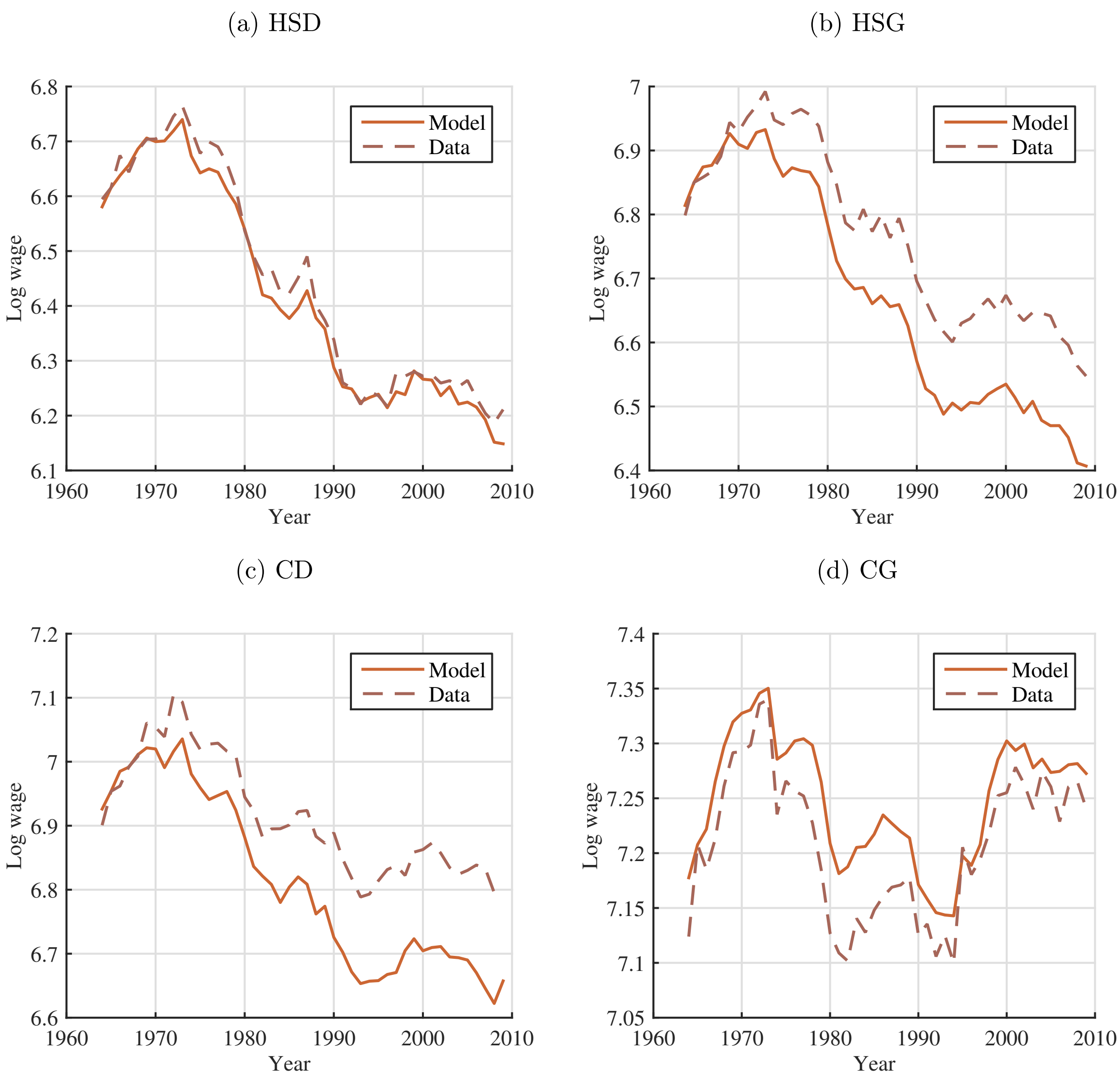


Figure 10: Model Fit: HSD

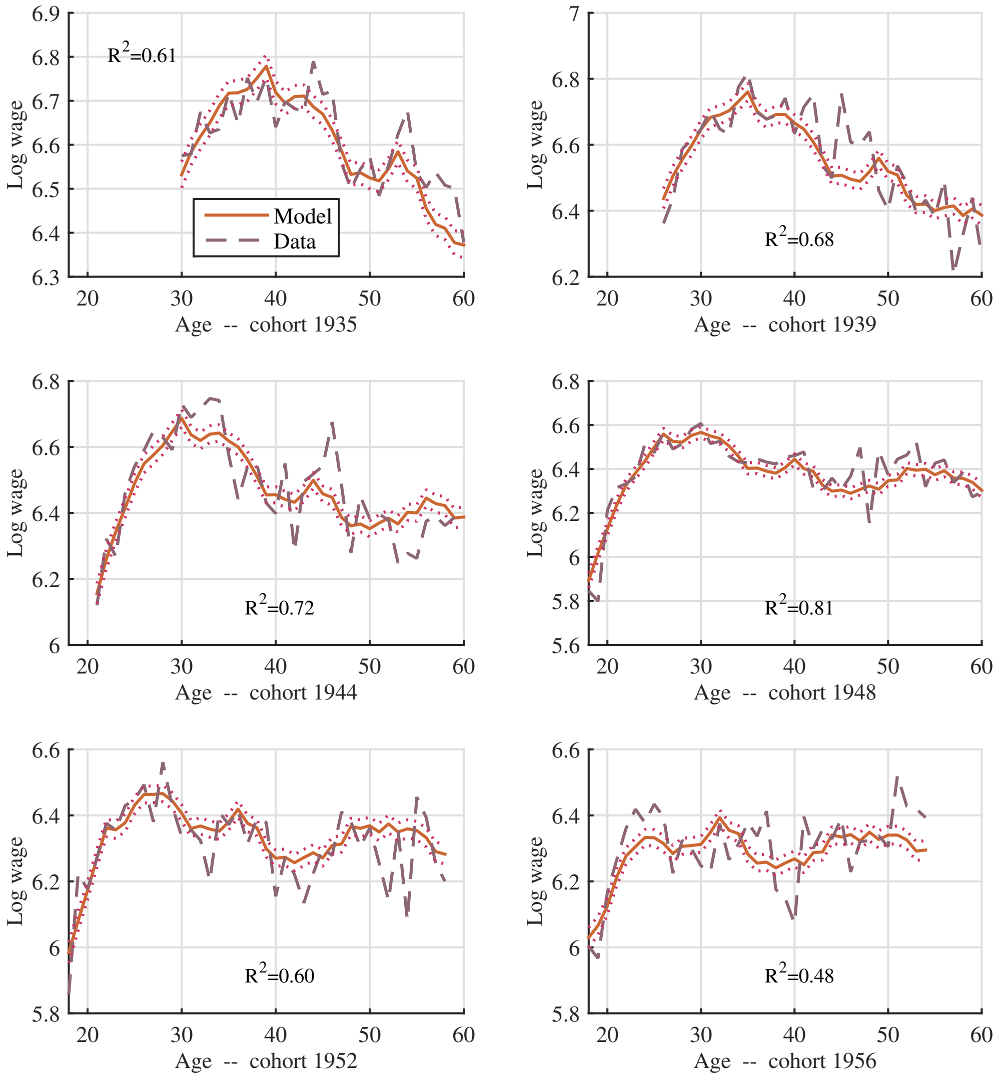


Figure 11: Model Fit: CD

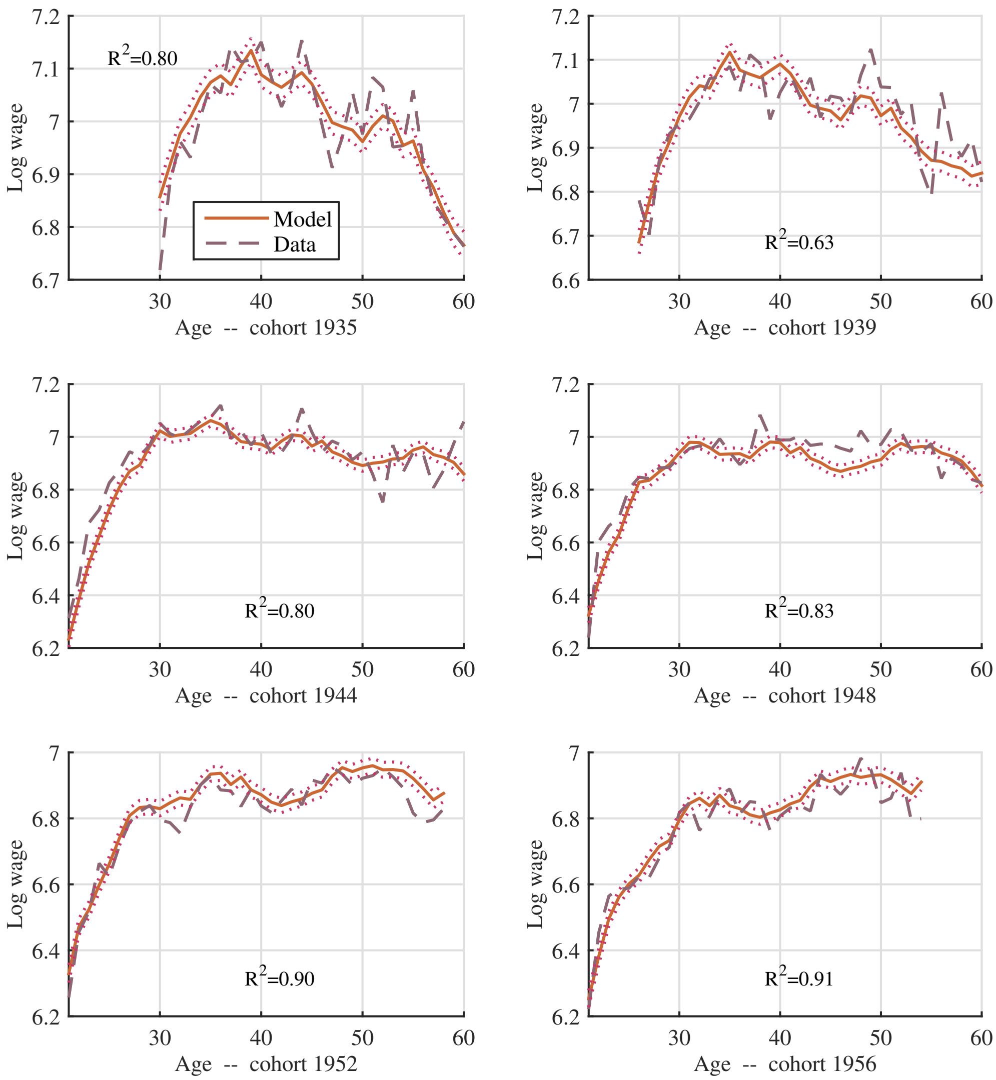


Figure 12: Model Fit: CG