Accounting for Changing Returns to Experience

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Abstract

To be written.

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

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1 Introduction

A growing literature documents that wage returns to experience change over the post-war period in the U.S.

Early: Katz and Murphy (1992) show that cross-sectional wage profiles get steeper between 1963-1987.

Later: change in perspective to longitudinal wage growth as a given cohort accumulates experience.

Kambourov and Manovskii (2009) find a flattening of experience profiles over birth cohorts 1950-1970.

Kong et al. (2015) document a similar flattening over cohorts 1915-1955.

Related, Card and Lemieux (2001) show that the college wage premium for young/old workers grows differently.

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Explanations

These findings have spawned a literature that seeks to explain time-varying returns to experience.

Two strands:

1. Changing price of experience: the old and young supply different labor inputs. As their relative supplies change over time, so does their relative price (Katz and Murphy, 1992; Card and Lemieux, 2001; Jeong et al., 2012)

2. Changing quantity of experience: the rate at which different cohorts accumulate human capital varies over time (Guvenen and Kuruscu, 2010; Kong et al., 2015)

Purpose of this paper Offer an alternative view: cohort effects.

Motivation is Figure 1. This shows experience wage growth for men, ages +++ to +++, from CPS data. By schooling.

It also shows changes in log median wages over the same years.[1]

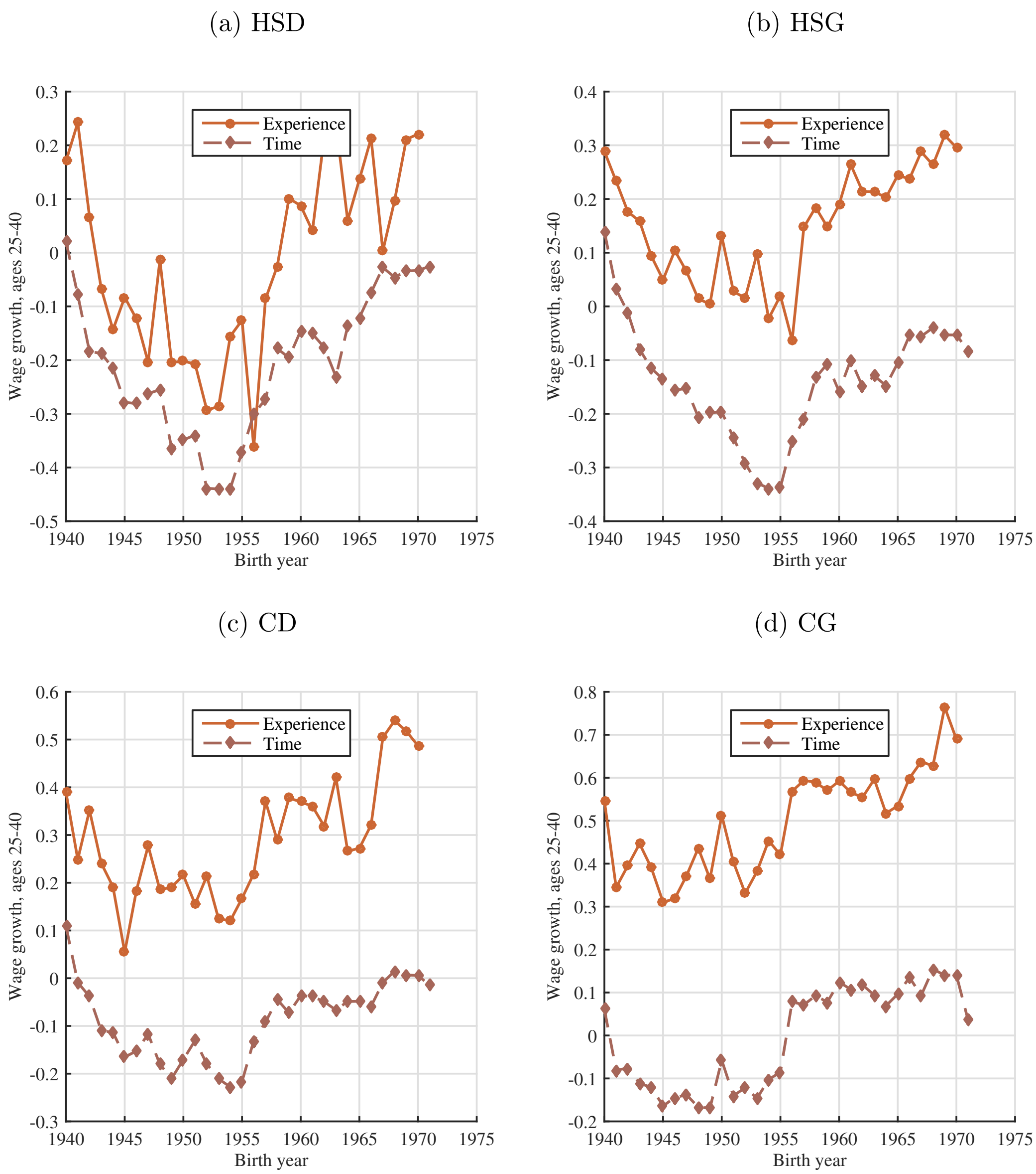
For all school groups, returns to experience exhibit a U shape with a minimum in the 1950s.

Key point: Aggregate wage growth as a cohort ages obeys very similar patterns.

Implication: when it comes to accounting for longitudinal changes in returns to experience, there is no need for time-varying age-efficiency profiles.

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

Figure 1: Experience wage growth



To make this precise,

suppose that wage is given by $w_{a,s,t} = p_{s,t} h_{a,s} q_{s,c}$.

where p is a skill price, h denotes the age efficiency profile, and q is a cohort effect.

Then wage growth over the life-cycle is given by $\Delta_a \ln w_{a,s,t} = \Delta_t \ln p_{s,t} + \Delta_a h_{a,s}$. [not great notation]

Assuming that skill prices are approximately proportional to aggregate wages, the lines shown in Figure 1 should be parallel, tracing out skill price growth over a cohort's life-cycle. The gap equals efficiency growth as a cohort ages.

This motivates the question posed in the paper: How far can I go towards understanding the facts highlighted in the literature in a model with "standard" ingredients, including constant age efficiency profiles?

Specifically, the model studied consists of the following ingredients, all of which are well known from the literature:

1. Fixed experience efficiency profiles
2. An aggregate production function with constant skill biased technical change similar to Katz and Murphy (1992)
3. Cohort effects that vary with cohort schooling (similar in spirit to Hendricks and Schoellman (2014))

Show that this model goes a long way towards accounting for the observations highlighted in the literature.[2]

The remainder of the paper is organized as follows. section 2 describes the data construction. The model is described in section 3 and estimated in section 4. section 5 investigates how well the model accounts for the observations highlighted in the literature.

2 Data

This section: explain data construction.

Individual level data on schooling and earnings are taken from the March CPS files for 1965 – 2011 (King et al., 2010). Earnings are observed for the previous calendar year.

The count sample contains men born between 1920 and 1980 who report valid schooling.

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

Table 1: Summary statistics for CPS data

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

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

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.

Robustness analysis: only include working for wages; not shown. Results similar (gNo 7?). See github.

Details of the CPS data are described in Hendricks (2015). Summary statistics are shown in Table 1.

For each year, I calculate

1. $N_{a,s,t}$: the mass of persons in each (age, school, year) cell;
2. $L_{a,s,t}$: total hours worked in each cell.
3. $w_{a,s,t}$: median wage.

School categories: high school dropouts (HSD), high school graduates (HSG), college dropouts (CD), and college graduates (CG).

Cohort wage profiles are simply $w_{a,s,t}$ collected for each birth cohort. Only partial profiles are observed for most cohorts.

Each cohort's average years of schooling is calculated by averaging over the age range $30 - 50$. Not all ages are observed for all cohorts.

Do not show data features at this point. Defer discussion to section 5 where I compare model and data. Additional detail in Appendix A.

3 The Model

The model has 3 standard ingredients:

1. A nested CES aggregate production function with constant skill-biased technical change. A minor extension of Katz and Murphy (1992), who consider only 2 school classes.
2. Time invariant age-efficiency profiles $h_{a,s}$.
3. Cohort qualities $q_{s,c}$ that are a function of the cohorts average years of schooling

Aggregate production function: Output is produced from human capital augmented labor according to

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

where

$$G_\tau = \left[\sum_{s=HSD}^{CD} (\mu_{s,t} H_{s,t})^{\rho_{HS}}\right]^{1/\rho_{HS}} \tag{2}$$

is a CES aggregator for unskilled labor (with less than a college degree) and H denotes labor input in efficiency units.

The motivation for separating out college graduates is the large rise in the median wage earned by college graduates relative to each of the other groups (see Katz and Murphy 1992 and more recently Autor et al. 2008).

Following Katz and Murphy (1992), relative skill weights, $\mu_{s,t}/\mu_{HSG,t}$ are assumed to grow at constant rates.

$\ln \mu_{s,t} - \ln \mu_{HSG,t} = \bar{\mu}_s + g(\mu_s)(t - 1964)$

Normalize skill weights to sum to 1.

No restrictions on the evolution of neutral productivities B_t.

Labor inputs: Labor inputs in efficiency units are given by

$$H_{s,t} = \sum_{a=a_s}^{A} L_{a,s,t} h_{a,s} q_{s,c} \tag{3}$$

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.

Wages: Skill prices equal marginal products:

$$p_{s,t} = \frac{\partial Y_{s,t}}{\partial H_{s,t}} \tag{4}$$

Observed wages equal skill prices times labor efficiency:

$$w_{a,s,t} = p_{s,t} h_{a,s} q_{s,c} \tag{5}$$

Cohort quality: Assume that cohort quality is quadratic in average years of schooling:

$$q_{s,c} = Q(\bar{s}_c; s) \tag{6}$$

$$= \phi_{s,0} + \phi_{s,1}\bar{s}_c + \phi_{s,2}\bar{s}_c^2 \tag{7}$$

The motivation is that expanding schooling is associated with declining average abilities of all school groups (see Hendricks and Schoellman 2014).

Important for identification: no time trend in cohort quality. This is what allows the model to decompose wage growth into the contributions of skill price growth and human capital growth.

Note, however, that an observationally equivalent model would feature trend growth in cohort qualities and suitably adjusted trend growth rates of skill prices and experience efficiency growth.

The point: while the model generates estimates of all parameters, its implications for skill price and human capital growth should be interpreted with caution.

4 Estimation

The following parameters are estimated jointly:

- neutral productivities B_t
- skill weights: $\bar{\mu}_s$, $g(\mu_s)$
- $h_{a,s}$: dummies
- parameters of cohort quality function: $\phi_{s,j}$ for $j = 0, 1, 2$.

The strategy:

Find the parameters that minimize the sum of squared deviations between log model wages (see (5)) and log median data wages.

Objective is

$$D = \sum_{s=1}^{S} \sum_{a=a_s}^{60} \sum_{c=1920}^{1980} \omega_{a,s,c} \left[\ln w_{a,s,c} - \ln \hat{w}_{a,s,c}\right]^2 \tag{8}$$

where it is understood that observations for which data do not exist ($t(a,c) < 1964$ or > 2010) are dropped.

weighted by the square root of the number of observations in each data cell (ω).

Total number of parameters: +++

Number of data moments: +++ [here is where one would really like to go quartic +++]

In practice, I do something simpler.

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

4.1 Estimation Results

Figure 2a shows implied age-efficiency profiles. They have the usual hump-shaped form.

Figure 2b shows cohort effects relative to high school graduates. Large decline in relative cohort effects for college graduates during the expansion of educational attainment, roughly until the birth year 1950. Then flattening. Consistent with a narrative where expanding college education reduces the quality of college students.

Figure 2c shows skill weights relative to HSG. Consistent with a constant time trend, except for HSD, where the trend growth rate increases after 1990.

How worried should one be about the poor fit for HSD?

Expect fit to be poorest for a number of reasons.

The fraction of HSD drops to around 10%. Possible that some dropouts lack basic skills that exclude them from labor market.

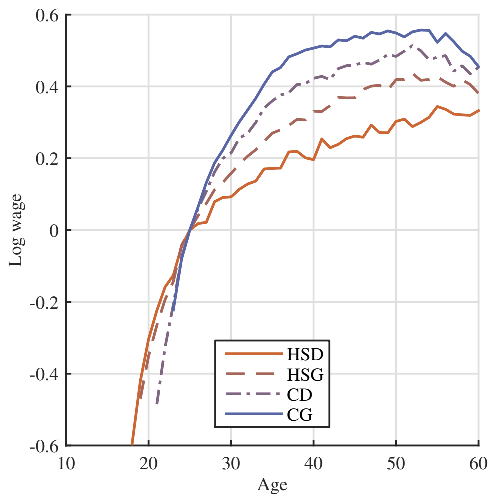
Serious concern about selection into work. Small samples.

Keep in mind that linear trends in age-efficiency profiles, cohort effects, skill weights, and skill prices are only identified because I assume that cohort quality is a function of cohort schooling.

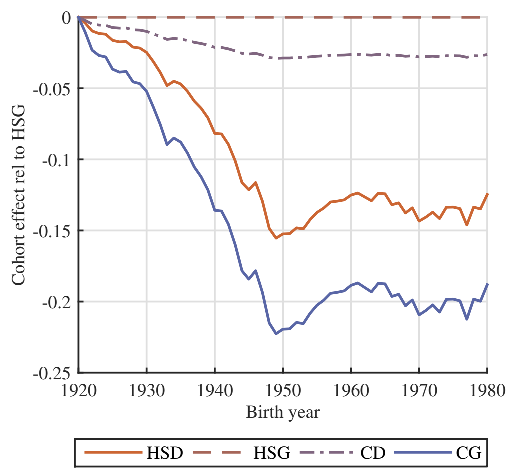
Additional detail shown in Appendix B.

Figure 2: Estimation Results

(a) Age-efficiency profiles



(b) Cohort effects



(c) Skill weights relative to HSG

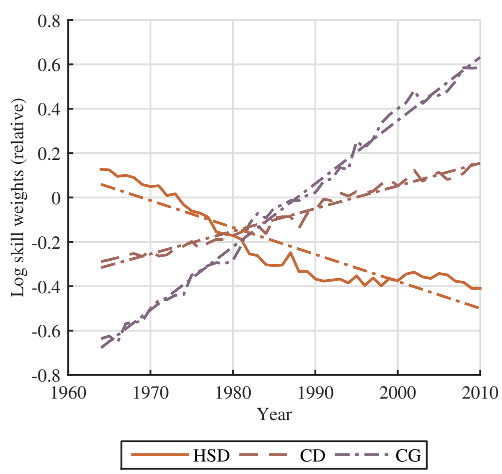


Table 2: Model Fit

	Median	25th	75th	N
HSD	0.71	0.59	0.83	61
HSG	0.82	0.71	0.91	61
CD	0.82	0.62	0.95	61
CG	0.90	0.72	0.96	59

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.

4.2 Model Fit

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

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

Table 2 summarizes. Median R^2 ranges from +++ to +++. Visual comparison of model and data age-wage profiles for high school graduates and selected cohorts in Figure 3

other school groups in Appendix C.

Properties: There is substantial variation in the "shape" of the profiles across cohorts

Early: typical hump shape. Later: steep rise early on followed by flattening documented by Murphy and Welch (1990).

Model replicates well these low frequency changes.

Examining all cohorts: fit is generally worse for earlier cohorts. There are some low R^2 values, but even in these cases the model replicates the low frequency variation of log wages as cohorts age.

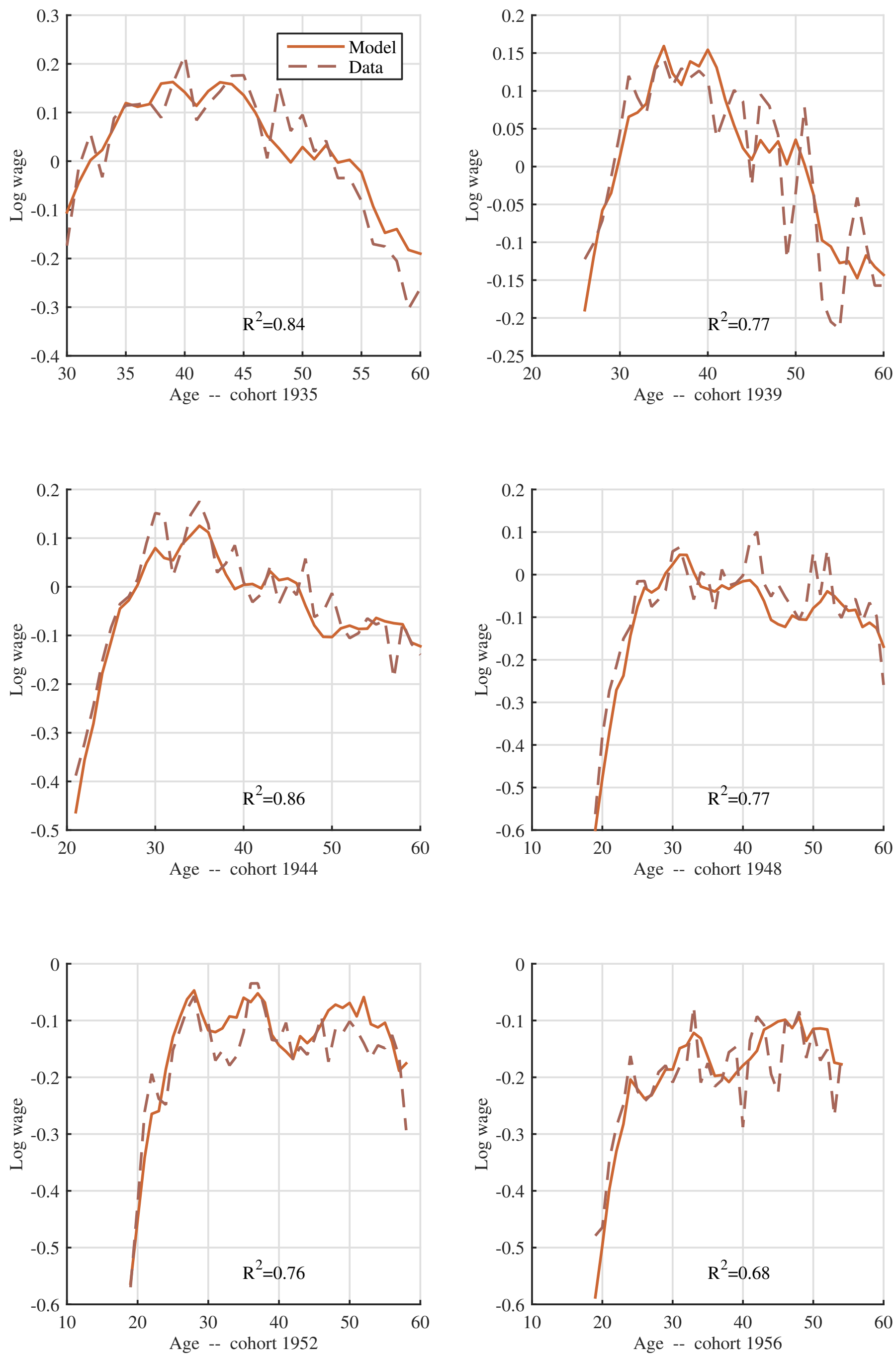
5 Results

This section examines to what extent the model accounts for time-series variation in returns to experience and related stats discussed in the Introduction.

5.1 Returns to Experience

Consider first longitudinal returns to experience. Figure 4 shows change in log wage as each cohort ages (from age +++ to age +++).

Figure 3: Model Fit: HSG



For all school groups, slopes have a U shape with min in 1950-55 birth cohorts.

Figure 5 shows the intercepts of the longitudinal wage profiles (log wages at age $+++$).

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

The model replicates both patterns.

How the model accounts for time-varying returns to experience is clear from the Introduction.

Wage growth over a cohort's life-cycle has 2 parts:

1. change in $h_{a,s}$ - the same for all cohorts
2. changes in skill prices as the cohort ages - this is *the only* source of variation in longitudinal returns to experience in this model.

As Figure 1 shows, changes in skill prices and returns to experience comove closely. The model implies skill prices that evolve very similarly to median log wages (see Figure 9 in Appendix B). It follows that returns to experience in the model closely track those in the data.

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

they do 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).

5.1.1 Cross-sectional Returns to Experience

Figure Figure 6 shows cross-sectional returns to experience.

In this model, these are simply differences in cohort qualities

Cross-sectional return $= \Delta \ln h_{a,s} + \Delta \ln q_{s,c}$ where the first difference is taken over ages (time-invariant) and the second is taken over the associated birth years (time varying).

The model's ability to replicate the observed time variation in returns is mixed. For high school dropouts, the model is essentially unsuccessful. The general theme: the model does not work that well for this group.

For other groups, the model replicates low-frequency movements, but amplitudes are somewhat smaller than in the data.

Figure 4: Cohort Returns to Experience

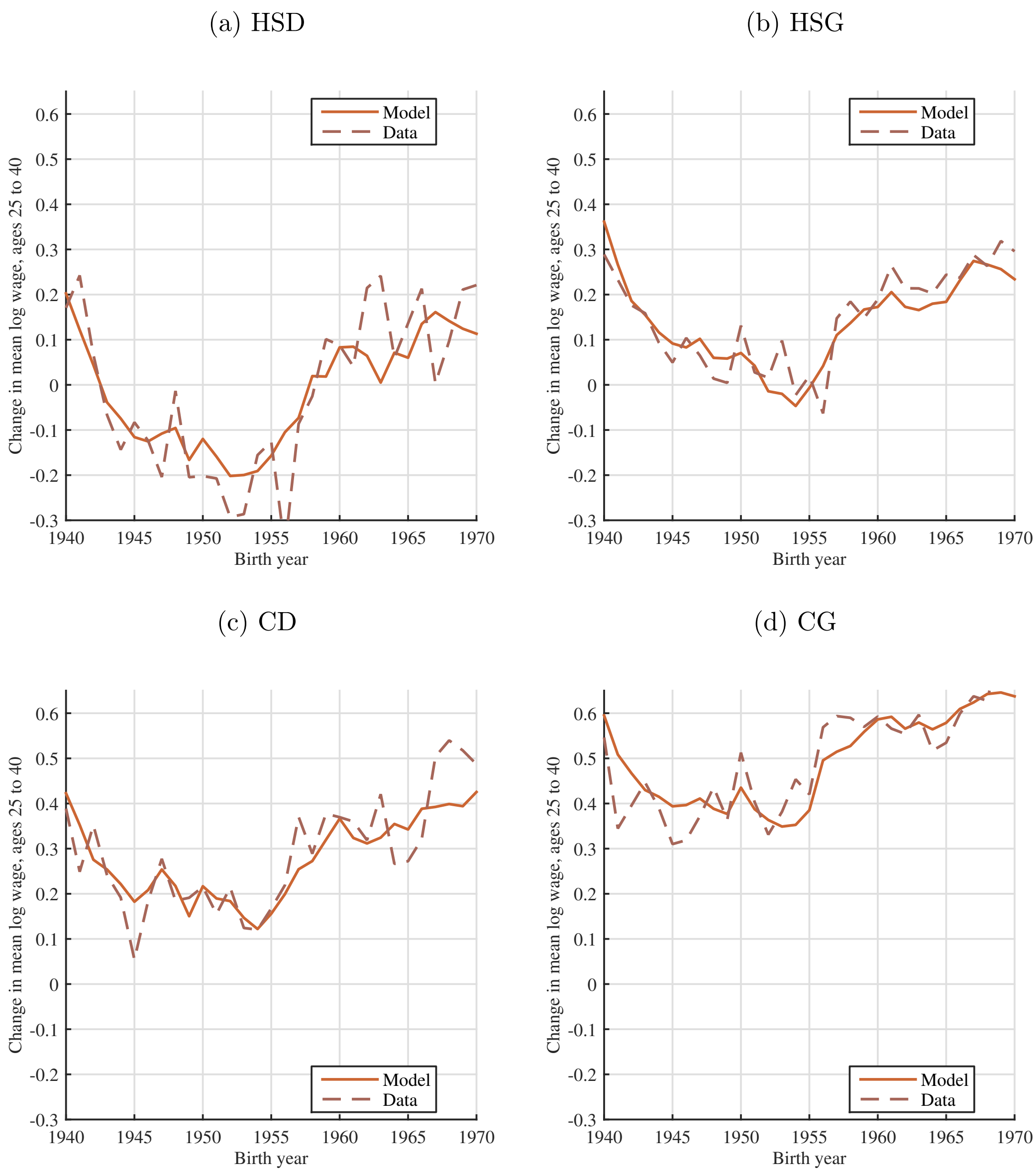
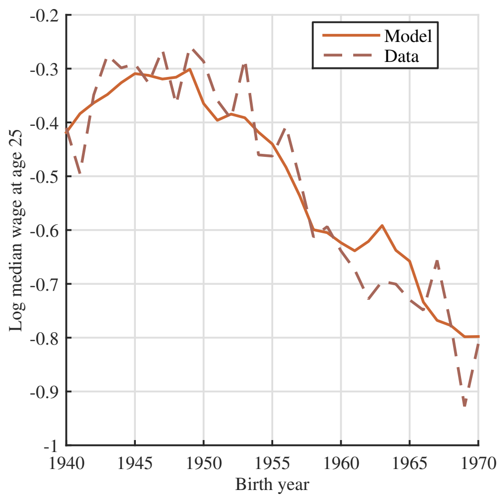
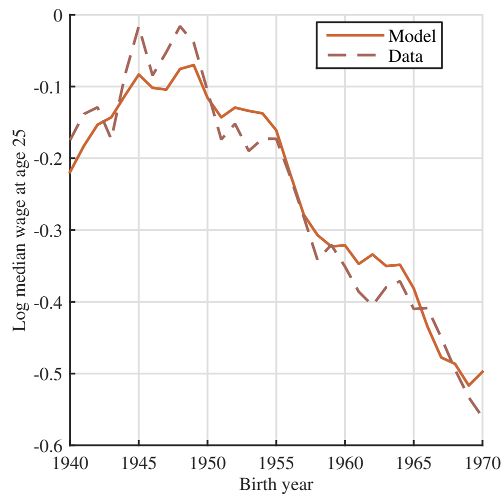


Figure 5: Cohort Wage Intercepts

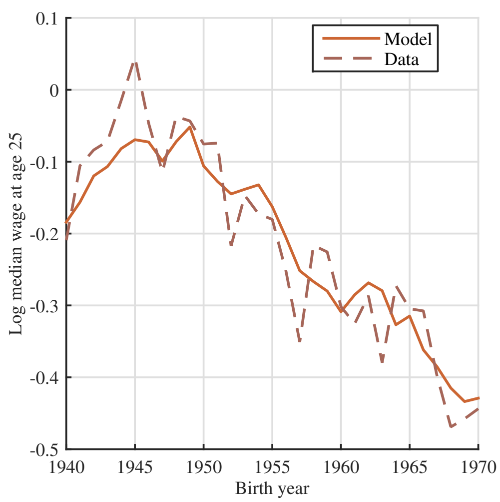
(a) HSD



(b) HSG



(c) CD



(d) CG

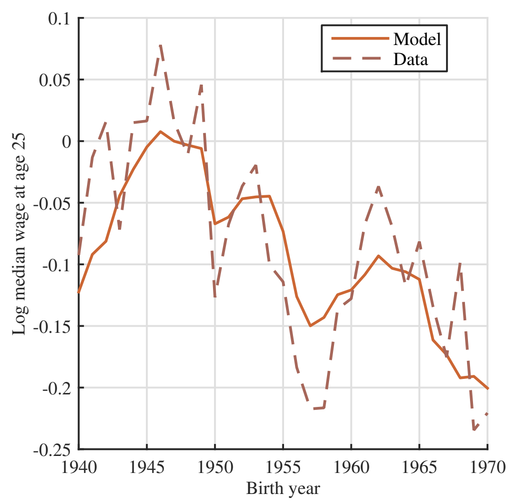
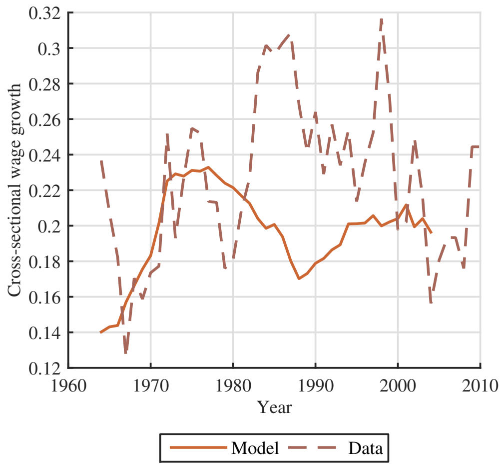
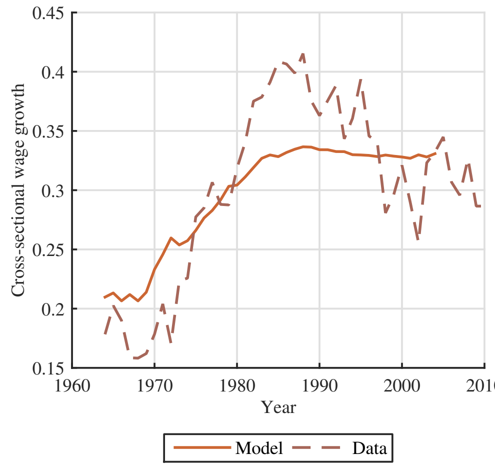


Figure 6: Cross-sectional Returns to Experience

(a) HSD



(b) HSG



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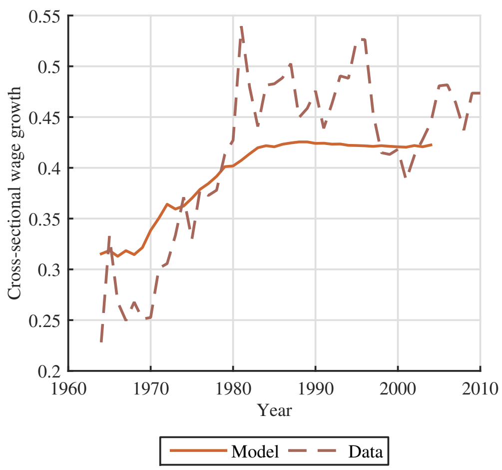


(d) CG

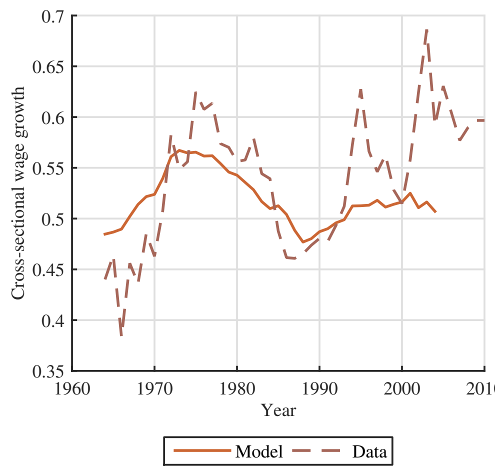
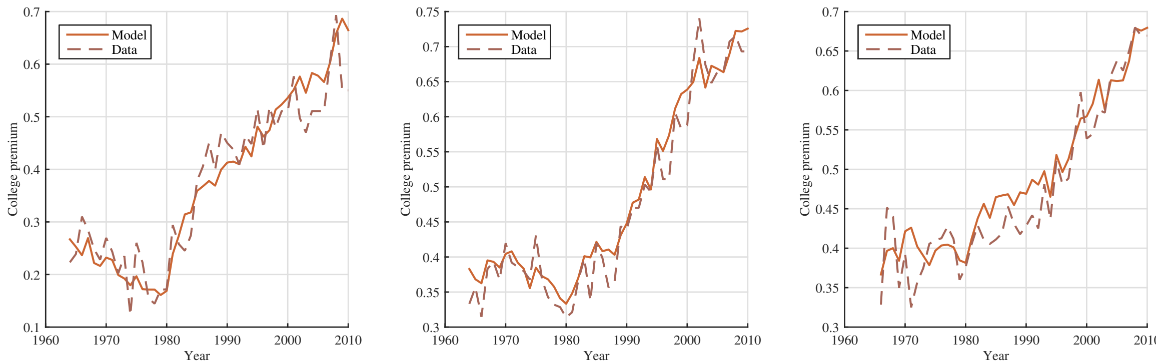


Figure 7: College Wage Premium

(a) Young workers (b) Middle-aged workers (c) Older workers



5.2 The College Wage Premium

Card and Lemieux (2001) document differential evolution of the college wage premium for young workers (ages $26-35$) versus older workers (ages $45-60$).

Suggest imperfect substitution of age groups.

Related idea: Jeong et al. (2012) where workers supply raw labor and experience. Older workers supply relatively more experience. Over time, the relative price of experience changes.

Here: an alternative interpretation.

How does it work?

Cross-sectional college premium is $\Delta_s p_{s,t} + \Delta_s \ln q_{s,c}$

The first create a common trend for all ages: the college premium rises starting around 1980.

The second creates divergent trends for young and old workers.

So that implies we should have nothing without cohort effects? +++

continue here +++

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

6 Conclusion

Data: time-varying returns to experience. Commonly interpreted as time-varying age-efficiency profiles or imperfect substitution of young and old workers.

Here: alternative interpretation. Constant efficiency profiles, but time-varying skill price growth.

Generated by a simple model with standard ingredients.

Future work +++

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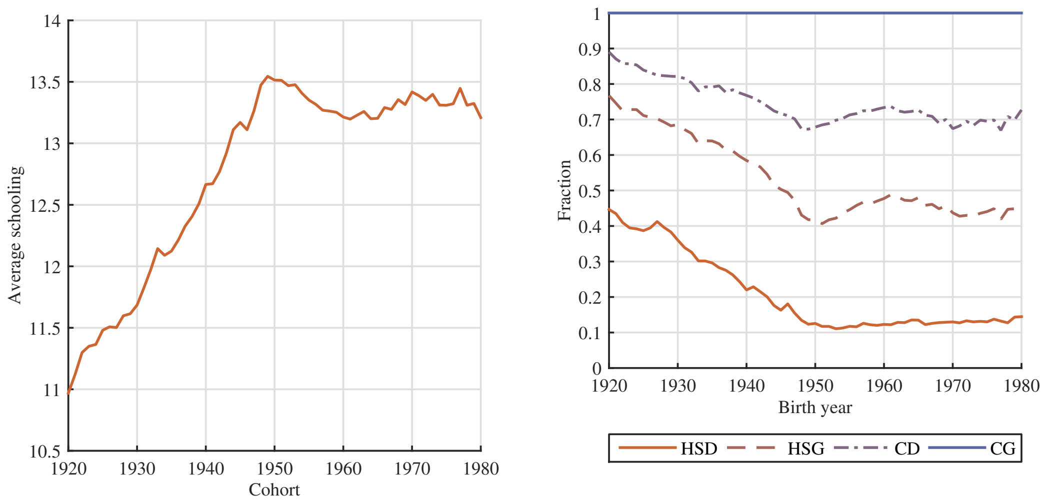
Figure 8: Cohort Schooling

(a) Average years of schooling (b) Fraction in each school group



A Data Details

This section shows addtional data results.

Figure 8 shows estimated years of schooling (panel Figure 8a) and school fractions (panel Figure 8b) by cohort.

B Estimation Results

This section shows additional estimation results.

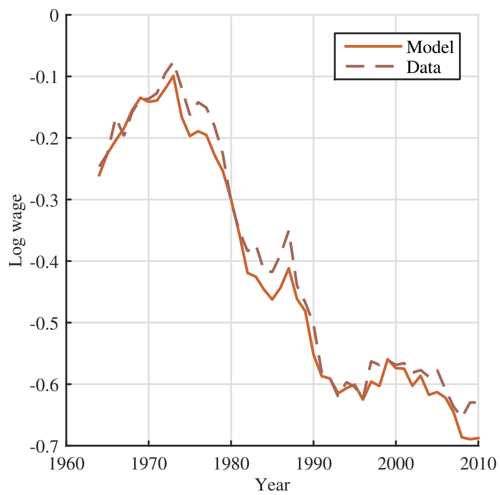
Figure 9 shows model skill prices and log median wages from data. Aside from linear trends, which are not identified, skill prices are quite close to model wages.

C Model Fit

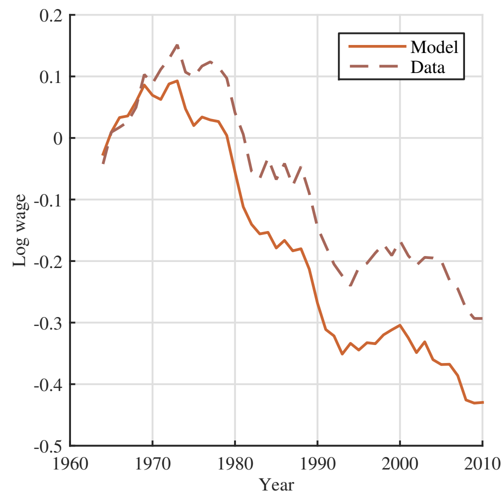
Figures Figure 10 through Figure 12 compares observed and model predicted age-wage profiles for selected cohorts.

Figure 9: Skill Prices and Wages

(a) HSD



(b) HSG



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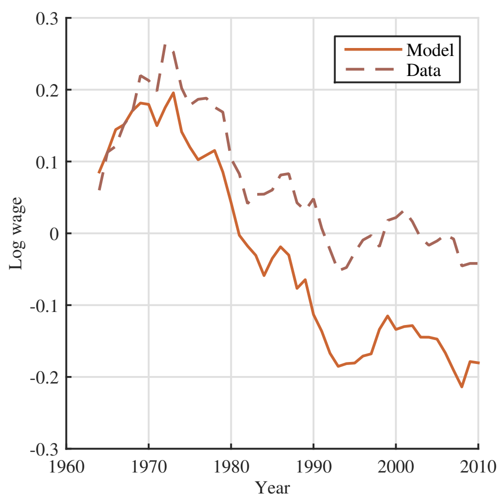

(d) CG

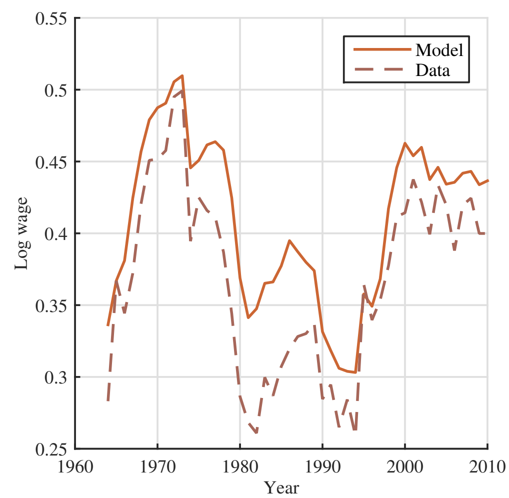

Figure 10: Model Fit: HSD

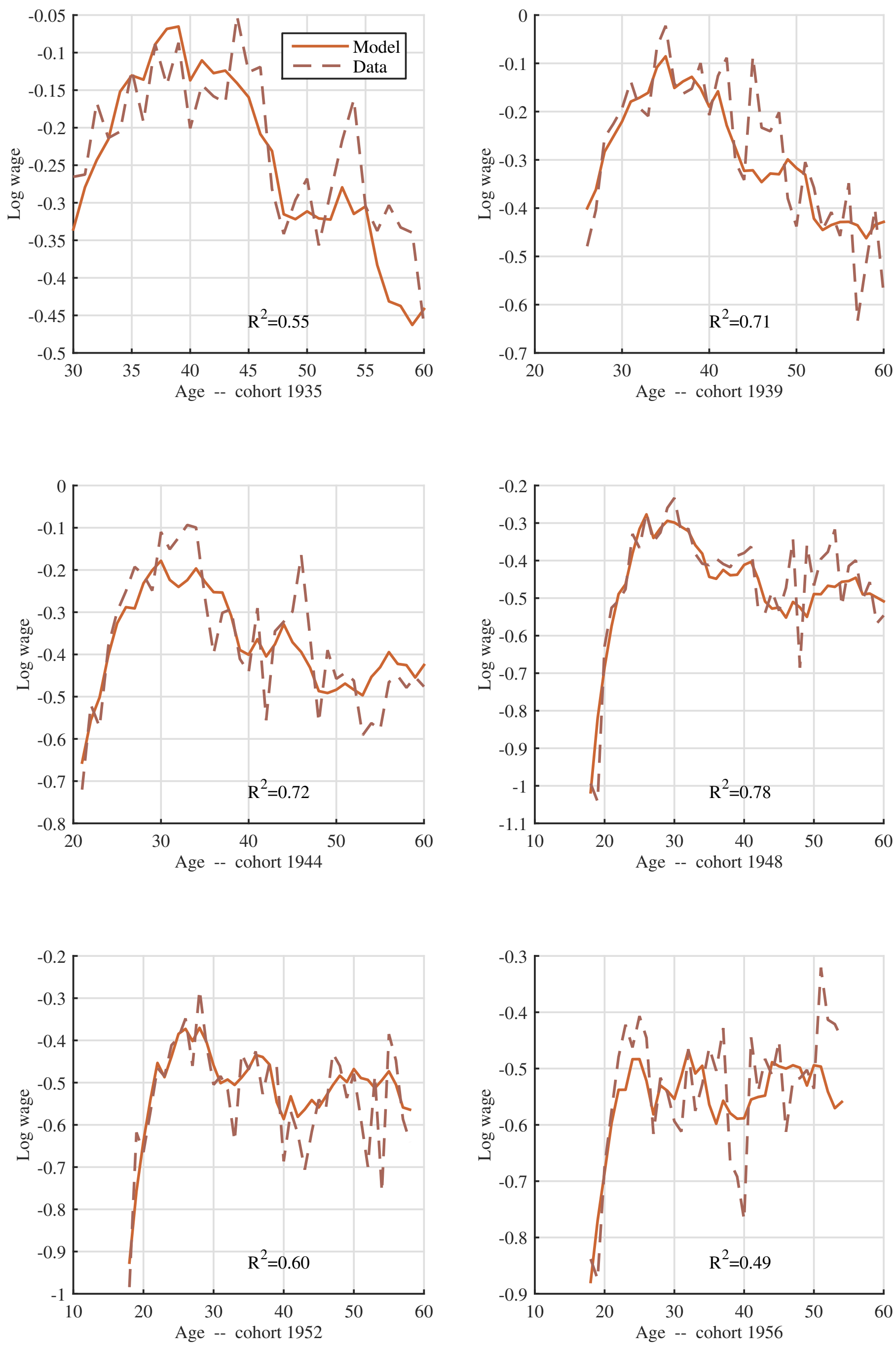

Figure 11: Model Fit: CD

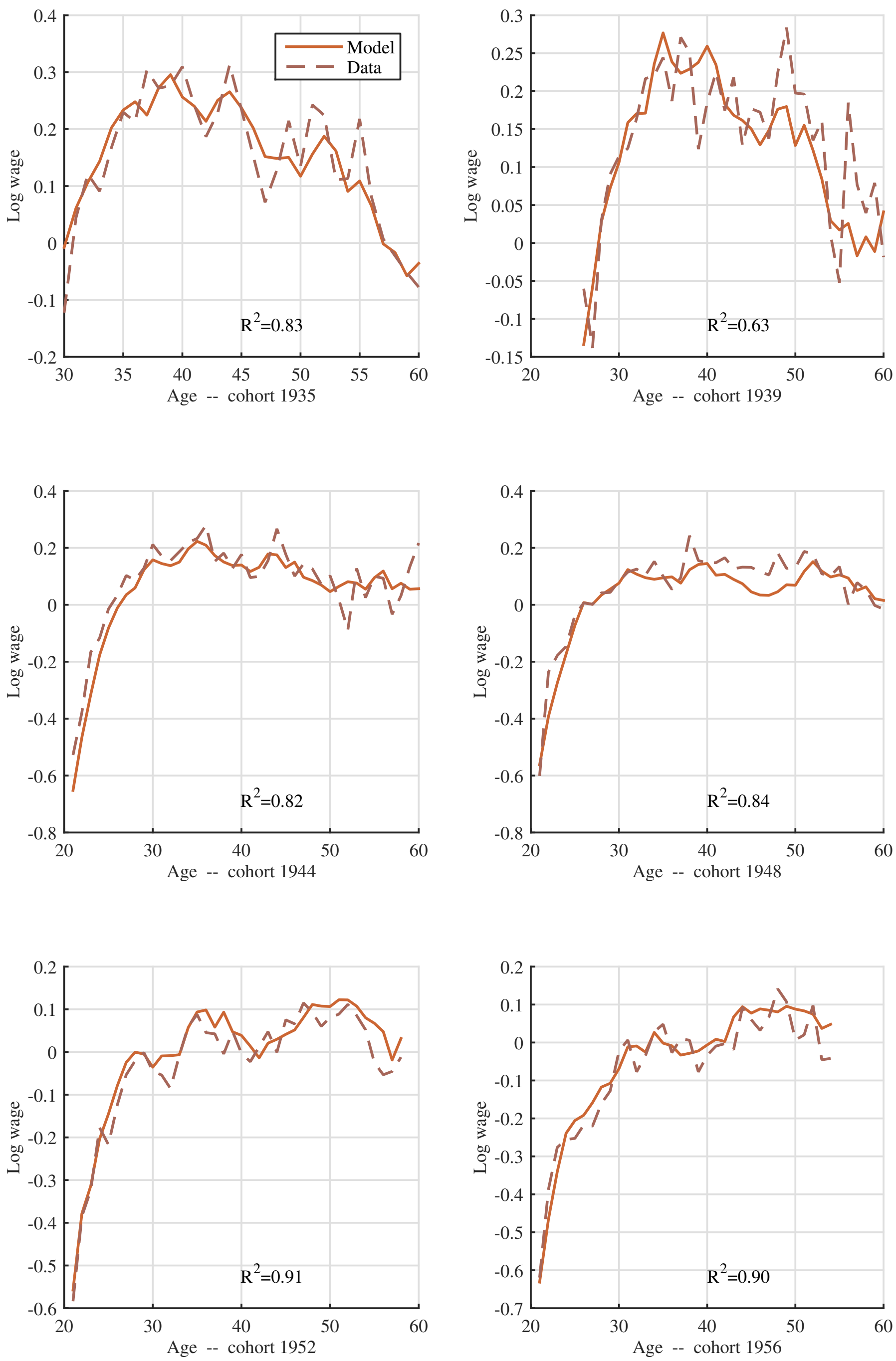

Figure 12: Model Fit: CG