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ESSAYS ON SCHOOLING, OCCUPATIONS, AND EARNINGS

by

Elisa Keller

An Abstract

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
in the Graduate College of
The University of Iowa

May 2013

Thesis Supervisors: B. Ravikumar
Assistant Professor G. Vandenbroucke

ABSTRACT

This thesis consists of two chapters. The first chapter investigates the causes of the recent slowdown in college attainment in the United States. The second chapter studies the gender wage gap by occupational complexity.

For white males born in the United States after 1950, there is a stagnation in the fraction of high school graduates that go on to complete a four-year college degree. At the same time, across successive cohorts, those with a four year-college degree achieve increasingly higher lifetime earnings than those with a high school degree. What caused this phenomenon? I formulate a life-cycle model of human capital accumulation in college and on the job, where successive cohorts decide whether or not to acquire a college degree as well as the quality of their college education. Cohorts differ by the sequence of rental price per unit of human capital they face. My model reproduces the observed pattern in college attainment for the 1920 to 1970 birth cohorts. The stagnation in college attainment is due to the decrease in the growth rate of the rental price per unit of human capital commencing in the 1970s. My model also generates 79% of the increase in earnings for college graduates relative to those for high school graduates. Part of this increase is reinforced by a stronger association between college and ability.

Female to male wages are U-shaped across occupations ordered by increasing complexity, where complexity is defined as the ratio of abstract to manual tasks content. The U-shape flattens over the lifecycle and across successive cohorts. I develop an occupational choice model with learning by doing on the job. Male and female individuals differ by their level of skill. Occupations differ by the skill required to perform and the marginal product of skill. The model reproduces the gender wage gap across occupations for cohorts born between 1915 and 1955 in the United States. The small work experience of females relative to that of males decreases female wages disproportionately across occupations and influences female occupational selection. I find that 69% of the lifecycle gender wage gap is attributable to work experience. Removing differences in work experience between genders results in a larger fraction of females choosing occupations for which the gender wage differential is smaller.

Abstract Approved: ______________________________
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ESSAYS ON SCHOOLING, OCCUPATIONS, AND EARNINGS

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Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Elisa Keller

has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Economics at the May 2013 graduation.

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Yuzhe Zhang

To Agnese, Gino, and Valentina.

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This thesis consists of two chapters. The first chapter investigates the causes of the recent slowdown in college attainment in the United States. The second chapter studies the gender wage gap by occupational complexity.

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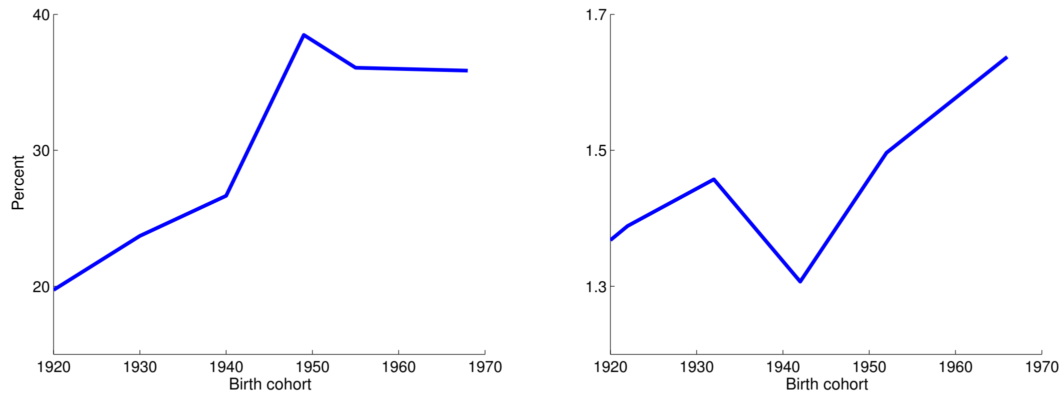
CHAPTER 1
THE SLOWDOWN IN AMERICAN EDUCATIONAL ATTAINMENT

1.1 Introduction

Throughout American history, almost every generation has acquired substantially more education than its parental generation. This is no longer true. Figure 1.1a shows the fraction of white males with a high school diploma that went on to complete a four-year college degree (hereafter "college") for the 1920 to 1970 cohorts, which are grouped by year of birth. The fraction for the 1950 cohort was nearly twice as large as that for the 1920 cohort. However, for cohorts born after 1950, the fraction of high school graduates that completed college remained flat (college attainment also remained flat for cohorts born after 1970, but is not shown in the figure A.1, see Appendix A.1). These trends have been documented by, among others, Altonji, Bharadwaj, and Lange (2008) and Goldin and Katz (2008).[1] In this chapter, I ask the following question: What accounts for the trend observed in college attainment of white males and, in particular, the lack of intergenerational progress starting with the 1950s cohorts?

I take a novel view that the changes in the growth rate of the rental price per unit of human capital (hereafter "price growth") are crucial for generating the

[1] College attainment for females rose throughout the century, with only one brief stall during the 1950s cohorts (see Appendix A.1). This increase, however, was arguably part of a more secular trend in both education and labor force participation influenced by reasons beyond the scope of this thesis. Although this thesis deals only with the college attainment of white males, general equilibrium price effects that come from the college attainment of other demographic groups and influence the college decisions of white males are taken into account within the quantitative strategy.



(a) Attainment (b) Premium

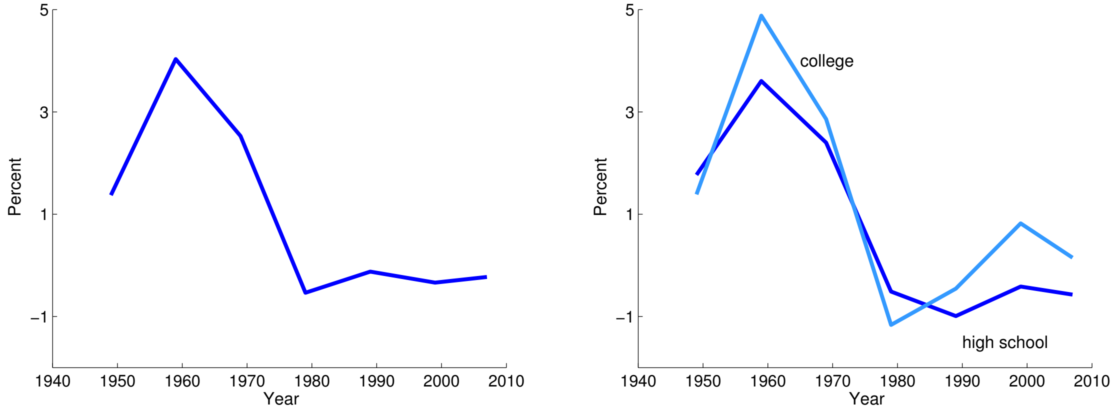
Figure 1.1: College attainment and college premium in the United States (employed white males). College attainment is measure as the fraction of individuals with a high school diploma that went on to complete a four-year college degree.

Source: IPUMS-USA.

observed pattern of college attainment. I illustrate this point with a simple back-of-the-envelope calculation. Consider the earnings (E_t^S) of full-time workers of education level S at time t : $E_t^S = w_t \times h_t^S$. In this identity, h_t^S is the quantity of human capital for education level $S \in \{H, C\}$ (H stands for high school and C stands for college) at time t, and w_t is the price per unit of human capital at time t. Suppose individuals live for two periods and college involves sacrificing current earnings for future human capital, h_{t+1}^C. Lifetime earnings of a high school graduate are: $LE^H = w_t \times h_t^H + w_{t+1} \times h_{t+1}^H$. Lifetime earnings of a college graduate are: $LE^C = w_{t+1} \times h_{t+1}^C$. Individuals choose the option that yields the highest lifetime earnings. Thus, college is chosen if $LE^C \geq LE^H$, i.e., if $\frac{h_{t+1}^C}{h_{t+1}^H} \geq \frac{w_t \times h_t^H}{w_{t+1} \times h_{t+1}^H} + 1$. Figure 1.1b plots college-graduate lifetime earnings relative to high school-graduate lifetime earnings (hereafter "college premium") for the 1920 to 1970 cohorts and shows that the premium has steadily increased starting with the 1940 cohort.[2] The college premium corresponds to $\frac{h^C_{t+1}}{h^H_{t+1}}$. Assuming $\frac{w_t \times h^H_t}{w_{t+1} \times h^H_{t+1}}$ is constant over time, the inequality will grow larger, which implies that more people will go to college. This would contradict Figure 1.1a for those born after 1950. Figure 1.2 plots the reciprocal of $\frac{w_t \times h^H_t}{w_{t+1} \times h^H_{t+1}}$, i.e., gross earnings growth of high school graduates. Earnings growth drops significantly after the 1970s, the same time that the 1950s cohorts graduated from high school. The drop in earnings growth reconciles Figure 1.1b and Figure 1.1a for those born after 1950. Earnings are the product of prices and quantities, which are both unobservable. To explore the quantitative role of price growth for the pattern of college attainment, I develop a model of human capital accumulation in college and on the job that identifies prices and in turn produces the observed pattern of US college attainment. The model takes the rental price of human capital w as exogenous and endogenously produces patterns of earnings growth and the college premium along with the pattern of college attainment.

My model builds on Heckman, Lochner, and Taber (1998) and Huggett, Ventura, and Yaron (2006). It features lifecycle human capital accumulation à la Ben-

[2]The college premium for a cohort is constructed as the ratio of median earnings for individuals in that cohort that graduated from college relative to those that graduated from high school only. Earnings for cohorts are measured over one year when individuals in the cohort are between ages 33 and 38, depending on data availability. Figure 1.1b reports the college premium for cohorts grouped in six-year bins. Patterns similar to those in Figure 1.1b are reported for other measures of the returns to college. Heckman, Lochner, and Todd (2008) report that cohort-based returns to college increased continuously over time for white men entering the labor market between 1960 and 1985.



(a) Unconditional. (b) High-school and college

Figure 1.2: Earnings growth in the United States between the age of 35 and 46 (employed white males).

Source: IPUMS-USA.

Porath (1967) and a college choice. Individuals start off with a high school degree and they differ by their innate ability and their initial human capital. Each individual decides whether or not to acquire college education. Once schooling is completed, individuals join the labor market and can accumulate human capital on the job. Accumulation of human capital in college requires both time and goods (that is, college quality) as inputs, while accumulation on the job requires only time. Cohorts differ by the sequence of price per unit of human capital (hereafter "price sequence") they face (a time effect) as well as by the distribution of initial human capital across individuals (a cohort effect). A decrease in price growth influences the college decision in two ways. First, it decreases the returns to human capital investment and, therefore, the returns to college. Second, it increases the opportunity cost of human capital accumulation in college relative to that on the job because of the lower relative price of time. These two effects decrease the incentives to go to college more for individuals with high human capital and low innate ability.

I use earnings from the National Longitudinal Survey of Youth (NLSY) for the cohorts 1961 through 1964 to calibrate the structural parameters of the model. I calibrate the price sequence and the evolution of the distribution of initial human capital to Integrated Public Use Microdata Series USA (IPUMS-USA) earnings data for the cohorts 1920 through 1970. The shape of the distribution of individuals' endowments determines the elasticity of college attainment to changes in the price. Since endowments cannot be directly measured, I follow the strategy in Huggett, Ventura, and Yaron (2006) and include the college premium as an additional source of discipline. I use the NLSY dataset as it has a fixed-panel structure and allows me to infer endowments from life-cycle earnings.

The model produces three main quantitative findings. First, I find that the rate of growth of the rental price per unit of human capital declines commencing in the 1970s. Price growth declines from 1.7 percent per year before the 1970s to 0.1 percent per year after the 1970s. Second, the model reproduces the observed pattern in US college attainment. For the 1920-1950 cohorts, the fraction of high school graduates attaining college increases from 12 percent to 37 percent in the model and from 18 percent to 38 percent in the data. For the 1950-1970 cohorts, the fraction remains constant at the level of the 1950 cohort both in the model and in the data. The slowdown in college attainment is generated almost exclusively by the slowdown in price growth. Individuals born after 1950 face diminished returns to human capital investment on the job and a flat profile of returns to college quality, as the rental price of human capital grows very slowly after 1970. Third, the model generates 79 percent of the increase in the college premium for the 1920-1970 cohorts. The increase is generated by both the slowdown in price growth and a decrease in the average and an increase in the dispersion of the initial human capital of successive cohorts born after the mid-1930s. Pre-1970s price growth fuels the increase in college attainment for the cohorts 1920 to 1950, which has a significant selection effect on the average innate ability and average human capital associated with college and high school. The decline in price growth of the 1970s causes selection into college to depend more on an individual's innate ability over time, which reinforces the increase in the college premium. As the rental price of human capital at high school graduation increases and its growth over the lifecycle decreases, initial human capital becomes less important for the college decision; and the college decision is ruled more by an individual's innate ability. My uncovering of decreased average human capital for more recent cohorts of high school graduates is consistent with anecdotal evidence on tests scores in Taubman and Wales (1972) and Bishop (1989).

The papers that are the closest to the analysis in this chapter are Restuccia and Vandenbroucke (forthcoming), Heckman, Lochner, and Taber (1998), and Guvenen and Kuruscu (2010). Restuccia and Vandenbroucke (forthcoming) study the rise of educational attainment and the evolution of relative earnings across education groups. I consider both the rise and the flattening in college attainment. Heckman, Lochner, and Taber (1998) conduct a qualitative analysis of the dynamics of college attainment and earnings inequality resulting from skill-biased technical change. Guvenen and Kuruscu (2010) perform a quantitative study along the lines of Heckman, Lochner, and Taber (1998). Their results are consistent with the evolution of earnings inequality, the college premium, and the rise in college attainment. The analysis in this chapter replicates the pattern in earnings inequality, the college premium, and both the rise and the flattening of college attainment shown in the data.

By studying the slowdown in college attainment, the analysis in this chapter also relates to Bound, Lovenheim, and Turner (2010), Athreya and Eberly (2010), and Card and Lemieux (2001). Bound, Lovenheim, and Turner (2010) consider the role of college resources in the decline in the college completion rate. Athreya and Eberly (2010) address the question of why college attainment has remained flat in spite of the fact that the college premium has been increasing. They propose an answer based on the risk associated with college investment. Card and Lemieux (2001) study the contribution of the expected college premium on college enrollment and completion rates for those born after 1950. Unlike these authors, I consider the quantitative importance of price growth, as a component of the returns to college education, for the slowdown in college attainment.

The rest of this chapter is organized as follows. Section 2 outlines the model and section 3 calibrates it. Section 4 details the results of the quantitative experiment. Section 5 concludes.

1.2 Model

I extend the Ben-Porath (1967) framework to include an explicit college decision and to let the rental price per unit of human capital change over time. Time is discrete and runs from $t = 1, 2, \ldots, T$. The economy is populated by individuals who live for 20 periods. Each period corresponds to two years of calendar time. Individuals enter the model as high school graduates at age 19, which is age 1 in the model. I use τ to denote a cohort: cohort τ is composed of individuals of age 1 at time $t + 19$. I use j to denote age. Within a cohort, individuals are heterogeneous with respect to their innate ability, $z \in \Re^{+}$, and their level of initial human capital $h_1 \in \Re^{+}$, where the subscript indicates model age. Innate ability represents an agent's ability to learn and is fixed over his lifecycle. Initial human capital indicates the quantity of human capital an individual has at high school graduation. Endowments are distributed according to a cumulative distribution function, $\Gamma_{\tau}(z, h_1)$. This function varies across cohorts on the initial human capital dimension. The marginal distribution of innate ability is time-invariant. Individual types are pairs $b \equiv (z, h_1)$ on the set $\mathcal{B} = \Re^{2}_{+}$. I assume that individuals observe their type before any decision is made and that credit markets are complete and there is no uncertainty.

Individuals are endowed with one unit of time that can be spent either on working or on human capital accumulation. They can accumulate human capital in college and on the job. The college enrollment decision is made by cohorts at age 1. Individuals decide whether or not to attend college as well as the quality of their college education. After schooling is completed, human capital can be accumulated on the job by subtracting productive time to work. Human capital is homogeneous between and within schooling types. There is one price that clears the human capital market, w. The price grows exogenously at rate g_t. I use R to denote the gross interest rate that is exogenously given. Each cohort differs by the price sequence it faces and by the distribution of initial human capital.

1.2.1 No-college Path

Individuals who decide not to go to college join the labor market right after high school graduation at age 1. They maximize the present value of earnings over their working lifetime by dividing available time between human capital accumulation, i, and work $(1-i)$. The problem for an individual of type $(z, h_1) \in \mathcal{B}$, born in cohort τ, on the no-college path is given by

$$\max_{\{i_j\}_{j=1}^{20}} \quad \sum_{j=1}^{20} \left(\frac{1}{R}\right)^{j-1} E_j$$

$$\text{s.t.} \quad E_j = w_{\hat{\tau}+2(j-1)} h_j (1-i_j)$$

$$h_{j+1} = f(z, h_j, i_j \mid H) + \delta h_j$$

$$i \in [0,1], \ \hat{\tau} = \tau + 19$$

$$\text{given } h_1.$$

An individual's earnings at age j, E_j, equal the product of the amount of human capital accumulated up to age j, the price of human capital at age j, and the fraction of time allocated to market work at age j. The cost of human capital investment on the job is forgone earnings. Earnings are adjusted downward by the fraction of time spent in human capital investment. The return to human capital investment is higher future earnings. New human capital is produced by combining the existing stock of human capital with time and innate ability. Following Ben-Porath (1967),

$$f(z, h, i \mid H) = z(hi)^{\beta_H}.$$

The subscript H denotes the no-college path. The elasticity of human capital investment on the job, $\beta_H \in (0, 1)$, determines the degree of diminishing marginal returns of human capital investment. The productivity of human capital investment depends on an individual's innate ability, z. This specification is widely used in both the empirical literature and the human capital literature (see, for example, Mincer, 1997 and Kuruscu, 2006). Finally, notice that nothing is lost when studying human capital accumulation decisions by abstracting from consumption and saving decisions. In particular, the focus on lifetime income maximization does not require the assumption of risk neutrality: any concave utility function implies the same human capital investment behavior.

I formulate the problem in the language of dynamic programming. The value function, $V_j(h; z, \mathbf{w} \mid H)$, gives the maximum present value of earnings at age j from state h for an individual of innate ability z who faces the lifecycle price sequence $\mathbf{w}$. In its recursive formulation,

$$\begin{aligned} V_j(h; z, \mathbf{w} \mid H) = \max_{h', i \in [0,1]} \quad & w_j h\,(1 - i) + R^{-1} V_{j+1}(h'; z, \mathbf{w} \mid H) \\ \text{s.t.} \quad & h' = z(hi)^{\beta_H} + \delta h. \end{aligned} \tag{1.1}$$

For $\beta_H \in (0, 1)$ the problem is concave. Standard methods can be used to solve for the value function and the policy function for time investment in human capital i.

The first-order conditions for human capital investment and working time imply the Euler equation:

$$w_j h_j \leq \underbrace{z\beta_H h_j^{\beta_H} i_j^{\beta_H - 1}}_{\Delta \text{ in } h} \underbrace{\frac{w_j\,(1+g_j)}{R}\left(\sum_{u=0}^{19-j} \delta^u \prod_{k=1}^{u} \frac{(1+g_{j+k})}{R}\right)}_{\text{lifecycle return to a unit of } h}, \tag{1.2}$$

for $g_j = \frac{w_{j+1}}{w_j} - 1$. The equation holds with equality for $i \in (0,1)$, otherwise individuals spend their entire time on human capital accumulation. In eq. 1.2, the left-hand side is the marginal cost of human capital accumulation, that is, forgone earnings; the right-hand side is the marginal benefit of human capital accumulation, that is, the present discounted value of the future stream of earnings derived from a marginal increase in the time attributed to human capital accumulation. The amount of time spent accumulating human capital depends on individual characteristics, prices, and the parameters of the model. Individuals with higher innate ability invest more time accumulating human capital on the job and thus have steeper earnings profiles. Individuals with higher human capital at high school graduation spend less time accumulating human capital on the job and therefore have flatter earnings profiles. Time allocation decisions are independent from price units. Because the cost of human capital accumulation on the job is forgone earnings, multiplying the price sequence by a positive constant increases the marginal benefit of and the marginal cost of human capital accumulation equally, leaving the trade-off between the two unaffected. The time-allocation decision depends instead on the shape of the price sequence, that is, the rate of growth of the price over the lifecycle. Because human capital investment involves sacrificing earnings today for higher human capital tomorrow, an increase in price growth increases the marginal benefit of human capital accumulation, leaving the marginal cost unchanged. Following an increase in price growth, individuals with higher innate ability change their human capital investment, hi, more than individuals with lower innate ability. This implies that, despite the fact that individuals with higher innate ability are always investing more in human capital than those with lower innate ability, the magnitude of the difference in human capital investment between the two types increases with price growth. The forward-looking nature of eq. 1.2 implies that the overall stream of future price growth throughout the lifecycle influences current human capital investment.

The value of the no-college path for an individual of type $(z, h_1) \in \mathcal{B}$, born in cohort τ, is:

$$\begin{aligned} V_H(h_1, z, \mathbf{w}_\tau) &= V_1(h_1; z, \mathbf{w}_\tau \mid H) \\ &= \left(\frac{1}{R}\right)^{\underline{j}-1} V_{\underline{j}}(h_{\underline{j}}; z, \mathbf{w}_\tau \mid H) \\ &= \left(\frac{1}{R}\right)^{\underline{j}-1} w_{\hat{\tau}+2(\underline{j}-1)} \left[a_{\underline{j}} h_{\underline{j}} + b^H_{\underline{j}} z^{\frac{1}{1-\beta_H}}\right], \end{aligned}$$

where $\underline{j}$ denotes the first age at which earnings are positive. The constant a_j represents the discounted lifetime return at age j to renting out a unit of human capital net of depreciation. For the case of no full-time accumulation on the job, that is, $\underline{j} = 1$, the first addend denotes the contribution of initial human capital to lifetime earnings, while the second addend adjusts lifetime earnings for the new human capital accumulated on the job throughout the lifecycle. The constant b^H is indexed by schooling, H, since it depends on the elasticity of on-the-job accumulation, β_H. Both constants a and b^H have closed-form solutions when the parameter values satisfy some restrictions. See Appendix A.2 for details.

1.2.2 College Path

Individuals on the college path stay in college for two periods and join the labor market at age 3. When they start college, they pick the quality of their college education. After graduation from college, they maximize the present value of earnings over their working lifetime by dividing time between work and human capital accumulation, as with the no-college path. The problem for an individual of type $(z, h_1) \in \mathcal{B}$, born in cohort τ, on the college path is given by

$$\begin{aligned}
\max_{\{i_j\}_{j=3}^{20}, e} \quad & \sum_{j=3}^{20} \left(\frac{1}{R}\right)^{j-1} E_j - \left(1 + \frac{1}{R}\right) e \\
\text{s.t.} \quad & E_j = w_{\hat{\tau}+2(j-1)} h_j (1 - i_j) \\
& h_{j+1} = q(z, h_j, e) + h_j, \; j = 1, 2. \\
& h_{j+1} = f(z, h_j, i_j \mid C) + \delta h_j, \; j \geq 3. \\
& i \in [0, 1], \; \hat{\tau} = \tau + 19 \\
& \text{given } h_1.
\end{aligned}$$

A college graduate's on-the-job human capital accumulation technology differs from the no-college case by the value of the elasticity of human capital investment, β_C. I assume that college requires full-time investment, therefore earnings are zero for the first two periods for those in college. Human capital accumulation in college requires innate ability, college quality e, and human capital as inputs. Individuals who invest more on their college quality acquire more human capital while in college given their endowments. Investment in college quality represents all sorts of college expenditures, such as tuition and room and board, as well as the disutility associated with putting a certain effort in learning.[3] I assume that college quality is chosen once and for all at the beginning of college and corresponding expenditures are paid in two equal amounts each period. The in-college human capital accumulation function is[4]

$$q(z, h, e) = zh^{\eta}e^{1-\eta}.$$

Given human capital at college graduation, $h_3(h_1, e)$, the on-the-job human capital accumulation problem for the college path is identical to the one for the no-college path up to the elasticity of human capital investment on the job, β_C. The college quality problem can be formulated as $\max_e V_3(h_3(h_1, e); z, \mathbf{w}_\tau \mid C) - \left(1 + \frac{1}{R}\right) e$, for V_3 as in eq. 1.1 with $j = 3$. The first-order conditions are

$$\left(1 + \frac{1}{R}\right) = \underbrace{\frac{\partial h_3}{\partial e}}_{\Delta \text{ in } h_3} \underbrace{\left(\frac{1}{R}\right)^2 \frac{\partial V_3(h_3; z, \mathbf{w}_\tau \mid C)}{\partial h_3}}_{\text{lifetime return to a unit of } h_3}, \tag{1.3}$$

that is,

$$\left(1 + \frac{1}{R}\right) = \frac{\partial h_3}{\partial e} \left(\frac{1}{R}\right)^{\underline{j}-1} w_{\hat{\tau}+2(\underline{j}+2)} a_{\underline{j}} \left[\prod_{u=4}^{\underline{j}} \left(A\beta_C h_{u-1}^{\beta_C - 1} + \delta\right)\right],$$

where $\underline{j}$ and a are defined as for the no-college path. The left-hand side of eq. 1.3 is the marginal cost of increasing college quality — that is, the present value of additional

[3]The disutility cost of learning can be thought of as the cost of obtaining education in the signaling literature.

[4]Similar functional forms for the production of human capital in school have been considered by, among others, Manuelli and Seshadri (2010) and Erosa, Koreshkova, and Restuccia (2010).

expenses on college quality derived from a marginal increase in college quality. The right-hand side of eq. 1.3 is the marginal benefit of increasing college quality — that is, the present discounted value of the future stream of earnings derived from a marginal increase in college quality. Individuals with higher innate ability and higher initial human capital invest more on college quality. Both a higher initial level and a higher growth over the lifecycle of the price imply a higher optimal college quality. When the price at high school graduation increases, the return to college quality increases proportionally with it, while the cost of college quality remains unaltered. When price growth increases, the benefit of human capital accumulation increases (a increases in price growth) and so does the return to college quality, while the cost of college quality remains unaltered once again.

The value of the college path for an individual of type $(z, h_1) \in \mathcal{B}$, born in cohort τ, is the discounted value of lifetime earnings net of total expenditures on college quality:

$$\begin{aligned} V_C(h_1, z, \mathbf{w}_\tau) &= V_3(h_C(h_1, e^\star); z, \mathbf{w}_\tau \mid C) - \left(1 + \frac{1}{R}\right) e^\star, \\ &= \left(\frac{1}{R}\right)^{\underline{j}-1} w_{\hat{\tau}+2(\underline{j}-1)} \left[a_{\underline{j}} h_{\underline{j}} + b_{\underline{j}}^C z^{\frac{1}{1-\beta_C}}\right] - \left(1 + \frac{1}{R}\right) e^\star, \end{aligned}$$

where $e^\star$ denotes optimal college quality (from eq. 1.3) and b^C is indexed by schooling, C, because it depends on the elasticity of on-the-job accumulation as for the no-college case.

1.2.3 College Decision

Individuals within a cohort choose their education level upon graduation from high school. They do so based on their type, (z, h_1), and the price sequence observed during their lifetime, $\mathbf{w}$. A college education is pursued if and only if

$$V_C(h_1, z, \mathbf{w}) \geq V_H(h_1, z, \mathbf{w}). \tag{1.4}$$

Let the indicator function $\mathbf{1}(h_1, z, \mathbf{w})$ take the value of 1 if an individual pursues a college education and 0 if he does not. Thus,

$$\mathbf{1}(h_1, z, \mathbf{w}) = \begin{cases} 1, & \text{if (1.4) holds,} \\ 0 & \text{otherwise.} \end{cases}$$

There are three assumed trade-offs between the college and no-college paths: 1) Human capital is not productive during college education but is when work is chosen. 2) The technology for human capital accumulation in college is not the same as the technology for human capital accumulation on the job. 3) The elasticity of human capital investment on the job differs between education levels. Each of these three trade-offs shape the effect of the price sequence on the college decision. The decision rule in eq. 1.4 can be rewritten as

$$\begin{aligned} \left(\frac{1}{R}\right)^2 [V_3(h_3(h_1, e^\star); z, \mathbf{w} \mid C) - V_3(h_3; z, \mathbf{w} \mid H)] \geq \\ \left(1 + \frac{1}{R}\right) e^\star + V_1(h_1; z, \mathbf{w} \mid H) - V_3(h_3; z, \mathbf{w} \mid H), \end{aligned} \tag{1.5}$$

where $e^\star$ indicates the optimal level of college quality. In eq. 1.5, on the left-hand side are the gains of college and on the right-hand side are the costs of college —

that is, total expenses on college quality and forgone earnings. By substituting the functional forms for the value function and earnings:

$$\left(\frac{1}{R}\right)^2 w_3 \left\{a_3 \left(h_3^C(h_1, e^\star) \ - h_3^H(h_1, i_1, i_2)\right) + \left(b_3^C z^{\frac{1}{1-\beta_C}} - b_3^H z^{\frac{1}{1-\beta_H}}\right)\right\} \geq \left(1 + \frac{1}{R}\right) e^\star + w_1 h_1 (1 - i_1) + \frac{w_2}{R} h_2^H (1 - i_2),$$

where, for ease of notation, the time subscript $\hat{\tau}$ is omitted and I focus on the case of no full-time accumulation on the job — that is, $\underline{j} = 1$ for the no-college path and $\underline{j} = 3$ for the college path. Starting from the latter of the three trade-offs, higher price growth over the lifecycle implies higher returns to human capital investment. When the elasticity of human capital investment on the job is higher for the college path than it is for the no-college path, the returns to college increase as price growth increases (notice the term $b_3^C z^{\frac{1}{1-\beta_C}} - b_3^H z^{\frac{1}{1-\beta_H}}$).[5] On the second trade-off, a higher rental price per unit of human capital at high school graduation (henceforth "price level") increases the net return to college quality, where else it leaves the net return to accumulating human capital on the job unchanged. The cost and benefit of human capital accumulation on the job both increase proportionally with the price level. However, only the benefit of college quality increases with the price level (compare the pair $1/R^2 w_3 a_3 h_3^H$ and $w_1 h_1 i_1 + 1/R w_2 h_2^H i_2$ to the pair $1/R^2 w_3 a_3 h_3^C$ and $\left(1 + \frac{1}{R}\right) e^\star$). Lastly, on the first trade-off, the opportunity cost of accumulating human capital in college relative to accumulating human capital on the job decreases with higher price growth. The commitment to four-year full-time investment in human capital after

[5]This mechanism is related to the reverse causality mechanism from anticipated TFP growth to individual educational attainment in Bils and Klenow (2000).

high school graduation associated with college becomes relatively less burdensome as price growth increases.

Who goes to college? Individuals with high innate ability and individuals with low initial human capital. Individuals with high innate ability are more productive learners, both in college and on the job. On the other hand, because human capital is not productive during college, individuals with low initial human capital have a small opportunity cost of spending four years in college in terms of small forgone earnings. Notice that the importance of the margin associated with initial human capital in the college decision depends on the lifetime price sequence. As the price level increases and its growth over the lifecycle decreases, initial human capital becomes less and less important in the college decision and the college decision is ruled more and more by an individual's innate ability.

The fraction of cohort τ acquiring a college education is determined from the cumulative distribution of initial endowments $\Gamma_\tau(z, h_1)$:

$$\int_{(z,h_1)\in\mathcal{B}} \mathbf{1}(h_1, z, \mathbf{w}_\tau)\; d\Gamma_\tau(z, h_1).$$

1.3 Calibration

The quantitative strategy consists of setting the model in line with the path of unconditional earnings for the 1920-1970 cohorts and then exploring the model implications for education-specific earnings and college attainment for those cohorts. I use two main data sources: the Integrated Public Use Micro Data Series for the United States (IPUMS-USA by Ruggles, Alexander, Genadek, Goeken, Schroede, and Sobek, 2010) and the 1979 National Longitudinal Survey of the Youth (NLSY79 by Bureau of Labor Statistics, 2002). IPUMS-USA provides quantitative information on long-time changes in earnings; the NLSY79 provides a constant panel that follows a limited number of individuals over time. Parameters that are common to all cohorts (deep parameters) are calibrated to NLSY79 data for the early-1960s cohorts. Cohort-specific parameters are calibrated to IPUMS-USA data for the 1920-1970 cohorts. I focus on a sample of employed white males between the ages of 19 and 58 who have achieved either a high school diploma or a four-year college degree. Since earnings statistics in the data are computed for employed people only, earnings statistics in the model ignore agents with full-time post-schooling investment. The IPUMS-USA data is not a fixed panel, and therefore I compute cohort data by constructing synthetic cohorts.[6]

1.3.1 Deep parameters

I assume parameter values for which the literature provides evidence. The parameters that I calibrate without computing the model are reported in Table 1.1 together with the assigned values. I set the gross interest rate R to 1.04 (annual rate). Estimates of the elasticity of human capital investment on the job in the literature typically vary from 0.5 to almost 0.95 (see Browning, Hansen, and Heckman, 1999). My specification of the on-the-job accumulation function is a particular case

[6]See Appendix A.1 for full descriptions of each data set and details on sample selection.

Table 1.1: Calibration. Deep parameters: parameters chosen without solving the model.

Parameter	Symbol	Value
Model period		2 years
Gross interest rate	R	1.086
OTJ accumulation: college	β_C	0.871
OTJ accumulation: high-school	β_H	0.832
OTJ accumulation: depreciation rate	$1-\delta$	0

of Heckman, Lochner, and Taber (1998).[7] These authors provide estimates of the elasticity of on-the-job human capital investment at two education levels: high school and four-year college or more. I set $\beta_H = 0.832$ and $\beta_C = 0.871$. I set the depreciation rate, $\delta - 1$, to zero to be consistent with Heckman, Lochner, and Taber (1998). Rupert and Zanella (2012) show that the declining portion of the earnings profile is mainly a result of a decreased labor supply rather than decreased hourly wage.

I calibrate the distribution of initial endowments, the in-college human capital accumulation function and the rental price in year 1980 to the age variation of unconditional earnings moments, college expenses, college attainment and college premium for the 1961 to 1964 cohorts. I assume that the distribution of initial endowments, Γ_τ,

[7]The human capital accumulation function in Heckman, Lochner, and Taber (1998) is $zi^{\eta_S} h^{\beta_S}$ for $S \in \{C, H\}$. They work with four ability types and two education levels (high school and 4 years of college or more) and estimate the human capital accumulation function with NLSY79 data on white-male earnings for the period 1979-1993.

is jointly log-normal.[8] This class of distributions is characterized by 5 parameters, $\{\mu_{\log(z)}, \mu_{\log(h_1)}, \sigma_{\log(z)}, \sigma_{\log(h_1)}, \rho\}$. Thus, the list of parameters that are calibrated within the model are[9]

$$\Lambda = \{\mu_{\log(z)}, \mu_{\log(h_1)}, \sigma_{\log(z)}, \sigma_{\log(h_1)}, \rho, \eta, w_{1980}\}.$$

I calibrate these parameters to the following statistics for the 1961-1964 cohorts:

1. Age variation of unconditional earnings moments: mean, coefficient of variation, and skewness of the distribution of unconditional earnings at six points over the life-cycle, $j \in \mathcal{J} = \{23-26, 27-30, 31-34, 35-38, 39-42, 43-45\}$ (Source: NLSY79.)

2. College premium for the 23- to 26-year-old: ratio of median earnings of four-year college graduates to median earnings of high school graduates (Source: IPUMS-USA.)

3. Education composition: fraction of high school graduates with a four-year college degree (Source: IPUMS-USA.)

4. College expenses: ratio of average tuition and fees and room and board for the period 1982 to 1988 to average earnings of 23- to 26-year-old four-year college graduates, (Source: IPUMS-USA and The College Board, 2007.)

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[8] Huggett, Ventura, and Yaron (2006) show that, in terms of replicating life-cycle earnings dynamics, the gains of going from a parametric to a non-parametric approach in this set-up are not substantial.

[9] At this stage only the distribution of initial endowments for the 1961 to 1964 cohorts is calibrated. The marginal distribution of initial human capital for the 1920 to 1970 cohorts in calibrated in the next section with the cohort-specific parameters.

There are a total of 20 targets.[10] Formally, the calibration strategy consists of minimizing the following equation:

$$\min_{\Lambda} \sum_{u=1}^{20} \left(\frac{x_u(\Lambda) - \tilde{x_u}}{\tilde{x_u}} \right)^2 .$$

For a given Λ, I compute the model moments, $x_u(\Lambda)$, that correspond to the targets described above, $\tilde{x_u}$.

Even though the parameter values are chosen simultaneously to match the data targets, each parameter has a first-order effect on some targets. The elasticity of substitution of the in-college human capital accumulation function is disciplined by data on college expenses. Data on college expenses combine (i) Trends in College Pricing (The College Board, 2007) data on average tuition and fees and room and board for private and public colleges in the United States and, (ii) Goldin and Katz (2008)'s data on the fraction of college students enrolled in public and private universities. The price in year 1980 is important for matching the education composition. The moments in targets 1 and 2 discipline the distribution of initial endowments. The NLSY79 dataset has a fixed-panel structure and allows me to infer endowments from lifecycle earnings. The argument for identification behind this exercise follows Huggett, Ventura, and Yaron (2006).

The only source of earnings inequality in my model is due to endowments. An individual's type (z, h_1) implies a profile of human capital accumulation over the

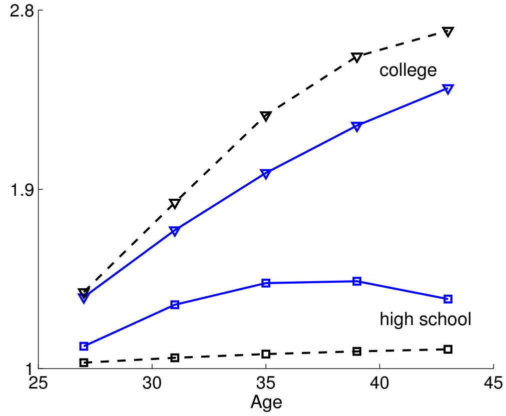
[10]Earnings in target 1 are normalized to mean earnings at ages 23-26. Because of the choice of units for the price, it is unreasonable to expect the model to match the level of earnings.

Table 1.2: Calibration. Deep parameters: parameters computed by solving the model.

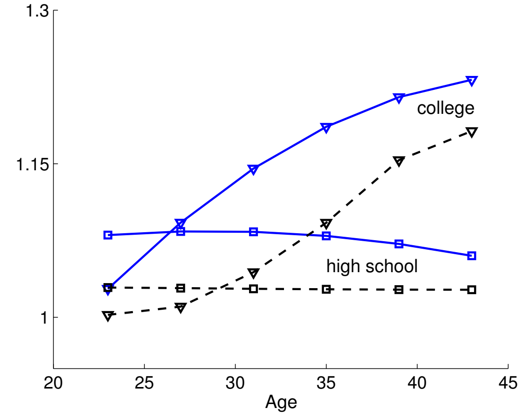
Parameter	$\mu_{\log(z)}$	$\mu_{\log(h_1)}$	$\sigma_{\log(z)}$	$\sigma_{\log(h_1)}$	ρ	η	w_{1980}
Value	-1.746	4.472	0.253	0.334	0.758	0.506	1.506

lifecycle and therefore a profile of earnings over the lifecycle. Within a cohort, a distribution of types maps into a distribution of earnings over the lifecycle. Thus, initial endowments can be identified through the evolution of the distribution of earnings over the lifecycle. The key assumption is that systematic differences in growth rates are the major driving force behind earnings dynamics over the lifecycle. This assumption is supported by empirical studies that estimate earnings processes from micro data sets (see, for example Guvenen, 2009). I include the college premium as an additional source of discipline. The college premium contains information on the college-selection mechanism in terms of the (z, h_1) types that choose college. Details on the identification of each parameter of the distribution of initial endowments in the context of my model are outlined in Appendix A.3.

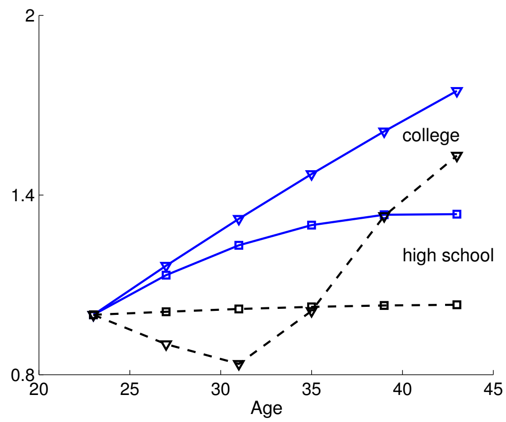
The model is solved numerically. I simulate the earnings and schooling paths of 100,000 individuals in each of the 1961-1964 cohorts. The parameter values are reported in Table 1.2, while the model's performance on targets is reported in Table A.1 and shown in Figure A.3. Overall, the model is successful in matching the data. The mean age-earnings profile is reproduced in its growth and concavity. Concavity



(a) Mean



(b) Median/mean



(c) Coefficient of variation

Figure 1.3: Results. Life-cycle earnings dynamics for high school graduates and for college graduates, 1961-1964 cohorts. Data (solid lines) vs. Model (dashed lines).

Source: NLSY79 and the author.

is entirely delivered by human capital investment, which is more profitable at younger ages. The lifecycle pattern of the coefficient of variation is well reproduced; however, the level is not. In the model, the coefficient of variation at ages 23-26 is two-thirds of that in the data. Small dispersion in initial human capital and small correlation between innate ability and initial human capital are set to match the college premium. Given the coefficient of variation for initial human capital and the correlation between initial human capital and innate ability, the coefficient of variation of innate ability is chosen to deliver both the level and the lifetime growth of earnings dispersion.[11] The inverse skewness is very well targeted in the level but the life-cycle growth is overestimated. Right skewness follows because the incentives for human capital investment increase more than proportionally with an individual's innate ability (see eq. A.2 and recall that $\beta < 1$).

I assess the merit of the model based on moments that are not targets of the calibration exercise. I pick those moments to my evaluation of the model as a model of lifecycle earnings in a context of a college choice. Figure 1.3 displays the model performance on the age variation of *education-specific* earnings moments for the 1961-1964 cohorts. The first panel shows the mean age-earnings profile for high school graduates and that for college graduates. First, notice that in the data the mean age-earnings profile for high school graduates is essentially flat, while that for college graduates has a positive slope. The model generates this fact as a result of positive association between college and innate ability. The average innate ability of college graduates is 0.2296, while that for high school graduates is 0.1526. The model predicts that, absent heterogeneity in human capital, agents with high innate ability have steeper

[11] Huggett, Ventura, and Yaron (2011) extend the Ben-Porath framework of human capital accumulation to consider idiosyncratic shocks to human capital. They find that 38.5 percent of the variance of lifetime earnings is due to idiosyncratic shocks to human capital. The remaining part of the variance is accounted for by initial endowments.

profiles of human capital accumulation than agents with low innate ability. However, the model overpredicts the difference between earnings growth for college graduates and that for high school graduates. Because initial endowments are pinned down and the education composition is matched, earnings growth conditional on education is pinned down.[12] The model is consistent with a faster rise in the dispersion of earnings over the lifecycle of college graduates relative to that of high school graduates. This is because college graduates have larger mean and larger dispersion of innate ability than high school graduates and the incentives to human capital investment increase more than proportionally with an individual's innate ability. Finally, the model generates lifecycle patterns of the asymmetry in the distribution of earnings (earnings skewness) close to the data. The positive association of innate ability with college is the reason for the following: (i) a higher average lifecycle skewness of college graduate earnings relative to that of high school graduate earnings and (ii) a higher rise in the skewness of college graduate earnings over the lifecycle relative to that of high school graduate earnings.

1.3.2 Cohort-specific parameters

Cohorts exogenously differ by two dimensions: they face different lifecycle price sequences (a time effect) and they face different distributions of initial human capital

[12]In the next section, I consider an alternative version of my model featuring education-specific prices of human capital, i.e., a price for high school human capital and a price for college human capital. This setup gives me the necessary degrees of freedom to match earnings growth for high school graduates and college graduates simultaneously.

across individuals (a cohort effect).[13] To set the model in line with the cohorts born between 1920 and 1970, I calibrate time and cohort effects to replicate the evolution of unconditional earnings, first and second moments, over the period of reference.

Figure 1.4 shows growth patterns of three earnings moments (solid lines): 1) average earnings for the 1940-2008 period, 2) coefficient of variation of earnings for the 1940-2008 period, and 3) average earnings late in the lifecycle for the 1884 to 1958 cohorts. Each trend can be summarized quite well by two distinct changes in growth rates: 1) pre-1970s and post-1970s growth for the time-series data and 2) pre-1933 and post-1933 growth for the cross-cohort data. I structure the paths of the time effect and the cohort effect in the model as follows. Trend breaks occur 1) in price growth in year 1970, 2) in the growth of the mean of the distribution of initial human capital for the 1933 cohort, and 3) in the growth of the standard deviation of the distribution of initial human capital for the 1933 cohort. More formally, the paths are as follows:

- for price growth: for $x = w$,

$$x_t = \begin{cases} x_{t-1}[1 + g_{x,1}] & t \leq 1969 \\ x_{t-1}[1 + 0.5(g_{x,1} + g_{x,2})] & t \in [1970, 1979] \\ x_{t-1}[1 + g_{x,2}] & t \geq 1980, \end{cases}$$

[13]The distribution of innate ability is assumed to stay constant across cohorts. This is possibly a restrictive assumption for the cohorts born between 1920 and 1940 considering the substantial expansion in high school education that happened during this period. Exogenous changes in the distribution of innate ability of high school graduates cannot be separately identified from those in the distribution of human capital of high school graduates in this framework due to data restrictions.

- for the distribution of initial human capital: for $x = \{\mu_{h_1}, \sigma_{h_1}\}$,

$$x_\tau = \begin{cases} x_{\tau-1}[1 + g_{x,1}] & \tau \leq 1933 \\ x_{\tau-1}[1 + g_{x,2}] & \tau \geq 1934, \end{cases}$$

where τ indicates the year of birth of the cohort.

I calibrate the path of the price, the path of the mean of initial human capital, and the path of the standard deviation of initial human capital to the earnings moments in Figure 1.4 (solid lines). In particular, the calibration targets, (†), are

1. growth of average earnings between the ages 39-45 and 49-55 for the 1884-1920 cohorts and the 1924-1958 cohorts (source: IPUMS-USA, Figure 1.4a),

2. growth of average earnings of white males between the ages of 35-46 for the 1940-1970 period and the 1980-2008 period (source: IPUMS-USA, Figure 1.4b), and

3. growth of the coefficient of variation of earnings of white males between the ages of 35-46 for the 1940-1970 period and the 1980-2008 period (source: IPUMS-USA, Figure 1.4c).

There is a total of 6 targets. Even though all the trends are pinned down simultaneously, each pair of targets disciplines primarily the pattern of one variable. Earnings growth toward the end of the lifecycle informs on price growth. The focus on a period late in the lifecycle is based on the model implication that the fraction of time attributed to investment in human capital on-the-job decreases with age. When investment in human capital is close to insignificant, the growth rate of the price is close to the growth rate of earnings (see Appendix A.3 for details).[14] Cross-sectional earnings growth informs on the evolution of the distribution of initial human capital. Given a sequence of prices and a sequence of distributions of initial human capital, the model produces a sequence of earnings. Thus, I choose the sequence of distributions of initial human capital (i.e., a sequence of means and standard deviations) to match changes in the first and second moments of earnings data for 35- to 46-year-olds. Formally, the calibration strategy consists of solving a system of 6 equations in 6 unknowns. For a given $\Gamma = \{g_{1,x}, g_{2,x}\}_{x=\{w,\mu_{h_1},\sigma_{h_1}\}}$, I compute the model moments, $X(\Gamma)$, that correspond to the targets described above. I then solve for the zero of the function $F(\Gamma)$ defined by

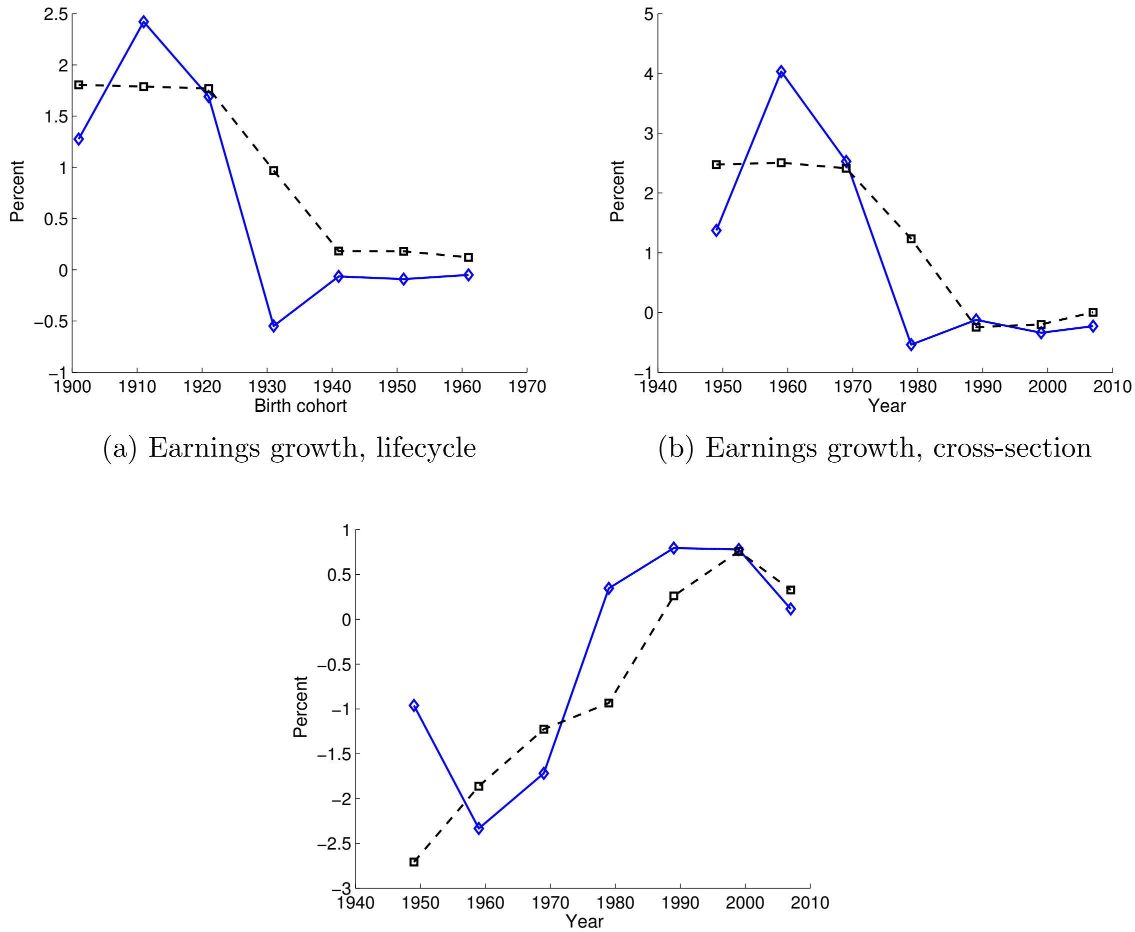
$$F(\Gamma) = \tilde{X} - X(\Gamma),$$

where $\tilde{X}$ are the targets described above.

I simulate the earnings and schooling path for 100,000 individuals in the 1994-1970 cohorts. Figure 1.4 shows the performance of the model on targeted moments. The calibrated g_w pair is $\{3.36\%, 0.29\%\}$, calculated as biannual rates. The calibration implies a slowdown in price growth starting in the 1970s.[15] The calibrated

[14]This observation is the foundation of the flat spot method used in Heckman, Lochner, and Taber (1998) and more recently in Bowlus and Robinson (2012).

[15]Bowlus and Robinson (2012) find similar patterns, in both direction and magnitude, for the paths of the rates of growth of the prices of human capital across various levels of education. Possible reasons for the slowdown in price growth include a slowdown in productivity growth, which influences the demand of human capital. Also, an increase in



(a) Earnings growth, lifecycle

(b) Earnings growth, cross-section

(c) Change in the CV of earnings

Figure 1.4: Model fit. Earnings: lifecycle growth, cross-sectional growth, and growth of the coefficient of variation. Data (solid lines) vs. Model (dashed lines).

Source: IPUMS-USA.

changes in the mean and standard deviation of the distribution of initial human capital are $g_{\mu_{h_1}} = \{0.5\%, -0.1\%\}$ and $g_{\sigma_{h_1}} = \{-6\%, 2\%\}$. What is the significance of

the supply of human capital following the increase in female labor force participation, the increase in average years of schooling of females and minorities, and the increase in cohorts size (the baby boom) can all have contributed to the slowdown in price growth.

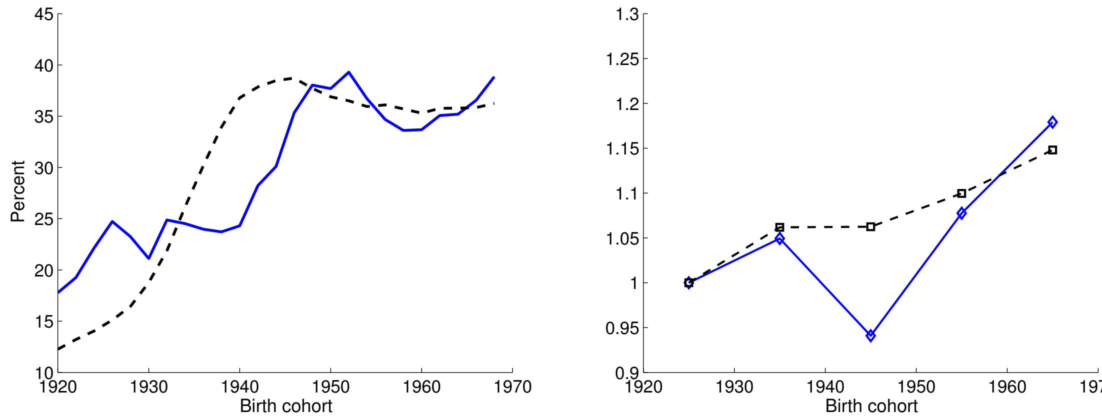
a change in the distribution of initial human capital over cohorts? An individual's human capital is the amount of knowledge he possesses. Hence, the distribution of initial human capital is a measure of the "quality" of the high school graduates. The calibration implies an increase in the average "quality" of high school graduates followed by a decline.[16] This pattern is consistent with anecdotal evidence presented by Taubman and Wales (1972) and Bishop (1989) on cognitive skills of high school graduates. Taubman and Wales (1972) observe that test scores of high school graduates decline starting with the late-1920s cohorts, after increasing from the beginning of the century. Bishop (1989) reports a decrease in the average scores of high school graduates on normed tests, such as the ITED and ITBS, starting with the late-1940s cohorts and following 50 years of uninterrupted improvement. Lastly, the calibration implies that the dispersion of initial human capital increases starting with the early-1930s cohorts. Even though the calibration is set to replicate average changes in earnings dispersion for the pre-1970s and post-1970s periods, the model matches the pattern of earnings dispersion for the various years within each period quite well.

[16]An evident reason for the decline in the quality of successive cohorts of high school graduates is the expansion in high school education that happened between the 1920 and the 1940 cohorts. Among those born in 1920, the fraction of white males with at least a high school diploma was 57 percent. This fraction was 82 percent for those born in 1940. A positive correlation between schooling and innate ability and/or human capital, as it transpires from evidence on tests scores, implies that large changes in high school attainment can potentially have a significant selection effect on the average innate ability and average human capital associated with high school education. A second potentially relevant force, influencing the quality of more recent cohorts of high school graduates, is the decrease in teachers' quality that came about as the occupational condition of females improved.

1.4 Results

The main results of this chapter are in terms of college attainment and college premium. In this section, I present the model implications for the patterns of college attainment and college premium for the 1920-1970 cohorts and then I investigate the quantitative contribution of changes in the rental price per unit of human capital along with changes in the distribution of initial human capital to those patterns.

College attainment of the 1920-1970 cohorts is shown in Figure 1.5a and summarized in Table 1.3, column “Baseline”. The model generates an increase and subsequent flattening of college attainment. After calibration, the model indicates that 36 percent of the 1961-1964 cohorts earned a college degree, which is close to the data. The fraction of high school graduates in the 1920-1950 cohorts that earned a college degree increases from 12.3 percent to 36.9 percent in the model and from 17.8 percent to 37.7 percent in the data. The positive trend contracts starting with the early-1950s cohorts. From the 1950 cohort to the 1970 cohort, college attainment decreases from 36.9 percent to 36.6 percent in the model, but increases from 37.7 percent to 39.7 percent in the data. Overall, for the 1920-1950 cohorts, the fraction of college graduates increases cohort-to-cohort on average 8.22 percentage points in the model and 5.94 percentage points in the data. In contrast, that for the 1950-1970 cohorts decreases 0.3 percentage points in the model but increases 0.3 points in the data. The flat college attainment the model generates for the post-1950 cohorts is a critical result of the this chapter: previous studies are not consistent with this aspect of college attainment. The timing of the slowdown is not well reproduced: in



(a) College attainment (b) College premium

Figure 1.5: Results. College attainment and the college premium in the United States. Data (solid lines) vs. Model (dashed lines).

Source: IPUMS-USA.

the model it starts with the early-1940s cohorts but in the data it starts with the late-1940s cohorts. A similar result appears for the rise in college attainment. The greatest increase in college attainment occurs for the 1930s cohorts in the model but for the 1940s cohorts in the data. In the next section, I consider the role of individuals' expectations on the timing of the slowdown in college attainment.

College attainment is mostly driven by the path of the rental price per unit of human capital (the time effect). The evolution of the distribution of initial human capital across cohorts (the cohort effect) plays only a minor role in the slowdown in college attainment. This is because the first-order determinant of the decision of attending college is innate ability rather than initial human capital. Figure 1.6 shows a decomposition exercise of the time and cohort effects on the slowdown in college

Table 1.3: Results. College attainment in the United States.

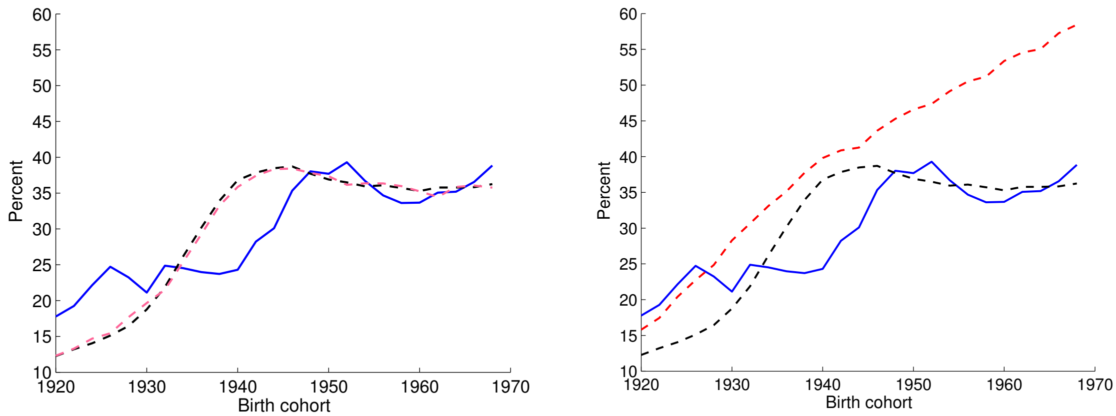
Birth cohort	Data	Baseline	Model H-C
1920s	21%	14%	21%
1950s	36%	36%	36%
1960s	36%	36%	40%

Source: IPUMS-USA and author.

attainment. In a first experiment ("Time effect only"), I keep the initial human capital distribution of each cohort the same, so that the only difference between cohorts is the lifecycle price sequence. The resulting pattern of college attainment is almost the same as that in the baseline exercise. In a second experiment ("Cohort effect only"), I keep price growth constant to its average between pre-1970s growth and post-1970s growth, so that the only differences between cohorts are the initial human capital distribution and the price at age 1. College attainment does not slow down in this second experiment.

Figure 1.5b plots the college premium for the 1920 to 1970 cohorts.[17] The

[17] The college premium is defined as median college-graduate earnings relative to high school-graduate earnings over ages 33 to 38. Several authors have documented that the fall and rise in the college premium in the United States in the twentieth century was largely due to changes among young workers, whereas the college premium among old workers wasn't very much muted (Murphy and Welch, 1992). In the model, starting in the 1990s, the college premium among older workers rises far less than it does among young workers. In the data, the college premium for old workers starts increasing earlier, in the 1980s.



(a) Time effect only

(b) Cohort effect only

Figure 1.6: Decomposition exercise. College attainment: time effect and cohort effect. Data (solid lines) vs. Model (dashed lines) vs. Model time effect only (dashed, pink line) vs. Model cohort effect only (dashed, red line).

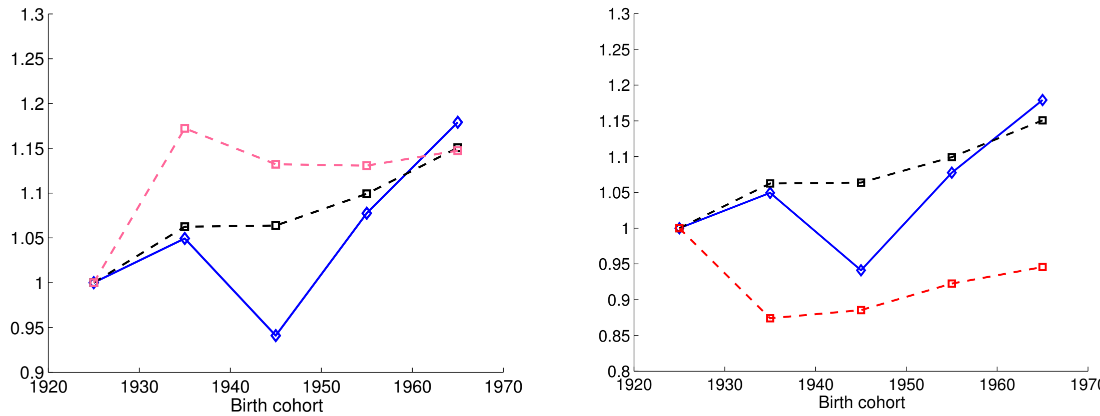
Source: IPUMS-USA.

model generates 79% of the increase in the college premium between the 1920 cohort and the 1970 cohort: the college premium increases 15 percent in the model and 19 percent in the data. The cohort-over-cohort pattern of the college premium in the model follows the data quite nicely. Both in the data and in the model, the college premium persistently grows across successive cohorts born between 1920 and 1970, with the exception of the 1930s cohorts. During the 1930s cohorts, the college premium does not change in the model, and it decreases by 10 percent in the data. Lastly, notice that the model generates an increasing college premium for the cohorts of the slowdown in college attainment, as shown in the data.

Because younger workers have a larger planning horizon, they respond to a change in prices much more strongly than older workers in the model.

The increase in the college premium is generated by a combination of both exogenous forces in the model: the time effect and the cohort effect. Figure 1.7 shows a decomposition exercise of these two effects on the pattern of the college premium. In a first experiment ("Time effect only"), I keep the initial human capital distribution of each cohort the same, so that the only difference between cohorts is the lifecycle price sequence. The resulting college premium increases almost exclusively during the 1920s and 1930s cohorts. The college premium rises 18 percent between the 1920 cohort and the 1950 cohorts, decreases 2 percent during the 1950s cohorts, and remains flat thereafter. The mean of initial human capital increases from the 1920 to the mid-1930s cohorts, lessening the increase in the college premium that would have otherwise resulted from the time effect. Symmetrically, the mean of initial human capital decreases after the mid-1930s cohorts, pushing up the college premium.

There is an interesting interpretation of a change in the mean of initial human capital. The effect of such a change on the college premium in my framework is equivalent to the effect of a change in the price of college human capital relative to high school human capital on the college premium in an extended framework that features education-specific prices of human capital. Consider a simple version of my model, with no heterogeneity and no human capital accumulation on the job, that is extended to include education-specific human capital prices. Earnings of full-time workers at various education levels are $E_S = h_S \times w_S$, where h_S is the quantity of human capital at education level S, and w_S is the price per unit of human capital at education level S, for $S \in \{C, H\}$. As in the baseline model, $h_C = h_H^{\eta} e^{1-\eta}$. The



(a) Time effect only

(b) Cohort effect only

Figure 1.7: Decomposition exercise. College premium: time effect and cohort effect. Data (solid lines) vs. Model (dashed lines) vs. Model time effect only (dashed, pink line) vs. Model cohort effect only (dashed, red line).

Source: IPUMS-USA.

college premium at each point in time equals the ratio of college-graduate earnings relative to high school-graduate earnings: $\frac{w_C}{w_H} \times h_H^{\eta-1} e^{1-\eta}$. For a given college quality e, a decrease in high school human capital h_H, and an increase in the price ratio $\frac{w_C}{w_H}$, both increase the college premium. Because both human capital and prices are unobservable, the two effects are not distinguishable from one another.

The time effect influences the pattern of the college premium along with the cohort effect. Figure 1.7, "Cohort effect only", presents the implied pattern of the college premium when price growth is constant and set to its average between pre-1970s growth and post-1970s growth, so that the only differences between cohorts are the initial human capital distribution and the price at age 1. The resulting college premium decreases between the 1920 cohort and the 1970 cohort. The college premium is the ratio of the median human capital supplied to market work by college graduates relative to that supplied by high school graduates. Price growth has a composition effect on the average human capital of high school graduates and on that of college graduates. Pre-1970s price growth fuels the increase in college attainment, which has a significant selection effect on the average innate ability and average human capital associated with a schooling level. This selection effect has a prominent role in the increase in the college premium during the cohorts 1920s to 1940s.[18] The *slowdown* in price growth after the 1970s, instead, reinforces the increase in the college premium by strengthening the association between college and innate ability.

Figure 1.8 shows the distribution of initial endowments, innate ability, and initial human capital, conditional on the education level for two groups of cohorts, 1931-1934 cohorts and 1961-1964 cohorts. While the less-recent group includes college graduates with lower innate ability than that of high school graduates, the more recent group includes perfect positive sorting by innate ability across schooling levels.[19] The initial human capital margin does not matter for the college decision of the more

[18]Previous studies highlight the importance of selection on the college premium during times of substantial changes in college attainment; see, for example, Laitner (2000) and Hendricks and Schoellman (2009).

[19]There is no direct way to measure such a change in college selection over time directly in the data. However, two pieces of anecdotal evidence can be used. First, Taubman and Wales (1972) report for cohorts born between 1907 and 1950 the average percentile score on IQ tests for those who continue on to college and for those who do not. The trend for the former is positive, while the trend for the latter is negative. Second, Bowen and Turner (1999) document sorting across majors by SAT math and verbal score, and Wiswall and Gemici (2010) document an increase in the fraction of students pursuing majors associated with higher SAT math and verbal scores starting with the late-1940s cohorts.

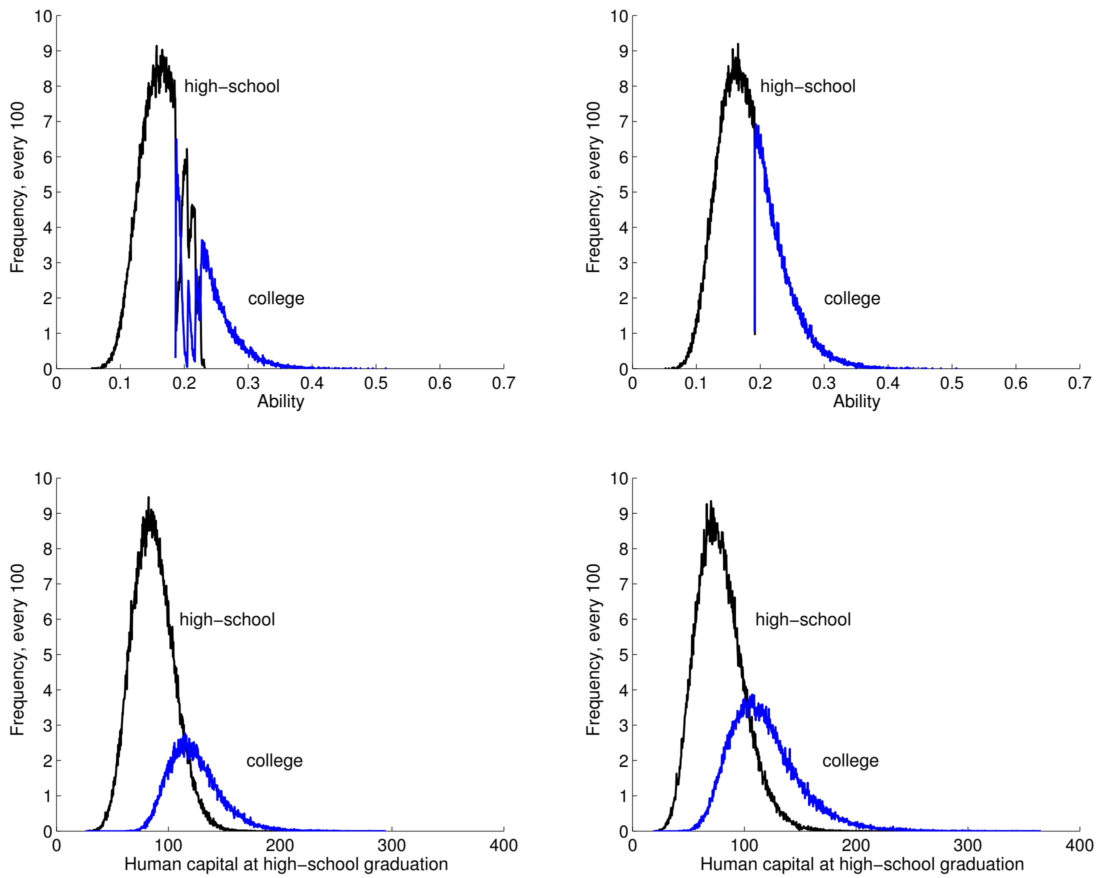


Figure 1.8: Results. Marginal distributions of initial endowments, by educational attainment. The first column refers to cohorts born between 1931 and 1934. The second column refers to cohorts born between 1961 and 1964.

recent cohorts of high school graduates, while it matters for the less-recent cohorts along with the innate ability margin. The reason is that the two sets of cohorts face differently shaped lifecycle sequences of the price. The 1930s cohorts face low price of human capital at high school graduation and high price growth over the lifecycle. On the other hand, the 1960s cohorts face high price of human capital at high school graduation and low price growth over the lifecycle. Overall, the path of the rental price per unit of human capital has both an intensive- and an extensive-margin effect on the average innate ability associated with college and so on the college premium.

1.4.1 Discussion

I consider two alternative exercises. In the first exercise, I extend the model to include separate prices for human capital supplied by college graduates and that supplied by high school graduates. In the second exercise, I consider the alternative of individuals having naive expectations on the path of the rental price per unit of human capital.

Education-specific prices. Previous studies on the evolution of college attainment in the United States consider the role of a changing college premium via college-biased technical change (see Acemoglu, 2002, for a review and Restuccia and Vandenbroucke, forthcoming, for a quantitative analysis). Table 1.4 reports education-specific patterns of earnings growth generated by the baseline model (rows "Baseline") and the data (rows "Data"), separated by lifecycle and time series. The model follows the general trend in the data, with the exception of the time-series for earnings growth of college graduates. However, there is room for improvement. The model over-predicts the flattening of lifecycle earnings growth for college graduates and under-predicts the one for high school graduates. The opposite occurs for the time-series of earnings growth. I extend the model to include separate prices for human capital supplied by college and high school graduates. I calibrate the growth rates of the education-specific prices to education-specific earnings growth, corresponding

Table 1.4: Earnings growth by education groups.

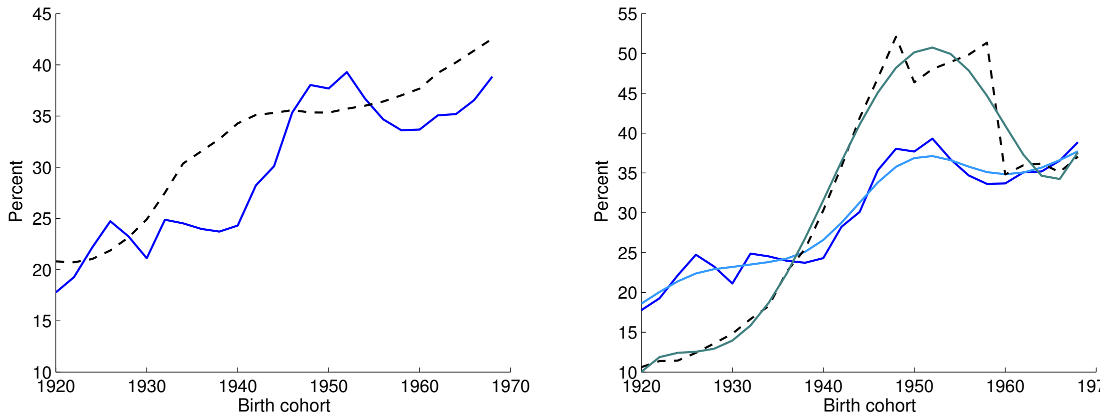
		Grwt 1	Grwt 2	Flattening
High School, Time-series	Data	0.0259	-0.0062	-0.0321
	Baseline	0.0237	-0.0011	-0.0248
	Model H-C	0.0407	0.0009	-0.0398
High School, Lifecycle	Data	0.0182	-0.0037	-0.0219
	Baseline	0.0178	0.0036	-0.0142
	Model H-C	0.017	0.0037	-0.0134
College, Time-series	Data	0.034	-0.0016	-0.0320
	Baseline	-0.0017	-0.0057	-0.0040
	Model H-C	0.0254	-0.0014	-0.0268
College, Lifecycle	Data	0.0168	-0.0003	-0.0172
	Baseline	0.0247	0.0051	-0.0207
	Model H-C	0.0185	0.0057	-0.0129

Source: IPUMS-USA and author.

Note: The column *Grwt 1* indicates the average growth rate for the pre-1970s period for time-series data and for the pre-1933 cohorts for lifecycle data. The column *Grwt 2* indicates the average growth rate for the post-1970s period for time-series data and for the for the post-1933 cohorts for lifecycle data. The column *Flattening* is the difference between the column *Grwth 2* and the column *Grwt 1*.

to the targets in (†) for high school graduates and college graduates. The targeted education-specific growth rates are reported in Table 1.4, row "Model H-C". The calibrated growth rates of the education-specific prices are $g_w^H = \{3.2\%, 0.3\%\}$ and $g_w^C = \{2.7\%, 0.5\%\}$, where g_w^H is the growth rate of the price of high school human capital and g_w^C is the growth rate of the price of college human capital. Notice that the ratio $\frac{w^C}{w^H}$ decreases up to the 1970s and increases thereafter. This pattern is consistent with the findings of the literature studying skill-biased technological change (see Acemoglu, 2002). The resulting pattern of college attainment for the 1920 to 1970 cohorts is shown in Figure 1.9a and summarized in Table 1.3, column "Model H-C". The model generates the increase in college attainment in the data between the 1920 and the 1950 cohorts and 30 percent of the slowdown in college attainment for the cohorts born after 1950.

Timing. In the baseline exercise, a slowdown in price growth that starts in the 1970s generates the flattening of college attainment. The flattening starts earlier in the model than in the data. How would the pattern of college attainment change if the slowdown in price growth was not foreseen by individuals? I consider an alternative to my baseline where I assume that individuals expect the price growth observed at market entrance to persist during their lifetime. I do not recalibrate the two growth rates of the price since they are irrelevant for the *timing* of the slowdown. Figure 1.9b shows the pattern of college attainment the model generates. Notice that the timing of the rise and of the flattening of college attainment in the model aligns with the data. This result supports the argument that expectations of future price growth may



(a) Model H-C

(b) Timing

Figure 1.9: Results. College attainment for alternative exercises. Data (solid lines) vs. Model (dashed lines). The light-colored solid lines are HP filtered observations.

Source: IPUMS-USA.

play a major role in choosing to attend college. For example, Cunha and Heckman (2007) compare the choice to attend college to ex post earnings and conclude that students foresaw only some of the recent rise in the college earnings premium.

1.5 Conclusion

In this chapter I assess the quantitative importance of changes in the growth rate of the price per unit of human capital in generating patterns of US college attainment for white males born between 1920 and 1970. I argue that these changes are the main cause of changes in college attainment. In particular, a decrease in price growth causes college attainment to remain flat for the cohorts born after 1950.

Since earnings reflect both the quantity and the price of human capital, the price of human capital is not observable. I write a model of human capital accumulation in college and on the job to identify the rental price per unit of human capital and to quantify its importance for the path of college attainment. I calibrate the model to major patterns of earnings growth and earnings inequality, both across time and over the lifecycle, for the 1920-1970 cohorts. The calibration implies a decrease in price growth starting in the 1970s. As price growth decreases, the returns to human capital investment decrease and the opportunity cost of human capital accumulation in college increases relative to that on the job. Hence, college attainment flattens.

One short coming of the model is that it generates a slowdown in college attainment that starts earlier than in the data. In an alternative exercise, I show that individual expectations influence the timing of the slowdown in college attainment. When I assume individuals expect price growth observed at market entrance to persist during their lifetime, the model replicates the timing of the slowdown in college attainment as shown in the data. However, I only scratch the surface of the potential role of individuals' expectations on the timing of the slowdown in college attainment.

The slowdown in college attainment is part of a wider phenomenon that involves all levels of education (see Appendix A.1). For example, Heckman and LaFontaine (2010) report a flattening of high school graduation rates. The mechanism I consider produces symmetric implications across schooling groups and, therefore, is qualitatively consistent with a general flattening of educational attainment. It would be interesting to extend the quantitative analysis in this chapter of my thesis to include levels of education beyond a four-year college degree.

CHAPTER 2
OCCUPATIONAL COMPLEXITY, EXPERIENCE, AND THE GENDER WAGE GAP

2.1 Introduction

On average, females earn less than males. While there is no dispute on the existence of a gap in wages between males and females, there is one as to what drives these differences. In this chapter, I use data on the tasks content of occupations to study the roles of skills and work experience in determining the gender wage gap. The task content of an occupation reveals two types of information about the individual employed in the occupation: the lower bound of his/her level of skill and the value of his/her skill. The intuition is straightforward. If an individual is employed in an occupation involving tasks of a certain complexity, then he/she needs to possess at least enough skills to perform these tasks at the lowest accepted standard. If an occupation involves simple tasks, there is little value to skill, both endowed and accumulated through work experience, since there is little room for improvement when performing simple tasks.

I use the Occupational Information Network (O*NET) dataset to construct an index of occupational complexity: the ratio of abstract to manual tasks content. I then combine these data with Census data on occupations and wages to document patterns of the gender wage gap across occupations of different complexity, for cohorts born between the years 1915 and 1955. I focus on two patterns in particular. First, the ratio of female to male wages for young individuals is U-shaped across occupations ordered by increasing complexity. The U-shape becomes flatter for successive cohorts of young individuals. Second, over the lifecycle, the ratio of female to male wages decreases faster for more complex occupations. This decrease becomes weaker for successive cohorts over the lifecycle.[1] In addition, the data reveals that females, especially those of earlier cohorts, systematically choose occupations with low wages relative to males.

The purpose of this chapter is to investigate the determinants of the above mentioned patterns of the gender wage gap by occupational complexity in order to shed light on the driving factors behind the overall gender wage gap. I argue that gender wage gap and occupational choices need to be analyzed jointly and develop a quantitative theory that delivers both as a result of differences in endowed skills and work experience between males and females. A counterfactual experiment reveals that work experience accounts for 69 percent of the lifecycle gender wage gap. Removing differences in work experience between genders results in a larger fraction of females choosing occupations for which the difference in wages between males and females is smaller.

I develop an occupational choice model with overlapping generations of female and male individuals who are heterogeneous in their level of skill. An individual's skill at a point in time depends on his/her exogenous initial level of skill along with his/her work experience. Individuals divide their time between work in the market

[1] Section 2.2 discusses these patterns of the gender wage gap by occupational complexity in more detail.

and work at home. Individuals accumulate skills while working, through learning by doing, and those with higher initial skill accumulate faster. Occupations differ by their level of complexity. Occupations with high complexity have high skill requirements and high marginal products of skill. Occupations produce *occupational goods*, which are aggregated to produce a final market good. Home production uses female time and market goods as inputs. I model technological change in both market and home good production by allowing input shares to change over time. Females are predicted to accumulate less work experience and therefore have flatter skill profiles over the lifecycle than males. This affects the ratio of female to male wages in two ways. First, it implies a flatter wage profile over the lifecycle, which pushes the ratio of female to male wages down. Second, it reduces the benefits of occupations with high complexity and thus increases the ratio of female to male wages. The fraction of females in occupations with high complexity decreases and therefore the average initial skill of females relative to males increases in each occupation.

For each occupation, I measure the minimum skill requirement with the index of the occupational complexity, which I construct from the O*NET dataset. I discipline the technology for learning by doing with the lifecycle profile of male wages and the technology for home production with female labor supply over the lifecycle, for the cohorts born between 1915 and 1925. I infer the distribution of initial skill for males from their relative wages across occupations and that for females from their occupational choices, for the cohorts born between 1915 and 1925. My calibration implies that the distribution of initial skill for females first order stochastically dominates that for males. This is consistent with Rendall (2010) and Yamaguchi (2013). Finally, I calibrate technological changes in the market and home good production to, respectively, the evolution of male occupational choices and that of female labor supply over successive cohorts born between 1915 and 1955.

I find that initial skill and work experience go a long way in explaining the observed patterns in the gender wage gap. Overall, the model generates the ratio of female to male wages for the cohorts born between 1915 and 1925 (the average ratio of female to male wages over the lifecycle is 0.68 both in the model and in the data), and 60 percent of the increase in the ratio of female to male wages for successive cohorts born between 1915 and 1955. More precisely, first, the model generates the U-shaped pattern of the ratio of female to male wages across occupations for young individuals as well as the successive flattening of that U-shape. Second, the model reproduces the lifecycle pattern of the gender wage gap for the cohorts born between 1915 and 1925. For these cohorts, the ratio of female to male wages decreases between age 25 and age 65 of 27 percent on average across occupations, compared to the 25 percent decrease in the data. The decrease is stronger in occupations with high skill requirements. Also, the model reproduces 50 percent of the attenuation of the decrease in the ratio of female to male wages over the lifecycle that happens for successive cohorts born between 1915 and 1955.

The gender wage gap is decided by two margins. The first margin is the gender difference in average skill within each occupation. The second margin is the gender difference in occupational choice. The second margin matters because there are differences in the price of occupational output and in the minimum skill requirement (hereafter "occupational characteristics) across occupations. I find that the first margin explains the majority of the gender wage gap. Blau and Kahn (2000) and Card and DiNardo (2002) draw similar conclusions. Over time, technological change reinforces the narrowing of the wage differential between females and males. In the home good production, it leads to a decline in the share of time, accounting for 80 percent of the increase in the work experience of females born between 1915 and 1955. In the market good production, it increases the price of occupational output requiring high levels of skill and improves the occupational composition of female labor supplied: females move toward occupations for which the difference in wages between genders is smaller.

My model is also broadly consistent with the structure of average wages across occupations. There is a large interest in understanding how much of what an individual earns is due to his/her skills and how much is due to the returns to skills (see for example Bowlus and Robinson, 2012, and Hendricks and Schoellman, 2009). I decompose average wages in each occupation in two components: one that depends on occupational characteristics and one that depends on individuals' skill. I find that occupational characteristics make up for about 60 percent of wages. Also, about 30 percent of the difference in wages between occupations requiring high levels of skill and occupations requiring low levels of skill is due to occupational characteristics.

The papers that are the closest to the analysis in this chapter are Erosa, Fuster, and Restuccia (2010), Rendall (2010), and Hsieh, Hurst, Jones, and Klenow (2013).

Erosa, Fuster, and Restuccia (2010) consider work experience as a determinant of the lifecycle pattern of the gender wage gap. I extend their analysis by exploring how work experience affects wages across occupations with a different scope for learning by doing. Rendall (2010) investigates the role of brain-biased technological change in explaining the narrowing of the gender gap in wages. She considers a single sector model and therefore cannot speak about the non-linearities of the gender wage gap across occupations. Hsieh, Hurst, Jones, and Klenow (2013) explain the evolution of the gender wage gap and gender differences in occupational choice using evolving education and labor market frictions. I explicitly model these frictions by endogenizing work experience through home production and learning by doing across heterogeneous occupations.

The rest of the chapter is organized as follows. I next describe the two main patterns of the gender wage gap by occupational complexity that are the focus of my analysis along with major patterns of occupational choice and labor supply. Section 3 outlines the model and section 4 calibrates it. Section 5 discusses the results and section 6 concludes.

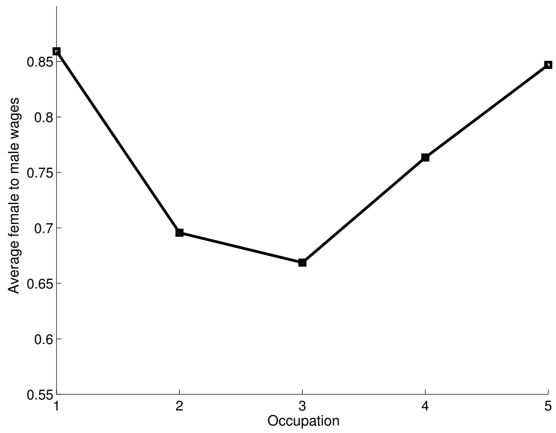
2.2 Facts

Building on the work of Acemoglu and Autor (2011), I construct an index describing the complexity of an occupation. Acemoglu and Autor (2011) utilize the O*NET Work Activities, Work Context, Skills and Abilities files to construct six tasks and measure their intensity for the three digit occupational categories of the

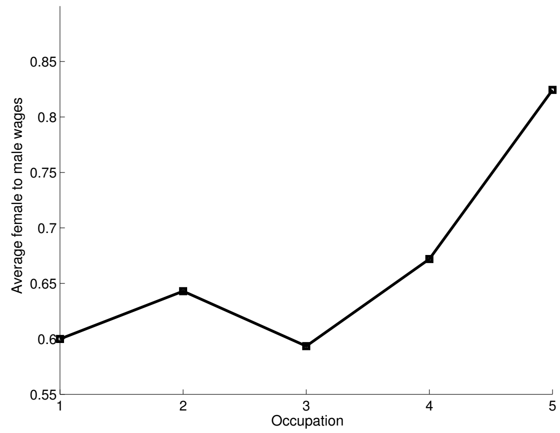
1990 Census. The tasks are: *(a)* non-routine cognitive analytic, *(b)* non-routine interpersonal, *(c)* routine cognitive, *(d)* non-routine manual physical, *(e)* non-routine manual interpersonal, and *(f)* routine manual. I combine these six tasks measures into two aggregates measures: *Brain*, summarizing the intensity of analytical tasks, and *Brawn*, summarizing the intensity of physical tasks. *Brain* is constructed as the average of tasks measures *(a)*, *(b)*, and *(c)*. *Brawn* is constructed as the average of tasks measures *(d)*, *(e)*, and *(f)*. Both aggregate tasks measures are standardized to zero mean and standard deviation of one. Appendix B.1 shows the distribution of occupations on the *Brain* and *Brawn* dimensions for the 1990 three-digit coding system of the Census. Finally, I define my index of tasks complexity for occupation i as follows:

$$o_i = \frac{e^{Brain_i}}{e^{Brawn_i}}$$

where $Brain_i$ and $Brawn_i$ are the two aggregate tasks measures for occupation i and e is the exponential operator. I order occupations according to their complexity, and group them into five groups that correspond to the five quintiles of the empirical distribution of o. The first group (hereafter "occupation 1") contains the occupations with complexity in the first quintile of the empirical distribution of o. Occupation 1 is the group with the lowest average complexity: $o_1 = 0.54$. The fifth group (hereafter "occupation 5") contains the occupations with complexity in the fifth quintile of the empirical distribution for o and has the highest average complexity, $o_5 = 2.17$. Occupations 2 to 4 have complexity in between o_1 and o_5: $o_2 = 0.69$, $o_3 = 1.18$, and $o_4 = 1.49$.



(a) 1920 cohort



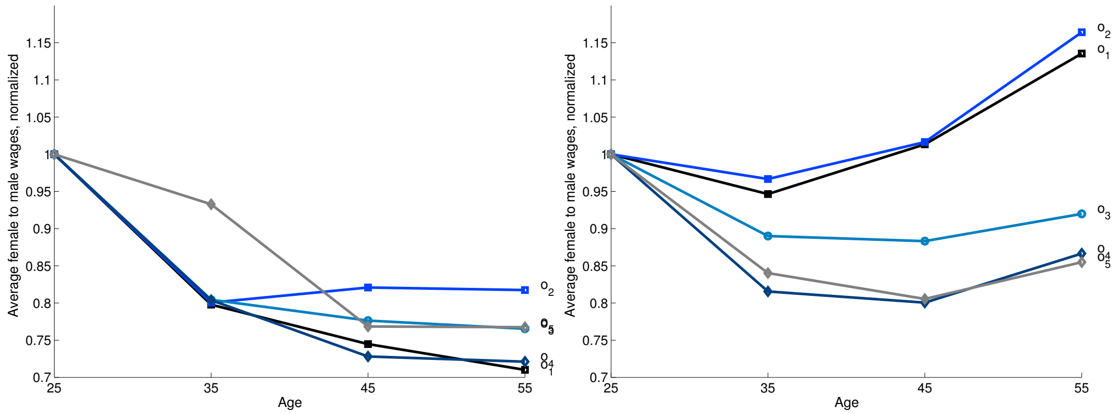
(b) 1950 cohort

Figure 2.1: Gender wage gap between the ages of 25 and 35.

Source: IPUMS-USA and O*NET.

I use IPUMS-USA data from years 1950 to 2010 to document patterns of the gender wage gap for occupations 1 to 5 for successive cohorts of married individuals. Details on sample selection are in Appendix B.1.[2] I focus on two sets of cohorts: the cohorts born between 1915 and 1925 (hereafter "1920 cohort") and the cohorts born between 1945 and 1955 (hereafter "1950 cohort"). Patterns of the cohorts born between 1925 and 1945 are smooth transitions from those of the 1920 cohort to those of the 1950 cohort. Figure 2.1 shows the gender wage gap, measured as the

[2]The focus on married individuals is motivated by the fact that the model I later develop naturally maps to a household composed of at least two individuals. However, the patterns here presented are not qualitatively dependent on sample selection criteria and the index of occupational complexity. In particular, the same qualitative patterns result under the three following alternative scenarios: 1) both married and un-married individuals are considered, 2) the index of occupational complexity is only a function of *Brain*, i.e., $o_i = e^{Brain_i}$, and 3) the occupational complexity index is computed from the Dictionary of Occupational Titles dataset for comparable tasks.

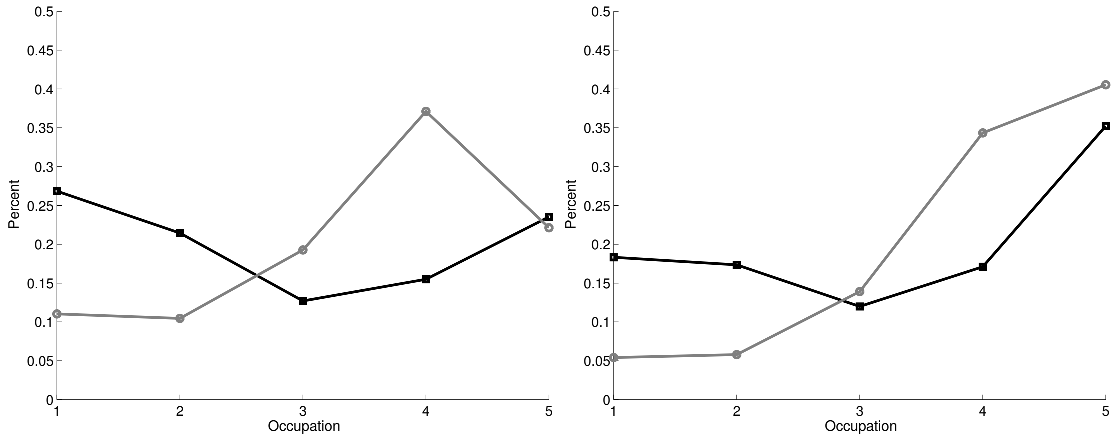


(a) 1920 cohort (b) 1950 cohort

Figure 2.2: Gender wage gap over the lifecycle. Data for each occupational group are normalized to the value between ages 25 and 35.

Source: IPUMS-USA and O*NET.

ratio of female to male wages, between ages 25 and 35 for the 1920 and the 1950 cohorts. The gender wage gap for young individuals is U-shaped across occupations in the 1920 cohort. The ratio of female to male wages is the highest in occupations 1 and 5, with value 0.85. The U-shape flatters across successive cohorts of young individuals: in the 1950 cohort, the ratio of female to male wages is the highest in occupation 5, with value 0.82, and the lowest in occupation 1, with value 0.6. Figure 2.2 documents how the gender wage gap evolves over the lifecycle for occupations of different complexity. The ratio of female to male wages decreases over the life-cycle in both the 1920 cohort and the 1950 cohort and the decrease is on average stronger for occupations with higher complexity. In the 1920 cohort, the ratio of female to male wages decreases 24 percentage points between ages 25 and 65 in occupation 2, and



(a) 1920 cohort (b) 1950 cohort

Figure 2.3: Occupational composition by gender. Females (light-gray line) vs. Males (black line).

Source: IPUMS-USA and O*NET.

28 percentage points in occupation 4. In the 1950 cohort, the ratio of average female to male wages decreases 8 percentage points between ages 25 and 65 in occupation 2 and 15 percentage points in occupation 4.

In addition, the data reveals three further relevant facts. First, females of the 1950 cohort supply significantly more hours to market work than those of the 1920 cohort. Among the married females of the 1920 cohort, 47 percent supply positive hours to market work between ages 45 and 55, and they supply on average 64 percent of the amount of hours supplied by males. Among the married females of the 1950 cohort, 85 percent supply positive hours to market work between ages 45 and 55, and they supply on average 75 percent of the amount of hours supplied by males. Second, males and females choose on average different occupations. As showed in Figure

2.3, males choose occupations with low complexity more frequently than females. Among the 1920 and the 1950 cohorts, on average 20 percent of male workers are in occupation 1, while only 8 percent of female workers are in occupation 1. Females tend to select occupations with complexity in the upper-half of the the distribution of o, with a substantial difference across successive cohorts. Females of the 1920 cohort concentrate for the most in occupation 3, while females of the 1950 cohort concentrate for the most in occupation 4.[3] Finally, females, especially those of less recent cohorts, systematically choose occupations with low wages relative to males. Define the *weighted gender wage gap* as the weighted average of the gender wage gaps across the five occupations, with weights the frequency of females in each occupation. For the 1920 cohort, the weighted gender wage gap is 15 percentage points lower than the gender wage gap; while for the 1950 cohort the weighted gender wage gap is 10 percentage lower higher than the gender wage gap.

2.3 Model

2.3.1 Setup

Time is discrete and runs from $t = 1, 2, \ldots, T$. Each model period corresponds to 10 years of calendar time. The economy is populated by overlapping cohorts of individuals who live for 4 periods: individuals enter the model at age 25 and exit at age 65. I use τ to denote a cohort: cohort τ is composed of individuals of age 1 at time t. For ease of notation, I denote age by j, that is $j = t - \tau + 1$.

[3]Similar improvements in the occupational condition of females have been reported by others in the literature. See for example Goldin (2006).

Within a cohort, individuals are heterogeneous with respect to their gender $g \in \{m, f\}$ and their initial skill level $s_0 \in \Re^+$. There is an equal mass of females and males. Skill summarizes an agent's ability to perform tasks that are valuable in the labor market. Initial skill is distributed across individuals in line with a gender-specific cumulative distribution function Γ_g. The CDF for females is a transformation of the CDF for males. Given a CDF for males Γ_m, the CDF for females is:

$$\Gamma_f(s_0^k) = \xi^k \Gamma_m(s_0^k)$$

$$\text{for} \quad s_0^k \in \Re^+, \ \Gamma_f(s_0) \leq 1 \ \forall s_0.$$

Individual types are pairs $p = (s_0, g)$ on the set $\mathcal{P} = \Re^+ \times \{m, f\}$. I assume that individuals observe their type before any decision is made. I assume that credit markets are complete and there is no uncertainty.

Within a generation, individuals of different gender, a husband and a wife, match to form a household. Household preferences are defined over joint consumption of market goods and home goods:

$$\sum_{j=1}^{4} \beta^{j-1}[U(c_j) + U(x_j - \bar{x}_{j\tau})], \tag{2.1}$$

where $\beta \in (0, 1)$ is the discount factor, c_j is the family consumption of the market good at age j, $c_j = c_j(\cdot, f) + c_j(\cdot, m)$, and x_j is the family consumption of the home good at age j. There is subsistence consumption for the home good, $\bar{x}$. It represents the amount of housework and child care that allows for the satisfaction of the (physical and mental) basic needs of family life. I do not model fertility. For this reason, I allow $\bar{x}$ to be indexed by age so to accommodate for changes in the amount of housework and child care that come about as family structure changes. The utility function abstracts from leisure. I interpret an individual's time endowment as his/her *working* time endowment. Knowles (forthcoming) finds that the fraction of time in a week allocated to leisure activities (non-working activities) remained basically unchanged for married men and women over the 1965-2003 period. In 1965, married men dedicated on average 57 hours per week to non-working activities, while in 2003 they dedicated on average 60 hours per week. In 1965, married females dedicated on average 61 hours per week to non-working activities, while in 2003 they dedicated on average 64 hours per week.

Individuals are endowed with one unit of time each period, which can be used for market production and for home production. Let ℓ denote hours supplied to market work. I assume that males supply their entire time to market work, that is $\ell(\cdot, m) = 1$.[4] At the beginning of each period females must decide whether or not to join the labor market during that period. If they decide to join the labor market, they choose the amount of hours they supply to market work $\ell(\cdot, f)$. There is a minimum

[4]Age-market-hour profiles of married men are essentially identical for cohorts born between 1915 and 1955. On the contrary, the age-market-hour profiles for married females change systematically for successive cohorts during this period. In Appendix B.2, I decompose the variance of the logarithm of market hours and show that most part of the variance for the 1950-2000 period is due to the dispersion of market hours within the female group. Moreover, most of the change in the variance over time is due to the change in market hours dispersion within the female group. In addition, Knowles (forthcoming) finds that females carry out most part of household chores within a married couple in 1975 and the picture looks very similar 30 years later. In 1975, males supply on average 7 hours to household chores and child care, while females supply on average 32 hours. In 2003, males supply on average 10 hours to household chores and child care, while females supply on average 26 hours.

amount of hours $\underline{\ell}$ that a person needs to supply to market work once she joins the labor market, that is $\ell(\cdot, f) \in \{0\} \cup [\underline{\ell}, 1]$.

Home goods are produced using a combination of market goods and the wife's time. That is, $x_j = f_{j\tau}(\ell_j(\cdot, f), y_j)$ where y_j is the input of market goods in the production of the home good at age j. The production function $f_{j\tau}$ is allowed to change over the lifecycle and across cohorts. The change over the lifecycle is meant to capture changes in the relative intensity of inputs that come about as family composition changes. An important fraction of home production is related to children. As children grow older, child care services involve more market goods and less time.[5] The change across cohorts is meant to capture changes in the technology of home production as in Greenwood, Seshadri, and Yorukoglu (2005) and changes in cultural norms with regard to working females as in Fernndez, Fogli, and Olivetti (2004). I assume the following functional form for $f_{j\tau}$:

$$f_{j\tau}(\ell_j(\cdot, f), y_j) = \begin{cases} [\varphi_{j\tau}(1 - \ell_j(\cdot, f))^\alpha + (1 - \varphi_{j\tau})(y_j)^\alpha]^{\frac{1}{\alpha}} & \text{if } x_j \leq \bar{x}_{j\tau} \\ y_j & \text{otherwise.} \end{cases} \tag{2.2}$$

Technological change in home production is modeled as a change in the share of the wife's time across cohorts: $\varphi_{j\tau+1} = \varphi_{j1} g_\varphi^\tau$. The production of home goods takes the wife's time and market goods as inputs up to the subsistence level. After that, any additional unit of home good is transformed one to one from the market good. I assume that the subsistence level of home production in each period can be satisfied by the wife devoting all her time to home production. That is, $\bar{x}_{j\tau} = \varphi_{j\tau}^\alpha$.

[5] Olivetti (2006) makes similar assumptions for the childcare production function.

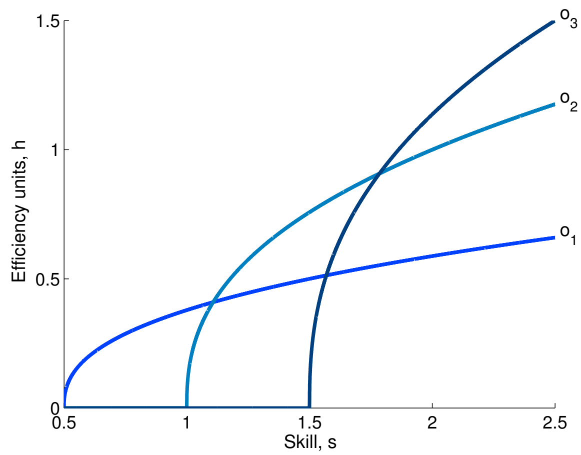


Figure 2.4: Skill-efficiency unit schedules.

Individuals decide the occupation they want to work in. They do so at the beginning of life. Once an occupation is chosen, it cannot be changed.[6] There is a finite number I of occupations indexed by i. Occupations differ by two features: 1) the skill required to perform, and 2) the marginal product of skill. An individual can be employed in occupation i if and only if his/her initial skill is at least o_i. o_i indicates the complexity of occupation i, takes non-negative values and increases with i. The marginal product of skill is assumed to increase with the complexity of an occupation. This reflects the idea that the value of skill in an occupation depends on the occupational complexity. If an occupation involves simple tasks, there is little room for improvement and so workers of different skill turn out to be similarly

[6]Kambourov and Manovskii (2008) find evidence of substantial mobility across occupations classified according to the three-digit coding system of the Census. However, they find little mobility when classifying the occupations according to the two-digit coding system of the Census. In the quantitative analysis, I consider only 4 occupational groups.

productive. For example, Newton and a monkey would be equally productive in an occupation that involves the only task of peeling a banana. However, this would not be true in an occupation consisting of assembling a computer. When occupation i is filled by an individual of skill s he/she produces $h(g,s,i)$ units of *occupational output* ("occupational output" and "efficiency unit" are used exchangeably hereafter):

$$h(g,s,i) = \begin{cases} 0 & \text{if } s < o_i \\ o_i^{1-\rho}(s-o_i)^{\rho}\omega_g & \text{otherwise.} \end{cases} \tag{2.3}$$

Figure 2.4 shows the skill-efficiency units schedules for three occupations. Efficiency units increase with an individual's skill. Across occupations, output is more sensitive to individuals' skills when occupations are more complex. I assume that $\omega_m = 1$; ω_f represents female TFP in occupational output production.

Individuals accumulate skill through learning by doing while working. The amount of skill an individual accumulates in a period depends on the amount of skill accumulated up to the current period and the amount of hours supplied to market work. In particular,

$$s_{j+1} = s_j(1-\delta) + \eta_j s_j^{\beta} \ell_j^{\psi}, \quad j = 0, ..., 3, \tag{2.4}$$

given initial skill s_0. Individuals with high initial skill are more efficient in learning new skills. Notice that learning on the job is not occupation-specific. However, because the marginal product of skill is occupation-specific, so is the scope of learning by doing and the value of acquired skill. In occupations with low complexity, acquired experience influences output only slightly, while the opposite is true in occupations with high complexity.

Individuals are paid wages, E:

$$E(g,s,i) = \underbrace{w_i}_{\text{price}} h(g,s,i),$$

for w_i the the price of occupational output i. Total earnings at age j are: $TE_j(g,s,i) = E(g,s,i)\ell_j(s_o,g)$. Notice that individuals who supply hours to an occupation with a requirement higher than their current skill but lower than their initial skill have zero earnings. I think of this case as that arising in the context of training programs. Individuals accept zero earnings for a period in exchange for higher future earnings that will follow from the newly acquired skills.

2.3.2 Individual Problem

Households maximize lifetime utility in eq. 2.1. They do so by choosing the occupation of the husband, that of the wife, the wife's hours of market work and family consumption of both the market good and the home good.

The setup of the model implies that occupational and time allocation decisions are independent from consumption decisions. Present value income maximization implies utility maximization. Husband and wife choose their occupation and hours of market work to maximize their discounted lifetime earnings net of the cost of market goods used in the production of the subsistence requirement of the home good. Then, given lifetime earnings of the family, they decide how to split their resources between market good consumption and discretionary consumption of the home good. Occupational and time allocation decisions are the only ones that matter for the determination of wages and therefore for the study of the gender wage gap.

In the rest of the chapter I will disregard consumption decisions. The occupational and time allocation decisions of the husband are independent from those of the wife, and vice-versa. This allows for the husband's and the wife's problem to be analyzed separately.[7]

Males. Males decide their occupation. They do so to maximize the present value of earnings over their lifetime. Let $V_j(s, m; i, \tau)$ denote the present value of future earnings at age j of a male individual of cohort τ and skill s who is employed in occupation i. $V_j(s, m; i, \tau)$ is:

$$V_j(s, m; i, \tau) = \sum_{u=j}^{4} \left(\frac{1}{R}\right)^{u-1} w_{it} h_u(m, s_u, i), \quad \text{for} \quad t = \tau + u - 1. \tag{2.5}$$

given eqs. 2.3 and 2.4. R is the gross interest rate, which is the reciprocal of the discount factor. The value of being employed in occupation i for a male individual of type $(m, s_0) \in \mathcal{P}$ in cohort τ is $V_1(s_0, m; i, \tau)$.

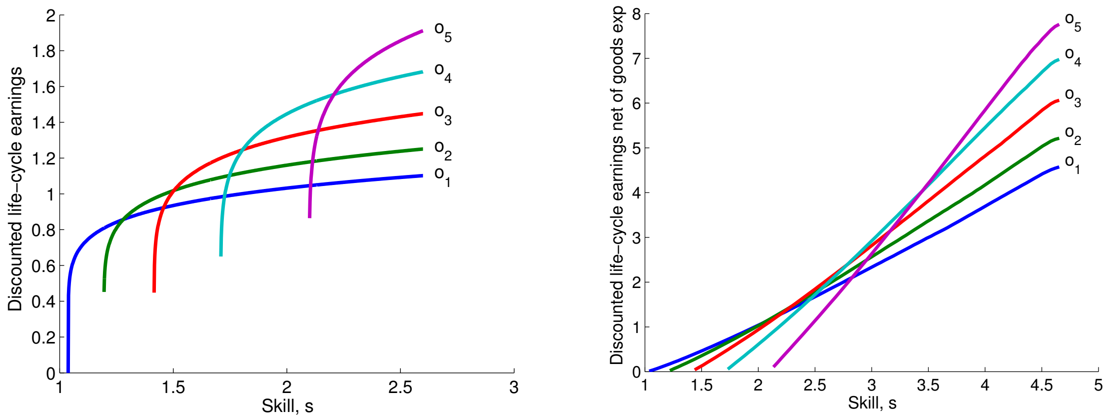
Females. Females decide their occupation and each period's amount of market hours. They do so to maximize the present value of earnings over their lifetime net of the cost of market goods used to satisfy the subsistence requirement. Let $V_j(s, f; i, \tau)$ denote the present value of future earnings at age j of a female individual of cohort

[7] With respect to occupational and time allocation decisions, my setup is equivalent to constraining the household to produce a level of the home good equal to the subsistence level and take the consumption of home good out of the utility function. **?** find that once conditioned by the number of children, marriage is not crucial for understanding female labor supply. The independence between the decisions of husband and wife implies that the conclusions drawn in this chapter for the gender wage gap do not depend on how mating in the marriage market is modeled.

τ and initial skill s that is employed in occupation i. $V_j(s, f; i, \tau)$ is:

$$\begin{aligned} V_j(s, f; i, \tau) = \max_{\{\ell_u^i, y_u^i\}_{u=j}^4} \sum_{u=j}^{4} & \left(\frac{1}{R}\right)^{u-1} \left[w_{it} h_u(f, s_u, i)\ell_u(s, f; i, \tau) - y_u(s, f; i, \tau)\right], \\ \text{for} \quad & y_u(s, f; i, \tau) = \left(\frac{\bar{x}_{u\tau} - \varphi_{u\tau}(1 - \ell_u(s, f; i, \tau))^{\alpha}}{1 - \varphi_{u\tau}}\right)^{\alpha}, \\ & y_u(s, f; i, \tau) \geq 0, \\ & \ell_u(s, f; i, \tau) \in \{0\} \cup [\underline{l}, 1], \\ & t = \tau + u - 1. \end{aligned} \tag{2.6}$$

subject to eqs. 2.3 and 2.4. $l_j(s, f; i, \tau)$ and $y_j(s, f; i, \tau)$ are the policy functions for market hours and for market goods used in the production of the subsistence requirement of the home good for a female individual employed in occupation i, at age j. The benefits of supplying hours to home production are saved expenses on market goods. Substituting market hours with home hours entails two costs. First, there is a direct cost due to the foregone earnings of the period ($wh\ell$). Second, learning-by-doing implies the additional cost of the lost future earnings that would have resulted from the additional skills accumulated through learning by doing while working in the current period. The benefits of increasing home hours do not depend on an individual's skill, while the costs of increasing home hours increase with an individual's skill. Therefore, females with high skill supply more time to market work than females with low skill. There is a threshold level of initial skill below which females do not join the labor market, i.e., $\ell(\cdot, f) = 0$. The value of being employed in occupation i for a female individual of type $(f, s_0) \in \mathcal{P}$ in cohort τ is $V_1(s_0, f; i, \tau)$.



(a) Males (b) Females

Figure 2.5: Occupational choice in the model.

Occupational choice. Individuals of cohort τ choose their occupation based on their initial skill s_0 and their gender g. The occupational problem is:

$$\max_i V_1(s_0, g; i, \tau),$$

for $(s_0, g) \in \mathcal{P}$ and $V_1(s_0, g; i, \tau)$ defined as in 2.6 and 2.5. The decision rule stemming from this problem can be characterized by a simple threshold rule:[8]

$$\mathbf{1}(s_0, g; i, \tau) = \begin{cases} 1, & \text{if } s_0 \in [\underline{s_0}^i(g;\tau), \bar{s_0}^i(g;\tau)] \\ 0 & \text{otherwise.} \end{cases}$$

Figure 2.5 characterizes the occupational problem for males and for females. As in

[8]It can be shown that the value functions for the different occupational options have the single crossing property for the case of males. For the case of females, the single crossing property holds for a region s_0 close to the equilibrium in which there are females working in each occupation. This is the case in the data. The single crossing property is violated for some values of s_0 to the left of $s_0^1(f)$ at which it is not optimal for females to join the labor market and the value functions for all occupational options equal zero.

Roy (1951) individuals sort across occupations based on their comparative advantage, which is determined by a combination of the individual's skill and occupational complexity. The model produces perfect positive sorting of individuals by initial skill across occupations of increasing complexity. Individuals with high initial skill choose occupations with higher complexity than those chosen by individuals with low initial skill. The advantage of occupations with high complexity over those with low complexity is that an increase in skill translates into a larger increase in efficiency units and so into a larger increase in the wage. Individuals with high initial skill have more use of this advantage since they are more productive learners and therefore have steeper lifecycle skill profiles than individuals with little initial skill. The discounted value of lifecycle earnings for females are more convex on the skill domain than those for males, for all occupations. Moreover, those for females intersect at higher values of skill respect to those for males skill, i.e., $\underline{s_0}^i(f;\tau) \geq \underline{s_0}^i(m;\tau)$ and $\bar{s_0}^i(f;\tau) \geq \bar{s_0}^i(m;\tau)$. Females supply less time to market work than males and therefore have flatter lifecycle skill profiles for the same initial skill. Notice that, as female experience decreases, so does the fraction of females in occupations with high complexity and, for the same distribution of initial skill, the average initial skill of females increases relative to that of males in each occupation.

2.3.3 Equilibrium

Market good production. There is one homogeneous final market good Y. This is produced by a representative firm that combines the aggregate occupational outputs:

$$Y_t = A_t \left(\sum_j a_{it} H_{it}^{\theta} \right)^{\frac{1}{\theta}},$$

where H_{it} is the aggregate output of occupation i at time t. A_t is general TFP at time t and a_{it} is the productivity of output i at time t. I assume that both general technological progress and occupation-specific technological progress occur at constant rates g and g_i respectively, $A_{t+1} = A_{t+1}(1+g)$ and $a_{i,t+1} = a_{i,t+1}(1+g_i)$. The representative firm maximizes profits as follows:

$$\max_{\{H_{it}\}_{i=1}^{I}} \quad Y_t - \sum_{i=1}^{I} w_{it} H_{it}.$$

The solution of the firm problem implies that prices for each occupational output equal their marginal products at each point in time, $w_{it} = \frac{\partial Y_t}{\partial H_{it}}$

Aggregation. The aggregate output of occupation i at time t is:

$$H_{it}^{S} = \sum_{j=1}^{4} \sum_{g \in \{m,f\}} \int_{s_0} \mathbf{1}(s_0, g; i, \tau) \ell_j(s_j(s_0, g; i, \tau), g; i, \tau) h(g, s_j(s_0, g; i, \tau), i) d\Gamma_g(s_0).$$

for $\tau = t-j+1$. Starting from the right, this equation sums total occupational output i produced by males and females of the four age groups considered in the model, for the cohorts alive at time t. Total consumption of market goods at time t is:

$$C_t = \sum_{i=1}^{I} \sum_{j=1}^{4} \sum_{g \in \{m,f\}} \int_{s_0} c_j(s_j(s_0, g; i, t-j+1), g; i, t-j+1) d\Gamma_g(s_0),$$

where $c_j(s_j, g; i, \tau)$ is the policy function for market good consumption for an individual of cohort τ, gender g, age i and skill s_j. Starting from the right, this equation sums total market good consumption of males and females of the four age groups considered in the model, employed in each of the I occupations, for the cohorts alive at time t. Lastly, total expenditures on market goods used in the production of the subsistence level of home goods and total expenditure on home goods on top of the subsistence requirement at time t, aggregate into:

$$Y_t^D = \sum_{i=1}^{I}\sum_{j=1}^{4}\sum_{g\in\{m,f\}}\int_{s_0}(x_j(s_j(s_0,g;i,\tau),g;i,\tau)-\bar{x}_{j\tau})+y_j(s_j(s_0,g;i,\tau),g;i,\tau))d\Gamma_g(s_0).$$

for $\tau = t - j + 1$. $x_j(s_j, g; i, \tau)$ is the policy function for home good consumption for an individual of cohort τ, gender g, age i and with skill s_j. The summation follows the same intuition as the previous one.

Equilibrium. Given R, a competitive equilibrium consists of (1) allocations for individuals of each type:

$\{\{\{\ell_j(s_j, g; i, \tau), c_j(s_j, g; i, \tau), x_j(s_j, g; i, \tau), y_j(s_j, g; i, \tau)\}_{j=1}^4, \mathbf{1}(p; i, \tau)\}_{i=1}^I\}_{\tau=1}^\infty$

for $p \in \mathcal{P}$, and allocations for the firm $\{\{H_{it}\}_{i=1}^I\}_{t=1}^\infty$; (2) prices $\{\{w_{it}\}_{i=1}^I\}_{t=1}^\infty$; Such that:

1. The allocations of the individuals solve the optimization problem of each individual $(s_0, g) \in \mathcal{P}$ given prices;
2. The allocations of the firm solve the firm's optimization problem given prices;
3. The price of the output of each occupation, w_{it}, clears the labor market for each occupation at each point in time, that is $H_{it} = H_{it}^S$;
4. The aggregate resource constraint holds: $Y_t = C_t + Y_t^D$.

2.4 Calibration

The calibration strategy is as follows. (i) Use the O*NET dataset to characterize the skill-efficiency unit profiles across occupations. (ii) Use the 1950-2010 IPUMS-USA data on male wages and female market hours to calibrate the learning on the job and the home production functions. (iii) Use the 1950-2010 IPUMS-USA dataset combined with the O*NET dataset to compute occupational choices of males and females and use these occupational choices to discipline the productivities of occupational outputs and the distribution of initial skill.

I assign values to some parameters using a-priori information, these are shown in Table 2.1. A model period corresponds to 10 years of calendar time: individuals enter the model at age 25 and exit at age 65. The number of occupations is set to 4. I set the occupational requirements o_i for each of the four occupations to the complexity index constructed in section 2.2. I merge occupations 1 and 2 in a single occupation since they have similar complexity indexes. I set the gross interest rate R to 1.4802 (decennial rate) and the lower bound for market hours to 0.2 to be consistent with the criteria used in sample selection. I set the depreciation rate $\delta - 1$ to 0. Rupert and Zanella (2012) show that the decrease in wages toward the end of the life cycle is marginal. The productivity of occupational output 1 at time $t = 1$ is normalized to 1. I let general TFP grow at 0.14 percent per year. There is little information on the elasticity of substitution across occupational outputs, θ. I avoid the perfect substitution case following Firpo, Fortin, and Lemieux (2011) and set θ to 2/3 as in Hsieh, Hurst, Jones, and Klenow (2013)'s baseline experiment. I assume that

Table 2.1: Calibration. Parameters computed without solving the model.

Parameter	Symbol	Value
Model period		10 years
Number of occupations	ℓ	4
Gross interest rate	R	1.4802
Min. hours	$\underline{\ell}$	0.2
Learning by doing, depreciation	δ	0
Market good prod., TFP growth	g	0.14%
Market good prod., elasticity	θ	2/3
Occupational requirements	o_i	brain/brawn index
Normalizations:		
Market good prod., share occ. output 1, $t = 1$	a_{11}	1
Lower bound males and females	$\underline{s_0}$	2.3923

the distribution of initial skill for males, Γ_m is uniform. This class of distributions is characterized by two parameters, $\Gamma_m(\underline{s_0}, \bar{s_0})$. I normalize the lower bound of the distribution, $\underline{s_0}$, to a number greater than the skill requirement of occupation 1 and calibrate the upper bound, $\bar{s_0}$, within the model.

The list of remaining parameters is:

$$\Lambda_1 = (\rho, \beta, \{\eta_j\}_{j=1}^4, \bar{s_0}, \{a_{i1}, g_i\}_{i=2}^4),$$

$$\Lambda_2 = (\psi, \alpha, \{\varphi_{j1}\}_{j=1}^4, \omega_f, \{s_0^k, \xi^k\}_{k=1}^3, A_1, g_\varphi).$$

Λ_1 is calibrated to data on male wages and male occupational choice. Λ_2 is calibrated to data on female wages, female working hours, and female occupational choice. I target the following moments:

1. Distribution of workers across the four occupations, for the 1920 cohort, measured between ages 45 and 55 – Gender: males and females;

2. Distribution of workers across the four occupations, for the 1950 cohort, measured between ages 45 and 55 – Gender: males;

3. Ratio of average wages in occupation 4 to that in occupation 1, for the 1920 cohort, measured between ages 25 and 35 – Gender: males and females;

4. Lifecycle profile of average wages in occupation 1 normalized to average wages in occupation 1 at ages 25 to 35, for the 1920 cohort, measured between ages 35 and 45, ages 45 and 55, and ages 55 and 65 – Gender: males;

5. Coefficient of variation of wages, for the 1920 cohort, measured between ages 45 and 55 – Gender: males;

6. Growth of the coefficient of variation of wages in occupation 1 from ages 25 to 55, for the 1920 cohort– Gender: males and females;

7. Average female to male wages, for the 1920 cohort, measured between ages 25 and 35;

8. Lifecycle profile of average female to male work hours, for the 1920 cohorts, measured between ages 35 and 45, ages 45 and 55, and ages 55 and 65;

9. Average female to male work hours, for the 1950 cohort, measured between age 25 and age 65;

10. Coefficient of variation of female to male work hours, for the 1920 cohort, measured between age 25 and age 65;

11. Ratio of number of female workers relative to that of male workers, for the 1920 cohort, measured between age 25 and age 65.

Even though the parameter values are chosen simultaneously to match the data targets, each parameter has a first-order effect on some targets. The production function of occupational output is characterized by two parameters: ρ and ω_f. ρ is important in matching cross-sectional earnings inequality (target 5). Within an occupation, the elasticity of wages to skill is:

$$\xi_{E,s} = \rho \frac{s}{s-o}.$$

Given the occupational requirements, as ρ increases, the distribution of skill maps into a more and more disperse distribution of wages. Female TFP in the production of occupational output is important in matching the overall gender wage gap for young workers (target 7). Because ω_f is not occupation-specific, it shifts the average gender wage gap leaving the pattern across occupations unaltered.

Table 2.2: Calibration. Parameters computed by solving the model: list of targets.

PARAMETER	SYMBOL	Targeted Moment
Market good prod., shares at $t = 1$	$a_{i,1}$	Occ. comp males, 1920 chrt
Market good prod., shares growth	g_i	Occ. comp males, 1950 chr
Market good prod., TFP at $t = 1$	A_1	Female LF part.
Distribution of s_o, males	$\bar{s_0}$	$E(m,\cdot,4)/E(m,\cdot,1)$
Occupational output elasticity, s	ρ	$cv(E(m,\cdot,\cdot))$,ages 45-55
Learning by doing, TFP	η_j	LC earn. growth
Learning by doing, skill elasticity	β	growth, $cv(E(m,\cdot,1))$,age 25-55
Learning by doing, hours elasticity	ψ	growth, $cv(E(f,\cdot,1))$,age 25-55
Occupational output, female TFP	ω_f	Avg. gwg, age 25-35
Home good prod., elasticity	α	Hours ineq.
Home good prod., shares at $\tau = 1$	φ_{j1}	LC avg. hours, 1920 chrt
Home good prod., shares growth	g_φ	vg. hours, 1950 chrt
Distribution of s_o, females	ξ^k	Occ. comp females
	s_0^k	$E(f,\cdot,4)/E(f,\cdot,1)$

Table 2.3: Calibration. Parameters computed by solving the model: parameter values and model fit.

PARAMETER	SYMBOL	TARGET		VALUE
		Model	Data	
Market good prod., TFP at $t = 1$	A_1	0.473	0.473	0.392
Distribution of s_o, males	$\bar{s_0}$	1.162	1.113	3.642
Occupational output elasticity, s	ρ	0.260	0.265	0.7
Learning by doing, skill elasticity	β	1.145	1.135	1.4
Learning by doing, hours elasticity	ψ	1.565	1.631	0.943
Occupational output, female TFP	ω_f	0.754	0.795	0.65
Home good prod., elasticity of substit.	α	0.113	0.084	0.45
Home good prod., shares growth	g_φ	0.746	0.778	0.924
Distribution of s_o, females	s_0^k	1.210	1.270	5.962

Source: IPUMS-USA and O*NET.

Note: The missing values are shown in Figures 2.6 and 2.7. The calibration matches the fraction of males and females in each occupation to the second decimal.

The parameters describing learning on the job, namely β, η_j, γ, are important in matching lifecycle wage profiles. In the model, an individual's wage evolves over the lifecycle as his/her skill grows:

$$\frac{\partial E_t}{\partial s_{t-1}} = \underbrace{w_i o^{1-\rho} \rho (s_t - o_i)^{\rho-1} \omega_g}_{\text{return per unit of skill}} \quad \underbrace{\frac{\partial s_t}{\partial s_{t-1}}}_{\text{learning by doing}} \quad ,$$

which implies

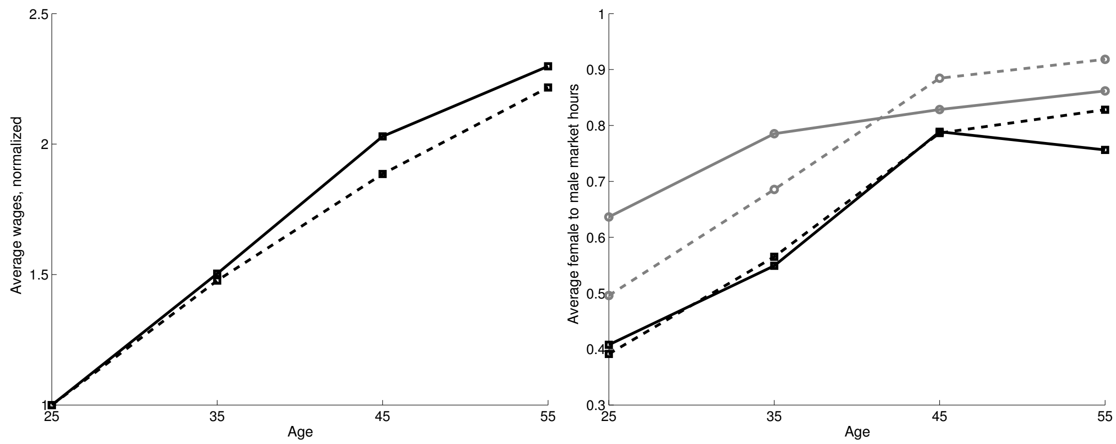
$$g_E = g_{wi} + \rho \frac{s}{s - o_i} g_s.$$

g_E is the growth rate of the wage, g_{wi} is the growth rate of the price of occupational output i, and g_s is the growth rate of skill. Higher η_j implies higher wage growth between ages $j-1$ and j for all males. The η_j's are calibrated to the lifecycle profile of average male wages in occupation 1 (target 4). The lifecycle pattern of wage inequality for males (target 6, males) disciplines β. Wage inequality among males decreases over the lifecycle if β is lower than one, while it increases if β is greater than one. Lastly, γ is important in matching the lifecycle pattern of wage inequality for females (target 6, females). Because females decide the amount of time they spend on the market, γ influences g_s and hence it influences the lifecycle pattern of female wage inequality.

The parameters describing home production, namely $\varphi_{j1}, g_\varphi, \alpha$, are important in matching female market hours. In the model, the cost of supplying hours to market work is the amount of additional market goods that needs to be bought to compensate with the decreased home labor supplied and satisfy the subsistence requirement of the home good. This cost varies with market hours supply as follows:

$$\frac{\partial y}{\partial \ell} = \frac{\varphi}{1-\varphi} \left(\frac{1}{1-\ell} \right)^{1-\alpha} \left(\frac{\bar{x}^\alpha - \varphi(1-\ell)}{1-\varphi} \right)^{\frac{1}{\alpha}-1}.$$

When $\alpha < 1$, the marginal cost of working in the market depends on the amount of hours worked in the market and it changes with it depending on the degree of complementarity between hours and market goods. Because the benefits of working



(a) Average wages in occupation 1 (b) Average female to male market hours

Figure 2.6: Model fit. Lifecycle moments, 1920 cohort. Data (dashed lines) vs. Model (solid lines).

Source: IPUMS-USA and O*NET.

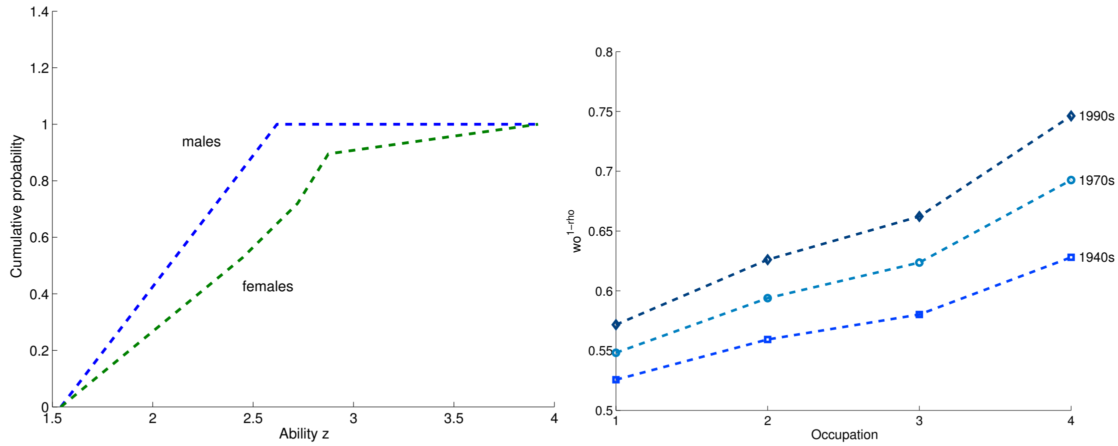
in the market increase with the individual's skill and there is positive sorting of individuals across occupations, α determines the dispersion of market hours across occupations. For example, with the baseline parameterization, increasing α from 0.25 to 0.35 decreases the difference of female market hours between occupation 1 and occupation 4 by 16 percent. I target the dispersion of the *ratio* of female to male market hours, since the time endowment in the model maps to market hours of full time workers (target 10). I set the lifecycle profile of φ, i.e., φ_{j1} and g_{φ}, to match the lifecycle profile of average hours worked in the market by females relative to those worked in the market by males (targets 8 and 9). As φ increases, the cost of supplying hours to market work increases and therefore female market hours decrease.

The production function for market goods is parameterized by a set of values for the productivity parameters, A, a_{i1}, g_i. General TFP is important in matching female labor force participation (target 11). I discipline the productivities of aggregate occupational outputs with data on male occupational choice (targets 1, for males, and 2). A variation in a_i changes the slope of the profile of lifecycle discounted wages of occupation i on the initial skill domain. When the a_i's change non-proportionally, the points of intersections on the initial skill domain of the profiles of discounted lifecycle wages for the four occupations change. Hence, the fraction of males in each occupation changes.

The distribution of initial skill for males is parameterized by a value for $\bar{s_0}$. I discipline $\bar{s_0}$ with average wages of male workers employed in occupation 4 relative to those employed in occupation 1 (target 3 for males). The ratio of average wages of individuals in occupation i relative to those in occupation $i^{'}$, at age j and time t is:

$$OP_{jt}(i, i^{'}, g) = \frac{w_{it}}{w_{i^{'}t}} \left(\frac{o_i}{o_{i^{'}}}\right)^{1-\rho} \left(\frac{\int_{s_0} \mathbf{1}(s_0, g; i, t-j+1)(s_j - o_i)^{\rho} d\Gamma_g(s_0)}{\int_{s_0} \mathbf{1}(s_0, g; i^{'}, t-j+1)(s_j - o_{i^{'}})^{\rho} d\Gamma_g(s_0)}\right).$$

Given the occupational requirements and ρ, $\bar{s_0}$ determines the conditional mean of initial skill in occupation 4 relative to that in other occupations. Hence, it determines average wages in occupation 4 relative to those in other occupations. For a given distribution of initial skill for males, the distribution of initial skill for females is characterized by the vector of parameters s_0^k, ξ^k. I pick four points on the s_0 domain, i.e., $k = 4$. Three points are the points of intersection on the initial skill domain of the occupational profiles of discounted lifecycle wages for females. The forth point is chosen to match the ratio of average female wages in occupation 4 relative to average



(a) CDF of initial skill (b) $wo^{1-\rho}$

Figure 2.7: Calibration. Implications on the gender-specific distributions of skill and on the occupation-specific returns to skill.

female wages in occupation 1. Finally, the ξ^k's are set to match the fraction of females in each occupation (target 1 for females).[9]

Formally, the calibration strategy consists of solving a system of equations. For a given $\Lambda = (\Lambda_1, \Lambda_2)$, I compute the model moments, $X(\Lambda)$, that correspond to the targets described above. I then solve for the zero of the function $F(\Lambda)$ defined by

$$F(\Lambda) = \tilde{X} - X(\Lambda),$$

where $\tilde{X}$ are the targets described above.[10] Table 2.2 lists the targets of the calibra-

[9]Schoellman (2010) uses a similar strategy for estimating immigrants skills compared to natives.

[10]Note that the maximizer in eq. 2.6 is not always concave. The policy function for female market hours is computed by using the grid search method. I compute aggregate statistics using numerical integration.

tion. Table 2.3 and Figure 2.6 display the calibration performance. Table 2.3 and Figure 2.7 display the calibrated values of the parameters. The distribution of initial skill for females first order stochastically dominates the one for males. From the 1940s to the 1990s, the price of output of occupations with high complexity increases relative to that of occupations with low complexity. Given the calibrated distributions of initial endowments, the evolution of prices over time favors the "working" condition of females relative to that of males. This results is consistent with the findings of Black and Spitz-Oener (2010) for the case of Germany.[11]

2.5 Results

The main quantitative implication of the model is in terms of the gender wage gap. I present the model implications on the gender wage gap for the 1920 and the 1950 cohorts. I then analyze the structure of wages across occupations, separately for males and for females.

2.5.1 Gender Wage Gap

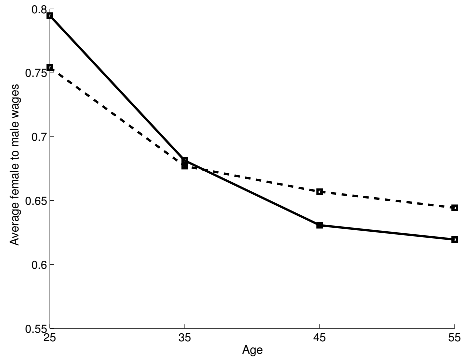
The gender wage gap is the ratio of average female to male wages. Measured for individuals of age j, in occupation i at time t, it reads:

$$GWG_{jt}(i) = \omega_f \left(\frac{\int_{s_0} \mathbf{1}(s_0, g; i, t-j+1)(s_i - o_i)^\rho d\Gamma_f(s_0)}{\int_{s_0} \mathbf{1}(s_0, g; i, t-j+1)(s_i - o_{i'})^\rho d\Gamma_m(s_0)} \right).$$

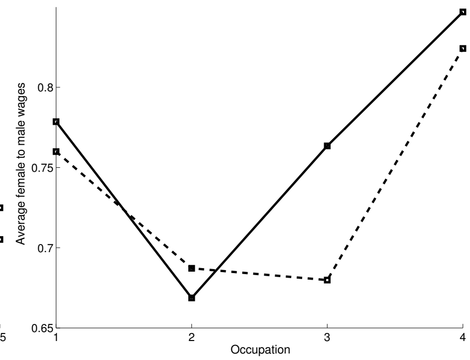
[11]Blau and Kahn (2000) argue that technological change is unfavorable to women in the 1980s since it appears to favor individuals with high education and work experience. In my model, female work experience is endogenous. Technological change favors females because it increases the price of output of occupations that require skill at levels for which the CDF of females is more dense than the one of males.

The gender wage gap in an occupation is determined by female TFP in occupational output production, ω_f, and the ratio of average skill of females in that occupation relative to that of males. Because ω_f is constant across occupations, the pattern of the gender wage gap across occupations is determined only by the pattern of the gender skill differential, which is in turn determined by individuals' initial skill and experience. The overall gender wage gap is decided by three margins. The first two margins are the female TFP in occupational output production and the gender skill differential. The third margin is gender differences in occupational choice. This third margin matters when occupations differ by the price of occupational output and the minimum skill requirement (hereafter "occupational characteristics"). That is, when $w_i o_i^{1-\rho}$ is not the same occupations.

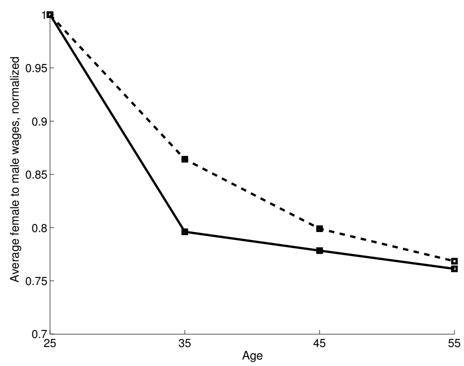
The gender wage gap for the 1920 cohort is summarized in Figure 2.8. Figure 2.8a shows the lifecycle pattern of the overall gender wage gap. The model generates the main features of the lifecycle gender wage gap in the data. The ratio of female to male wages between age 25 and 65 decreases of 14 percent (11 points) in the model and of 22 precent (17 points) in the data. The decrease in the model is due to the smaller work experience of females compared to that of males. The pattern of the gender wage gap across occupations is shown in Figure 2.8b for ages 25 to 35. The model replicates the U-shape in the data: the ratio of female to male wages is the highest in occupations 1 and 4. The U-shape is determined primarily by gender differences in the distribution of initial skill combined with gender differences in occupational choices. At a young age, skill is mainly a result of its initial level, s_0. The points



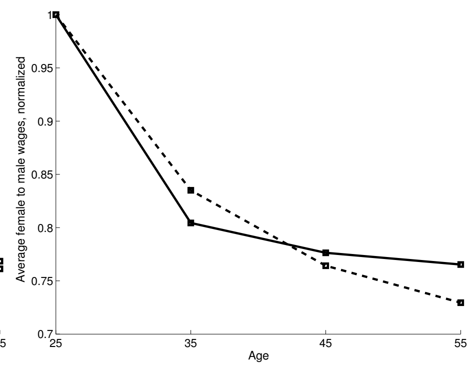
(a) overall



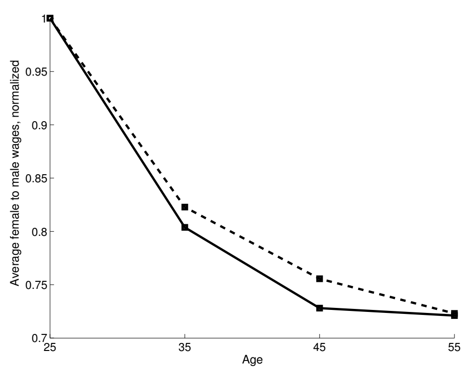
(b) ages 25 to 35



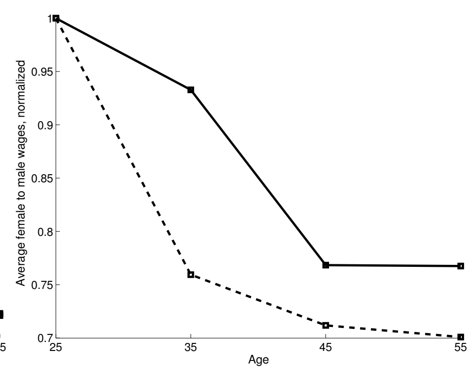
(c) lifecycle, occupation 1



(d) lifecycle, occupation 2



(e) lifecycle, occupation 3



(f) lifecycle, occupation 4

Figure 2.8: Results. Gender wage gap, 1920 cohort. Data (dashed lines) vs. Model (solid lines).

Source: IPUMS-USA and O*NET.

Table 2.4: Decomposition of wages, 1920 cohort.

OCCUPATION	MALES		FEMALES	
	$\Delta_{\log(o)}$	$\Delta_{\log(s)}$	$\Delta_{\log(o)}$	$\Delta_{\log(s)}$
1	62.19	38.85	65.01	37.07
2	62.15	39.14	65.50	36.85
3	62.18	39.18	65.54	36.87
4	62.46	38.98	64.76	37.65

Values in the table do not sum up to one across the rows because they reported as averages over the life cycle.

of intersection on the initial skill domain of the occupational profiles of discounted lifecycle wages for females are right shifts of those for males. These shifts are of similar magnitude. This causes the gender wage gaps in occupations 2 and 3 to be of similar magnitude. The ratio of female to male wages in occupation 1 is pushed up relative to that in other occupations because female labor force participation is low in the 1920 cohort. Finally, the flattening out of the slope of Γ_f for high values of s_0, increases the ratio of female to male wages in occupation 4 relative to that in other occupations.

Rows 2 and 3 of Figure 2.8, show the lifecycle properties of the gender wage gap by occupation. On average, the model matches the magnitude of the lifecycle decrease. The model generates a 26.9 percent decrease in average female to male wages between ages 25 and 65, compared to a 24.6 percent decrease in the data. This follows from the compound of two forces that work in opposite directions but have a common denominator: females supply less hours to market work than males. First, for a given initial skill, skill increases less over the lifecycle for females than it does for males since learning on the job increases with market hours. This effect pushes the ratio of female to male wages to decrease over the lifecycle. Second, the initial-skill thresholds for joining each occupation are higher for female than they are for males and so is the average initial skill in each occupation. This selection effect pushes average female to male wages to increase over the lifecycle since learning on the job increases with initial skill. Quantitatively, the first effect is the strongest and the ratio of female to male wages decreases over the lifecycle. The lifecycle decrease in the ratio of female to male wages in the model is stronger for more complex occupations. This is because the skill-efficiency profiles of more complex occupations are steeper, individuals with high skill are more productive in learning on the job and there is positive sorting of individuals by initial skill across occupations of increasing complexity.

As a first step in the analysis of the determinants of the gender wage gap, I study the determinants of wages. Table 2.4 decomposes log wages across occupations in a component that depends on occupational characteristics ($\Delta_{\log(o)}$) and in a component that depends on individual characteristics ($\Delta_{\log(s)}$), as follows:

$$\log(E(g,s,i)) = \underbrace{\log(w_i) + (1-\rho)\log(o_i)}_{\Delta_{\log(o)}} + \underbrace{\log(\omega_g) + \rho\left(\log(\int_{s_0} \mathbf{1}(\cdot,i)(s-o_i)^{\rho} d\Gamma_g(s_0))\right)}_{\Delta_{\log(s)}}.$$

The component that depends on occupational characteristics makes up for about 2/3 of average wages of both males and females. How much of the overall gender wage gap is due to occupational characteristics? Table 2.5 shows the ratio of female to male averages for three variables: wages (E), occupational characteristics (Δ_o), and individual characteristics (Δ_s). The aggregate gender wage gap is primarily determined by the Δ_s component, i.e., gender skill differential. The ratio of averages for Δ_o is greater than 1 because there are relatively more females in complex occupations than there are males, and complex occupations have higher values for the occupational characteristics (see Figure 2.7). On the other hand, the ratio of averages for Δ_s is lower than one because females supply hours to home production and therefore have lower experience than males have.

An individual's skill at a point in time depends on his/her initial level of skill along with his/her work experience. How much of the lifecycle gender wage gap is due to work experience? To answer this question, I run a counterfactual experiment in which I decrease the share of female time in home production, φ, to equalize female market hours to male market hour. Table 2.6 reports the gender wage gap over the lifecycle and across occupations for the baseline experiment (first row of each

Table 2.5: Decomposition of the gender wage gap, 1920 cohort.

Gap/Age	25-35	35-45	45-55	55-65	Average
E	0.7541	0.6770	0.6569	0.6443	0.6831
Δ_o	1.0230	1.0253	1.0275	1.0298	1.0264
Δ_s	0.7357	0.6603	0.6395	0.6259	0.6654

entry) and for the counterfactual experiment (second row of each entry).[12] Work experience influences the gender wage gap in two ways. First, as female market hours increase, females also choose complex occupations more often. This causes the average initial skill of females in each occupation to decrease and pushes down the ratio of female to male wages in each occupation. This composition effect decreases the ratio of female to male wages between ages 25 and 35 from 0.82 in the baseline to 0.79 in the counterfactual exercise. Across occupations, the decrease is the strongest in occupation 1. The average initial skill of females in occupation 1 decreases not only because females with high skill move to occupation 2, but also because females with low skill join the labor market. Second, as female market hours increase, the lifecycle decrease of the ratio of female to male wages disappears. Females employed in occupations with high complexity gain the most from this second effect. The

[12] I run an alternative counterfactual experiment in which I change the level of TFP in market good production, A, to equalize female market hours to male market hour. The results of this counterfactual experiment are very similar to the results for the counterfactual experiment in which I change φ.

Table 2.6: Counterfactual exercise. The importance of experience.

Occupation/Age	25-35	35-45	45-55	55-65	Average
1	0.7599	0.6719	0.6400	0.6197	0.6729
	0.6696	0.6618	0.6535	0.6481	0.6582
2	0.6872	0.5969	0.5640	0.5417	0.5974
	0.6784	0.6710	0.6641	0.6594	0.6682
3	0.6798	0.5906	0.5600	0.5388	0.5923
	0.6785	0.6702	0.6629	0.6579	0.6674
4	0.8242	0.7169	0.7000	0.6931	0.7336
	0.7905	0.7664	0.7686	0.7769	0.7756
Average	0.7541	0.6770	0.6569	0.6443	0.6830
	0.7474	0.7744	0.7916	0.8076	0.7802
Gap Δ_o	1.0230	1.0253	1.0275	1.0298	1.0264
	1.0379	1.0421	1.0463	1.0504	1.0442

compound of these two effects causes 1) the ratio of female to male wages to decrease in occupations with low complexity and to increase in occupations with high complexity, 2) the ratio of female to male wages to decrease for young individuals and to increase for old individuals, and 3) a larger fraction of females to choose occupations for which the difference in wages between genders is smaller. Overall, the ratio of average female to male lifecycle wages increases from 0.68 in the baseline to 0.78 in the counterfactual experiment.

In the data, female labor supply increases across successive cohorts. How well does the model reproduce the gender wage gap for the 1950 cohort? Figure 2.9 shows the lifecycle profile of the gender wage gap for the 1950 cohort along with that for the 1920 cohort. The model generates 50 percent of the decrease in the ratio of female to male wages for young workers that happens in the 1920 to 1950 cohorts: the ratio decreases from 0.75 to 0.73 in the model, and from 0.79 to 0.75 in the data. The model is also consistent with the change in the shape of the profile of the gender wage gap across occupations for young workers. In the model, this profile goes from a U-shape for the 1920 cohort to a non-decreasing shape for the 1950 cohort as it happens in the data.[13] Over the lifecycle, the decrease in the ratio of female to male wages over the lifecycle in the data is milder for the 1950 cohort than it is for the 1920 cohort. The model reproduces 50 percent of this attenuation. Overall, the model generates 60 percent of the increase in the ratio of female to male lifecycle wages for successive cohorts born between 1915 and 1955.

The cross-cohort patterns of the gender wage gap are reinforced by the increase in female labor force participation and by the improved occupational composition of female labor supply. Among the females of the 1950 cohort, 78.8 percent join the labor market in the model compared to 85 percent in the data. Consistent with Greenwood, Seshadri, and Yorukoglu (2005), the increase in the fraction of females

[13] I do not report figures for the gender wage gap across occupations for the 1950 cohort. These figures are available upon request.

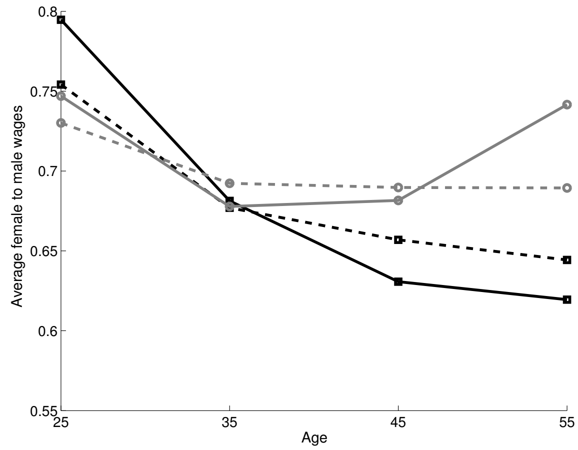
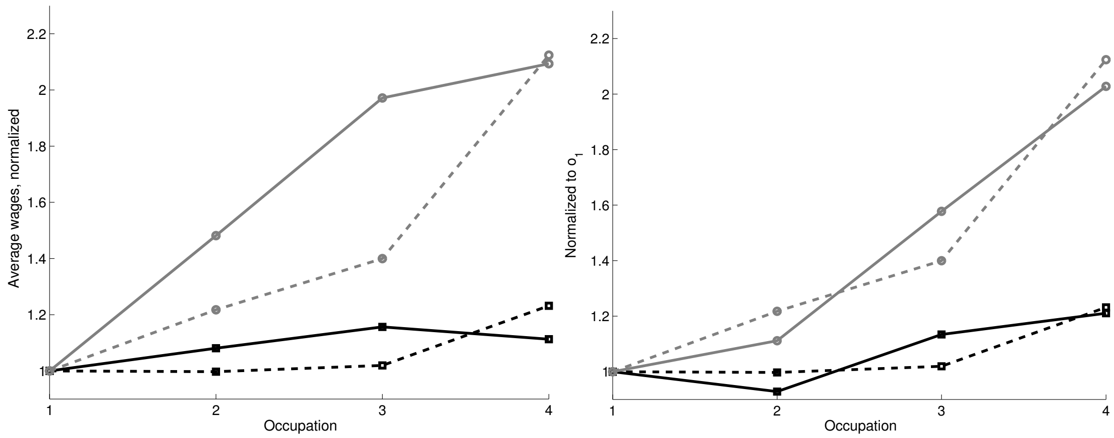


Figure 2.9: Results. Gender wage gap, 1920 cohort and 1950 cohort. Data (dashed lines) vs. Model (solid lines).

Source: IPUMS-USA and O*NET.

joining the labor market in the model is primarily caused by technological change in the home production technology, i.e., a decrease in φ. When I hold the home production technology constant across cohorts, the fraction of females that joins the labor market increases only 4 percentage points between the 1920 cohort and the 1950 cohort. The evolution of prices of the occupational outputs, instigated by technological change in the market good production, reinforces the improvement of the occupational composition of female labor supply. The prices of the more complex occupational outputs increase relative to those of less complex occupational outputs. Because the distribution of initial skill for females has higher density toward the right end of the skill domain compared to that of males, females migrate toward complex occupations faster than males. For the 1950 cohort, complex occupations are those



(a) Males (b) Females

Figure 2.10: Results. Skill premium, 1920 cohort. Black lines are for age 25 to age 35, and gray lines are for age 55 to age 65. Data (dashed lines) vs. Model (solid lines).

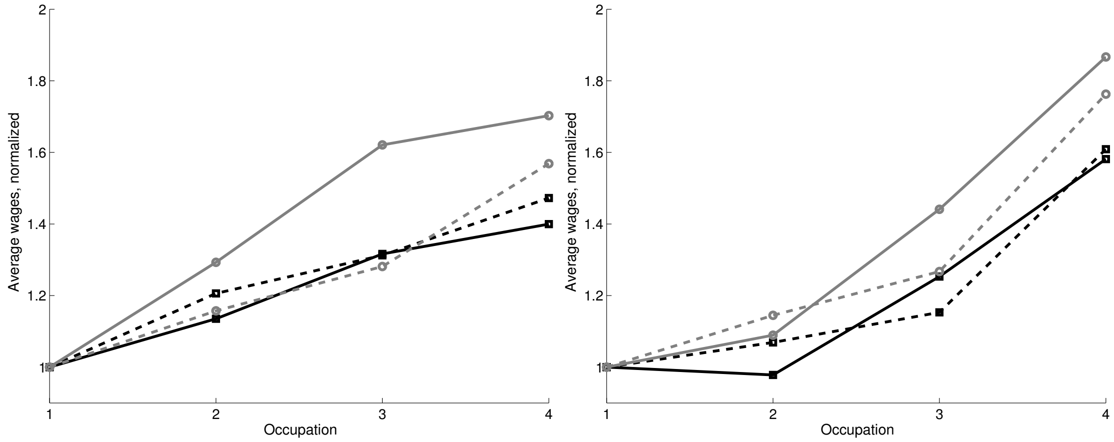
Source: IPUMS-USA and O*NET.

where the difference in wages between genders is the smallest.[14]

2.5.2 Skill Premium

One of the most remarkable features of the twentieth century United States is the rise in the wages of skilled workers relative to those of unskilled workers (hereafter "skill premium") staring in the 1980s. The literature has tied the concept of skill to various observables, such as the amount of schooling an individual has or the type of occupation an individual is employed in (see Goldin and Katz, 2008, and Acemoglu, 2002). In my model, the natural mapping is to occupations and the notion of the

[14]Others in the literature found evidence of a role of changes in the wage structure on the increase in female labor supply. See for example, Jones, Manuelli, and McGrattan (2003), Olivetti (2006), Rendall (2010) and Contessi, de Nicola, and Li (2012).



(a) Males (b) Females

Figure 2.11: Results. Skill premium, 1920 cohort (dark-colored lines) and 1950 cohort (light-colored lines). Data (dashed lines) vs. Model (solid lines).

Source: IPUMS-USA and O*NET.

skill premium that follows is the ratio of average wages across occupations. In this section, I define the skill premium in occupation i to be the ratio of average wages in occupation i relative to that in occupation 1. Figure 2.10 presents the model implications for the skill premium of the 1920 cohort at ages 25 and 35, and at ages 55 and 65. The model replicates the structure of the skill premiums for females across occupations quite nicely (Figure 2.11b). However, for the case of males, the skill premium is reproduced well only at ages 25 and 35. The skill premium for males in occupation 4 at ages 55 and 65 is 1.9 in the model, while it is 2.1 in the data.

What drives the skill premium across occupations? To answer this question, I decompose the logarithm of the skill premium in occupation i in a component that depends on occupational characteristics $(\Delta_{\log(o_i)} - \Delta_{\log(o_1)})$ and in a component that depends on individual characteristics ($\Delta_{\log(s_i)} - \Delta_{\log(s_1)}$) as follows:

$$\log(OP(i,1,g)) = \underbrace{\log(w_i o_i^{1-\rho}) - \log(w_{i'} o_1^{1-\rho})}_{\Delta_{\log(o_i)}-\Delta_{\log(o_1)}}$$
$$+ \underbrace{\rho\left(\log(\int_{s_0} \mathbf{1}(\cdot,i)(s-o_i)^\rho d\Gamma_g(s_0)) - \log(\int_{s_0} \mathbf{1}(\cdot,1)(s-o_1)^\rho d\Gamma_g(s_0))\right)}_{\Delta_{\log(s_i)}-\Delta_{\log(s_1)}},$$

Table 2.7 shows the results of the decomposition, separately for males and females. On average, the component that depends on occupational characteristics accounts for 30 to 40 percent of the skill premium for males. The importance of this component increases with the complexity of the occupation. For the case of females, the component that depends on occupational characteristics accounts for 65 percent of the skill premium in occupations 2 and 3, and for 40 percent of the skill premium in occupation 4.

Figure 2.11 presents the model implications for the skill premium of the 1950 cohort. The skill premium in occupation 4 for male workers increases from 1.5 to 1.6 in the 1920 to 1950 cohorts in the model; while it increases from 1.4 to 1.7 in the data. The skill premium in occupation 4 for female workers increases from 1.6 to 1.8 between the 1920 to 1950 cohorts in the model; while it increases from 1.6 to 1.9 in the data. The importance of the component that depends on occupational characteristics and that of the component that depends on individual characteristics for the skill premium across occupations change little across successive cohorts of male individuals. However, the importance of the occupational component in occupations 2 and 3 decreases across successive cohorts of female individuals. This is because as

Table 2.7: Log decomposition of the skill premium, 1920 cohort.

Occupation	Age			
	25-35	35-45	45-55	55-65
Males 2	0.0620	0.0681	0.0741	0.0801
	0.0357	0.1087	0.1455	0.1687
3	0.0987	0.1089	0.1190	0.1290
	0.0317	0.1470	0.2018	0.2359
4	0.1779	0.1969	0.2156	0.2339
	-0.0506	0.1673	0.2546	0.3052
Females 2	0.0620	0.0681	0.0741	0.0801
	-0.0649	-0.0097	0.0189	0.0342
3	0.0987	0.1089	0.1190	0.1290
	-0.0796	0.0180	0.0683	0.0960
4	0.1779	0.1969	0.2156	0.2339
	0.0306	0.2321	0.3443	0.4171

Note: For each entry, the first row shows the component that depends on occupational characteristics, while the second row shows the component that depends on individual characteristics.

more females join the labor market, the average initial skill in occupation 1 decreases faster than the average initial skill in other occupations.

2.6 Conclusions

In this chapter, I document two patterns of the gender wage gap across occupations of different complexity, for cohorts born between 1915 and 1955. First, the ratio of female to male wages for young individuals is U-shaped across occupations ordered by increasing complexity. The U-shape becomes flatter for successive cohorts of young individuals. Second, over the lifecycle, the ratio of female to male wages decreases faster for more complex occupations. The decrease becomes weaker for successive cohorts over the lifecycle. I argue that understanding these patterns is central to the understanding of the overall gender wage gap, since the value of an individual's skill and the scope of learning by doing in an occupation depend on the complexity of the tasks the occupation entails.

I write a model of occupational choice and learning by doing where individuals differ by their skill and occupations differ by the skill required to perform and the marginal product of skill. I calibrate the model to the task content of occupations, occupational choices, and major patterns of labor supply and male wages, for the cohorts born between 1915 and 1955. The model quantitatively reproduces the two patterns of the gender wage gap across occupations for the cohorts born between 1915 and 1955, the overall gender wage gap for the cohorts born between 1915 and 1925, and 60 percent of the decrease in the ratio of females to male wages for successive cohorts born between 1915 and 1955.

The overall gender wage gap is for the most determined by gender differences in skill, endowed and acquired through work experience, within each occupation.

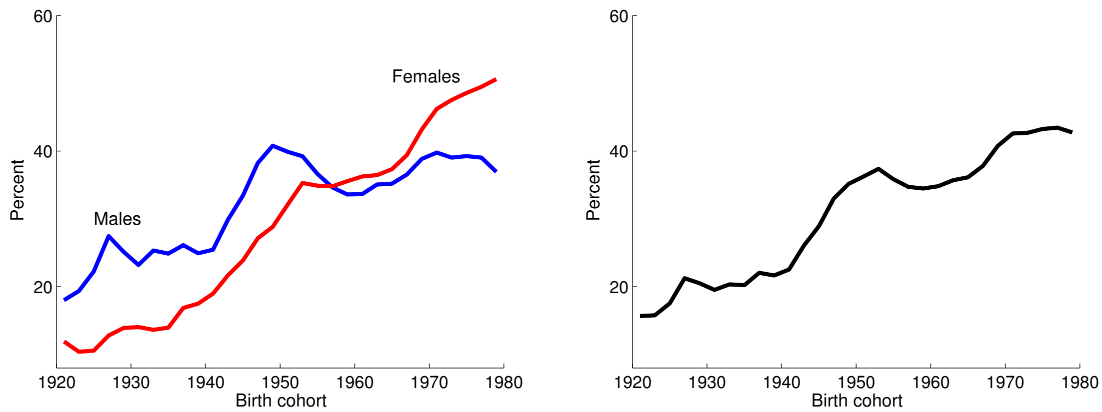
Through counterfactuals, I find that work experience alone accounts for 69 percent of the lifecycle gender wage gap. Part of this percentage is due to occupational choice. As differences in work experience between genders disappear, females migrate toward occupations for which the difference in wages between genders is small. Over time, technological change reinforces the narrowing of the gender gap in wages. In the home good production, it increases female experience and in the market good production, it improves the occupational composition of female labor supplied.

APPENDIX A
MATERIAL FOR CHAPTER 1

A.1 Data

IPUMS-USA. I use 1 percent samples for 1940-1970, and 5 percent samples for 1980-2008. I restrict the sample to employed white males. Observations are weighted. My measure of educational attainment is the IPUMS variable EDUC, which distinguishes among nine levels of education, of which I use two: (i) 12 years of schooling (high school, H), (ii) 16 years of schooling (four-year college, C). My measure of earnings is the IPUMS variable INCWAGE. It reports total pre-tax wage and salary income, i.e., money an employee received in the previous calendar year, as midpoints of intervals (instead of exact dollar amounts). I compute real earnings by applying Consumer Price Index (CPI) weights.

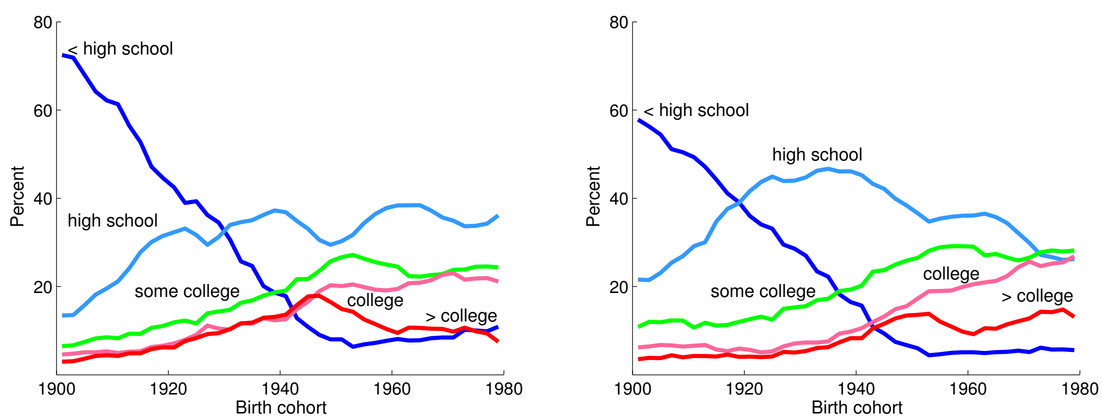
NLSY79. I restrict the sample to white males with no missing observations on earnings for ages 23 to 45. Among the available cohorts, I focus on cohorts born between 1961 and 1964, to maximize sample size. The final sample contains 403 individuals, 283 high school graduates (highest grade completed is 12th) and 120 4-year college graduates (highest grade completed is 16th). Observations are weighed. My measure of earnings includes wages, salaries, bonuses, and two-thirds of business income. I compute real earnings by applying CPI weights.



(a) Males and females (b) All

Figure A.1: College attainment in the United States (employed white individuals): fraction of high school graduates that went on to complete a four-year college degree.

Source: IPUMS-USA.



(a) Males (b) Females

Figure A.2: Educational attainment in the United States (employed white individuals): fraction of individuals in a cohort by highest degree attained.

Source: IPUMS-USA.

A.2 Model Derivations

On-the-job human capital accumulation. If an agent of type (z, h_1) never returns to full-time investment once he stops full-time investment, the on-the-job accumulation problem has a closed form solution. This condition is satisfied if (i) $\delta \in (0, 1]$, and (ii) price growth does not increase "too much" over the lifecycle. The analytical solution of the on-the-job accumulation problem is as follows:

$$V_j(h_j; z, \mathbf{w} \mid S) \begin{cases} w_j \left[h_j a_j + b_j^S z^{\frac{1}{1-\beta_S}} \right] & h_j \geq h_j^*(z, \mathbf{w} \mid S) \\ \frac{1}{R} V_{j+1}(z h_j^{\beta_S} + \delta h_j; z, \mathbf{w} \mid S) & h_j < h_j^*(z, \mathbf{w} \mid S). \end{cases}$$

Where $T = 20$, and h_j^* is the cutoff level of human capital at age j under which the individual spends all his time on human capital accumulation. The recursive formulation is:

$$a_j = \begin{cases} 1 & j = T \\ 1 + \frac{1+g_j}{R} a_{j+1} & j < T \end{cases}$$

$$b_j^S = \begin{cases} 0 & j = T \\ \gamma \left(\frac{1+g_j}{R} a_{j+1} \right)^{\frac{1}{1-\beta_S}} + b_{j+1} \frac{1+g_j}{R} & j < T, \end{cases}$$

for $\gamma = \beta_S^{\frac{\beta_S}{1-\beta_S}} - \beta_S^{\frac{1}{1-\beta_S}}$. This can be written in non-recursive form as:

$$a_j = \sum_{u=0}^{T-j} \delta^u \prod_{k=1}^{u} \frac{1 + g_{j-1+k}}{R},$$

$$b_j^S = \begin{cases} 0 & j = T, \\ \gamma \left(\frac{1+g_j}{R} \right)^{\frac{1}{1-\beta_S}} \left[\begin{array}{c} a_j^{\frac{1}{1-\beta_S}} + \sum_{u=1}^{T-j-1} \left(a_{j+u+1} \prod_{k=1}^{u} \frac{1+g_{j+k}}{R} \right)^{\frac{1}{1-\beta_S}} \times \\ \times \left(\prod_{k=1}^{u} \frac{1+g_{j+k-1}}{R} \right)^{\frac{\beta_S}{1-\beta_S}} \end{array} \right] & j < T. \end{cases}$$

College quality. For an agent of cohort τ and type (z, h_1), the first order conditions for college quality for the case of no full-time accumulation on the job are:

$$u_1 c^{-\eta^2} \left[\left(zh_1^{\eta-1}(ew_{\hat{\tau}})^{1-\eta^2} + (ew_{\hat{\tau}})^{\eta-\eta^2} \right) \right]^{\eta-1} \left[zh_1^{\eta-1}u_2 + e^{\eta-1}u_3 \right] + e^{-\eta}u_4 = u_5, \tag{A.1}$$

where

$$\begin{aligned}
\eta w_{\hat{\tau}}^{-\eta^2}(1+g_{\hat{\tau}})^{1-\eta} &= u_1 \\
w_{\hat{\tau}}(1+\eta) &= u_2 \\
w_{\hat{\tau}}^{\eta}\eta &= u_3 \\
w_{\hat{\tau}}^{1-\eta} &= u_4 \\
\frac{R^2}{(1+g_{\hat{\tau}})(1+g_{\hat{\tau}+2})}\left(1+\frac{1+g_{\hat{\tau}}}{R}\right)\frac{1}{(1-\eta)a_3 z h_1^{\eta}} &= u_5
\end{aligned}$$

The LHS of (A.1) is decreasing in e and the RHS of (A.1) is a constant greater than zero for $\eta \in (0,1)$. Moreover, it is true that:

$$\lim_{e\to\infty} LHS = 0, \ \lim_{e\to 0} LHS = \infty.$$

This assures that the solution for e exists and is unique for each type (z, h_1).

A.3 Calibration Details

A.3.1 Deep parameters

Identification: initial endowments. The distribution of initial heterogeneity is identified with the age variation of unconditional earnings moments and the college premium. Earnings of a j-year-old individual of type (z, h_1), born in τ, and with education S, are

$$E_j(h_1, z, \mathbf{w} \mid S) = \underbrace{w_{\hat{\tau}+2(j-1)} h_j}_{\text{potential earnings}} - w_{\hat{\tau}+2(j-1)} \underbrace{i_j h_j}_{\text{human capital investment}},$$

that is:

$$= w_{\hat{\tau}+2(j-1)} h_1 \delta^{j-1} -$$

$$w_{\hat{\tau}+2(j-1)} z^{\frac{1}{1-\beta_S}} \left(\left(\beta_S a_{j+1} \frac{1 + g_{\hat{\tau}+2(j-1)}}{R} \right)^{\frac{1}{1-\beta_S}} \right) -,$$

$$w_{\hat{\tau}+2(j-1)} z^{\frac{1}{1-\beta_S}} \left(\sum_{u=1}^{j-1} \left(\beta_S a_{u+1} \frac{1 + g_{\hat{\tau}+2(u-1)}}{R} \right)^{\frac{\beta_S}{1-\beta_S}} \delta^{j-1-u} \right),$$

for a as defined in Appendix A.2. Average innate ability influences the slope of the earnings profile. Agents with higher innate ability allocate more time to human capital accumulation and so have low initial earnings. Later in life, their earnings are higher following higher human capital investment (in college and) on the job. The level of initial human capital influences the intercept of an individual's earnings profile and its concavity. The coefficient of variation of innate ability and initial human capital influence the life-cycle dynamics of earnings dispersion. A higher dispersion in initial human capital implies a lower increase in the coefficient of variation of earnings; the opposite is true for innate ability dispersion. When all agents are born with equal innate ability but different initial human capital levels, the model generates a pattern of decreasing earnings dispersion through human capital accumulation. Dispersion in initial human capital determines the concavity of the life-cycle profile of earnings dispersion. The correlation of innate ability and initial human capital disciplines how the two dimension of heterogeneity come together to shape earnings dynamics. The college premium helps in the identification of the dispersion of initial human capital

Table A.1: Model fit. College attainment, college premium and college expenses.

	Data	Model
College attainment	35.26%	35.77%
College premium	1.365	1.382
Average college expenditures	41.54%	39.35%

Source: IPUMS-USA, The College Board, 2007, and author.

and the correlation between innate ability and initial human capital.

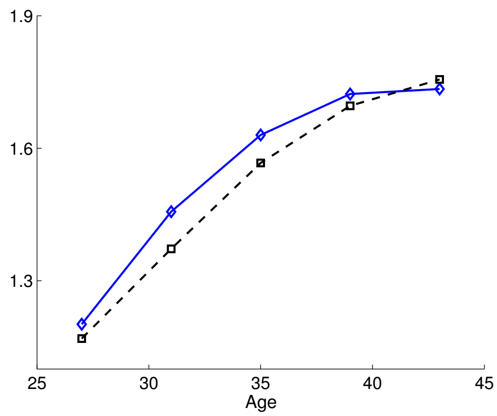
A.3.2 Cohort-specific parameters

Identification: price growth. When investment in human capital is negligible:

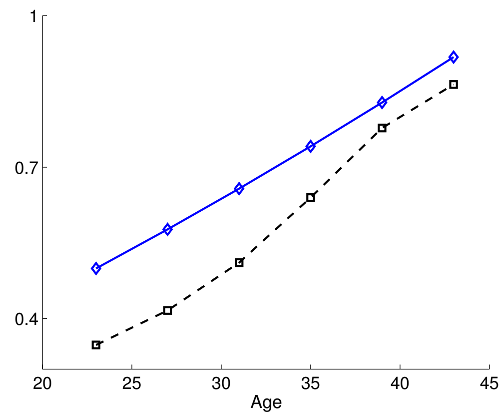
$$E_j = w_{\hat{\tau}+2(j-1)}h_j - w_{\hat{\tau}+2(j-1)}i_j h_j \simeq w_{\hat{\tau}+2(j-1)}h_j,$$

$$E_{j+1} = w_{\hat{\tau}+2(j)}h_j - w_{\hat{\tau}+2(j)}i_{j+1}h_j \simeq w_{\hat{\tau}+2(j)}h_j,$$

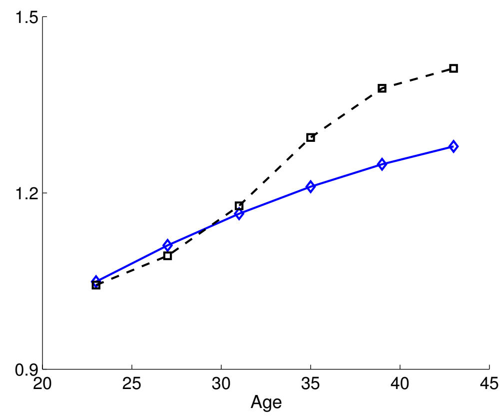
and therefore $g_{\hat{\tau}+2(j-1)} \simeq g_{E_j}$.



(a) Mean



(b) Coefficient of variation



(c) Median/mean

Figure A.3: Model fit. Life-cycle earnings dynamics, 1961-1964 cohorts. Data (solid lines) vs. Model (dashed lines).

Source: NLSY-79 and author.

APPENDIX B
MATERIAL FOR CHAPTER 2

B.1 Data sources

IPUMSUSA. I use 1 percent samples for the period 1950-1970, and 5 percent samples for the period 1980-2008. Observations are weighted. I restrict the sample to employed, married, white individuals who reported their occupation and a total amount of annual hours worked of at least 400. I construct a panel of occupations that includes all occupations that have complete crosswalks across the different Census Bureau occupational classification systems for the period 1950-2010. The panel contains a total of 272 occupations.[1]

My measure of earnings is the IPUMS variable INCWAGE. It reports total pre-tax wage and salary income, i.e. money received as an employee for the previous calendar year, as midpoints of intervals (instead of exact dollar amounts). I compute real earnings by applying the CPI weights.

My definition of an individual's occupation is the IPUMS variable OCC1950. This variable reports the occupation of an individual according to the three digits 1950 Census Bureau occupational classification system.

My measure of weekly working hours is the IPUMS variable HRSWORK2 for the period 1950-1970, and the IPUMS variable UHRSWORK for the period 1980-2010. HRSWORK2 reports the total number of hours the respondent was at work during the

[1]The list of occupation is available upon request.

previous week. UHRSWORK reports the total number of hours that the respondent usually worked during the previous year. My measure of the annual weeks worked is the IPUMS variable WKSWORK2. WKSWORK2 reports the number of weeks that the respondent worked for profit, pay, or as an unpaid family worker during the previous year. I compute annual hours as the product of weekly hours worked and the number of weeks worked in a year.

For each cohort, the number of females joining the labor market is computed as the total number of working females between age 45 and age 55 for that cohort. Similarly, the fraction of individuals of a cohort in an occupation is computed as the fraction of the individuals of that cohort that chooses that occupation between age 45 to age 55. For each cohort, average hours worked at age j are computed as the sum of total hours worked at age j for that cohort divided by the number of individuals in that cohort who are in the labor market between age 45 and age 55. For each cohort, average earning at age j are the sum of annual earnings at age j for that cohort divided by the number of individuals of that cohort who are in the labor market between age 45 and age 55. Finally, an individual's wage is the ratio of his/her annual earnings and his/her annual working hours.

O*NET. To build my index of tasks complexity of an occupation, I use the tasks measures constructed by Acemoglu and Autor (2011) using the Occupational Information Network (O*NET) Database. For these tasks measure, I compute two aggregate indexes, *Brain* and *Brawn*. Figure B.1 shows the distribution of occupations on the brain and brawn dimensions. Acemoglu and Autor (2011)'s tasks measures are

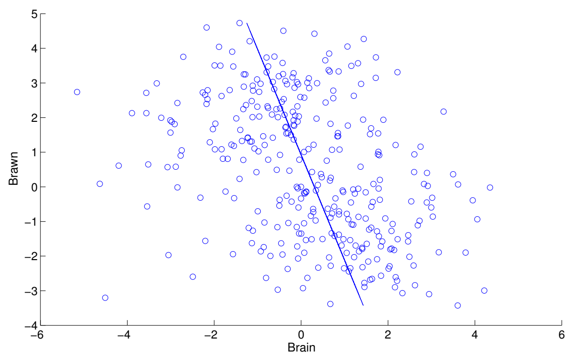


Figure B.1: Occupations on the brain/brawn space.

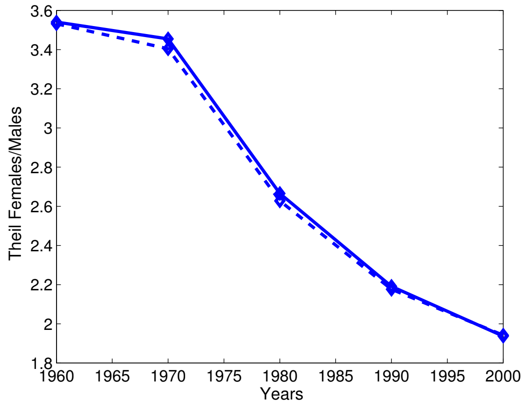
available for occupations classified according to the three-digit 1990 Census Bureau occupational classification system. I use the crosswalks provided by IPUMS-USA to attribute the tasks measures to occupations classified according to the 1950 Census Bureau occupational classification system. When a three-digit 1990 occupational entry is mapped to multiple three-digit 1950 occupational entries, I split the 1990 Census weight equally across the corresponding occupations.

B.2 Decomposition of the Dispersion of Market Hours

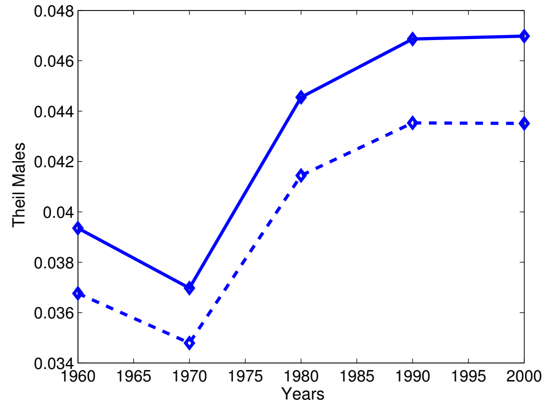
I use the Theil index to decompose the dispersion of market hours in two components: a component that captures within-group dispersion, and a component that captures between-group dispersion. I consider two grouping variables: gender and occupation. Take n to be the number of observations for variable z and define $T \in [0, log(n)]$ to be the Theil index for variable z under the grouping variable j. The decomposition is as follows:

$$\begin{aligned} T &= \sum_{j=1}^{J} y_j T_j + \sum_{j=1}^{J} y_j log(J y_j) \\ &= \underbrace{\sum_{j=1}^{J} y_j \sum_{i=1}^{n_j} y_{i,j} log(n_j y_{i,j})}_{\text{within group}} + \underbrace{\sum_{j=1}^{J} y_j log(J y_j)}_{\text{between group}}, \end{aligned}$$

where J is number of groups and $y_i = \frac{z_i}{\sum_{i=1}^{n} z_i}$. Figure B.2 plots the dispersion of working hours within gender groups. The left panel of Figure B.2 shows that the dispersion of working hours within females is three times the dispersion of working hours within males in 1960 and it decreases substantially over time. The left panel of Figure B.2, shows that the dispersion of working hours within males increases over time starting from 1970. However, the level it reaches in 2000 is still lower than the dispersion of working hours within females in 1960.



(a) Females to males dispersion



(b) Males dispersion

Figure B.2: Within group dispersion of market hours. The dash line considers only gender as a grouping variable. The solid line consider both gender and occupation as grouping variables. Source: IPUMS-USA.

Source: IPUMS-USA and O*NET.

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