The Evolution of Education: A Macroeconomic Analysis

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Abstract

Between 1940 and 2000 there has been a substantial increase of educational attainment in the United States. What caused this trend? We develop a model of schooling decisions in order to assess the quantitative contribution of technological progress in explaining the evolution of education. We use earnings across educational groups and growth in gross domestic product (GDP) per worker to restrict technological progress. These restrictions imply substantial skill-bias technical change. We find that skill-bias technical change can explain the bulk of the increase in educational attainment. In particular, a version of the model calibrated to data in 2000 and that includes on-the-job human capital accumulation is able to generate 2/3 of the increase in educational attainment observed in the data. We also find that the substantial increase in life expectancy observed during the period accounts for almost none of the change in educational attainment.

Keywords: educational attainment, schooling, skill biased technical progress, human capital.
JEL codes: E1, O3, O4.

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1 Introduction

One remarkable feature of the twentieth century in the United States is the substantial increase in educational attainment of the population. Figure 1 illustrates this point. In 1940, about seven percent of the the white males, aged 25 to 29, had completed a college education, 31 percent of them had a high school degree but did not finish college. Finally, 60 percent did not even complete high school.[1] The picture is remarkably different in 2000 when 28 percent completed college, 58 percent completed high school but not college, and less than 15 percent did not complete high school. Although our focus is on white males, Figure 2 shows that the trends of Figure 1 are shared across gender and races. The question we address in this paper is: What caused this substantial and systematic rise in educational attainment in the United States? Understanding the evolution of educational attainment is relevant given the importance of human capital on the growth experience of the United States as well as nearly all other developed countries.

Our approach is to build a model of educational attainment which emphasizes the importance of skill-biased technical change to generate trends in educational attainment. This focus is motivated by data. Using the IPUMS samples for the 1940 to 2000 U.S. Census, we compute weekly earnings across three educational groups for white males of a given age cohort: less than high school, high school, and college.[2] Relative earnings among educational groups exhibit noticeable changes since 1940 (see Figure 3). For instance, earnings of college relative to high school increased from 1.5 in 1940 to 2 in 2000, while the relative earnings of high school to less than high school increased from 1.5 in 1940 to 1.8 in 2000.[3] This focus will necessitate a framework with heterogeneous agents in order to capture the differential returns for schooling investment across educational categories.

Our model builds on the human capital literature, most notably Becker (1975), Ben-Porath (1967), Mincer (1974), and Heckman (1975). For the purpose of our specific question, the model has several key features. First, the schooling choice is discrete. This is relevant because the distribution of people across years of schooling in the data is concentrated around completion years. Also, the discrete choice allows the model to match distribution statistics such as those presented in Figure 1, as opposed to just averages for a representative

[1] In what follows we refer to the detailed educational categories simply as less than high school, high school, and college. See the appendix for details of data sources and definitions.

[2] Weekly earnings refers to pre-tax wage and salary income divided by the number of weeks worked. See the appendix for a detailed description of data sources and definitions. We refer to weakly earnings, earnings, and income interchangeably.

[3] Figure 3 illustrates patterns that have been emphasized in the wage-structure literature. Both the returns to college and high school exhibit increasing trends. The return to college decreased during the 1940s and the 1970s, and rose sharply during the 1980s and 1990s. Acemoglu (2002), for example, reports a similar pattern for the returns to college. The compression observed in the 1940s was documented and discussed by Goldin and Margo (1992).

agent. Second, there are two inputs in the production of human capital: time and goods. The first input, time, is measured in years of schooling. Again, this is a discrete choice so that a high school diploma requires the same years of schooling in 2000 as in 1940. The introduction of goods in the human capital technology, however, allows an agent to get more human capital from a given number of years of schooling. Thus, the efficiency units of labor of a high school person in 1940 may differ from the efficiency units of labor of a high school person in 2000. This quality effect can be found for instance in Ben-Porath (1967) and more recently in Manuelli and Seshadri (2006) and Erosa, Koreshkova and Restuccia (2007). Third, agents are heterogeneous in the marginal utility from schooling time. This assumption allows an equilibrium distribution of people across schooling categories. This sort of utility cost/benefit from schooling is common in both the macro literature (e.g. Bils and Klenow (2000)) as well as the empirical labor literature (e.g., Heckman, Lochner and Taber (1998)). Moreover, given the discreteness of schooling levels the model with heterogeneity implies that changes in exogenous factors have smooth effects on aggregate variables such as educational attainment and income. An additional source of heterogeneity may be through "learning ability." Navarro (2007) finds, however, that individual heterogeneity affects college attendance mostly through the preference channel. Fourth, the model is deterministic so that agents can perfectly forecast the returns to various schooling choices. This assumption is justified by our focus on aggregate trends. In addition, Cunha, Heckman and Navarro (2004) find that a sizeable share of the variability in returns to schooling is forecastable. Finally, at the aggregate level, a production function requires human capital from the three schooling groups, and the productivity of each group is driven by an exogenous, group-specific, technical parameter. The (potentially) uneven growth of these skill-biased technical variables is what drives the evolution of educational attainment in the model.

In the context of these key assumptions, our model is closest to Heckman, Lochner and Taber (1998). However, their emphasis is different from ours. Heckman, Lochner and Taber (1998) focus on explaining the increase in U.S. wage inequality in the recent past. Our focus is on the role of technological progress in explaining the historical rise in educational attainment. Our paper is closest in spirit to a recent literature in macroeconomics assessing the role of technological progress on a variety of trends in the U.S. and other developed countries such as women's labor supply (e.g., Greenwood, Seshadri, and Yorokoglu (2005)), fertility and the baby boom (e.g., Greenwood, Seshadri, and Vandenbroucke (2005)), the structural transformation across countries and regions (e.g., Gollin, Parente and Rogerson (2002) and Caselli and Coleman (2001)), the transition from stagnation to modern economic growth (e.g., Hansen and Prescott (2002)), among others.[4] In emphasizing the connection between technology and education our paper is also related to a labor literature, see for instance Goldin and Katz (2007) and the references therein.[5]

[4]See Greenwood and Seshadri (2005) for an excellent survey of this broad literature.

[5]Technological progress may not be the only force behind the increase in educational at-

In terms of the quantitative exercise we conduct, we discipline our measure of skill-biased technical change by using data on relative earnings among workers of different schooling groups. In other words, our exercise amounts to generate earnings dispersion across schooling levels through skill-biased technical change and, then, to assess how much of a change in educational attainment this mechanism generates. More specifically, the nature of the computational experiment is as follows. The parameters of the model are chosen to match a set of key statistics, including earnings differentials across schooling levels from 1940 to 2000, enrollment rates in 2000 and the overall growth rate of the economy between 1940 and 2000. The changes in educational attainment are left unconstrained in this procedure, that is: they are not used to calibrate the model. Instead, the model's performance can be assessed by comparing the predicted to actual trends in educational attainment.

The main findings are as follows. First, the baseline results show that skill-bias technical change – as measured by the changes in relative earnings across schooling groups – generate a substantial increase in educational attainment, an increase that is actually larger than the observed in U.S. data (a 48 percent increase in average years of schooling between 1940 to 2000 in the model vs. 27 percent in the data). The bulk of the increase in educational attainment in the model is due to high-school skill bias and less to the college skill bias. Overall growth in TFP plays almost no role in the increase in educational attainment although it explains more than 2/3 of the increase in labor productivity. The effect of skill-bias technical change on educational attainment is sensitive to the changes in relative earnings that we feed in from the data. Under conservative scenarios on the change in relative earnings across schooling groups the model replicates the change in educational attainment in the time-series data. Second, although changes in life expectancy have been substantial during the period of analysis, we find that these changes explain almost none of the increase in educational attainment. Returns to human capital are higher in the early part of the life cycle relative to the later part so changes in life expectancy accrue low returns for schooling investment. Third, when the model is extended to include on-the-job human capital accumulation, substantial returns to experience mitigate the quantitative increase in educational attainment. Even in this version of the model, skill-bias technical change still accounts for about 2/3 of the increase in average years of schooling observed in the time-series data. Moreover, there is evidence that the returns to experience have been falling for recent cohorts in the United States – see for instance Manovskii and Kambourov (2005). We conclude that skill-bias technical change is a quantitative important source in explaining the evolution of education in the United States.

We note that our theory abstracts from labor supply margins. The reason for abstracting from labor supply is twofold. First, as matter of facts, there has been little or no trends in labor supply during the period 1940-2000. McGrattan and Rogerson (2004, Table 2) show that weekly hours of work for male workers

tainment. For instance, Glomm and Ravikumar (2001) emphasize the importance of the rise in public-sector provision of education.

declined between 1950 and 1970 and, then, increased from 1970 to 2000. Overall, male hours per worker are less than 2 percent lower in 2000 than in 1940. Along the same lines, Hazan (2007, Figure 18) shows that, despite a significant increase in life expectancy, the expected lifetime labor supply of a cohort born in 1970 is about five percent below that of a cohort born in 1920. Second, as a matter of theory, the effect of an additional hour of work at the end of the life cycle on lifetime labor income is likely to be small due to discounting.

The paper proceeds as follows. In the next section we describe the model. In Section 3 we conduct the main quantitative experiments. In Section 4 we discuss our results by performing a series of sensitivity analysis and by placing the results in the context of the related literature. We conclude in section 5.

2 Model

In this section we develop a model of schooling decisions in order to assess the quantitative contribution of technological progress on the rise of educational attainment in the United States.

2.1 Environment

The economy is populated by overlapping-generations of constant size normalized to one. Time is discrete and indexed by $t = 0, 1, \ldots, \infty$. Agents are alive for T periods and are ex-ante heterogeneous. Specifically, they are indexed by $a \in \mathbb{R}$, which represents the intensity of their (dis)taste for schooling time, and is distributed according to the time-invariant cumulative distribution function A. We assume that the utility cost is observed before any schooling and consumption decisions are made. We also assume that there is no uncertainty in the model.

An individual's human capital is denoted by $h(s, e)$ where s represents the number of periods spent at school and e represents expenses affecting the quality of schooling. Both s and e are choice variables. There are three levels of schooling labeled 1, 2 and 3. To complete level i an agent must spend $s \in \{s_1, s_2, s_3\}$ periods in school and, therefore, is not able to work before he reaches age $s_i + 1$. The restriction $0 < s_1 < s_2 < s_3 < T$ is imposed so that level 1 is the model's counterpart to the less-than-high-school level discussed previously. Similarly, level 2 corresponds to high-school and level 3 to college. Aggregate human capital results from the proper aggregation of individual human capital across generations and educational attainment. It is the only input into the production of the consumption good. The wage rate per unit of human capital is denoted by $w(s)$ for an agent with s years of schooling. Credit markets are perfect and r denotes the gross rate of interest.

2.2 Households

Preferences are defined over consumption sequences and time spent in school. They are represented by the following utility function, for an agent born at date t:

$$\sum_{\tau=t}^{t+T-1} \beta^{\tau-t} \ln\left(c_{\tau}^{\tau-t+1}\right) - as,$$

where $\beta \in (0,1)$ is the subjective discount factor, $c_{\tau}^{\tau-t+1}$ is the consumption of date τ, when the agent is $\tau - t + 1$ periods old and, finally, $s \in \{s_1, s_2, s_3\}$ represents the number of years of schooling. Note that a can be positive or negative, so that schooling provides either a utility benefit or a cost. The distribution of a is normal with mean μ and standard deviation σ :

$$A(a) = \Phi\left(\frac{a-\mu}{\sigma}\right),$$

where Φ is the cumulative distribution function of the standard normal distribution. The production function for human capital is

$$h(s,e) = s^{\eta} e^{1-\eta}, \ \eta \in (0,1).$$

The optimization problem of a just born individual at t, conditional on going to school for s periods, is

$$\tilde{V}_t(a,s) = \max\left\{\sum_{\tau=t}^{t+T-1} \beta^{\tau-t} \ln\left(c_{\tau}^{\tau-t+1}\right) - as\right\},$$

subject to

$$\begin{aligned} \sum_{\tau=t}^{t+T-1} \left(\frac{1}{r}\right)^{\tau-t} c_{\tau} &= h(s,e_t)W_t(s,T) - e_t, \\ W_t(s,T) &= \sum_{\tau=t+s}^{t+T-1} w_{\tau}(s) \left(\frac{1}{r}\right)^{\tau-t}, \end{aligned}$$

where the maximization is with respect to sequences of consumption and the quality of education e_t. The budget constraint equates the date-t value of consumption to the date-t value of labor earnings, $h(s,e_t)W_t(s,T)$, net of investment in quality, e_t. The function $W_t(s,T)$ indicates the date-t value of labor earnings per unit of human capital. Observe that the time cost of schooling is summarized in $W_t(s,T)$. Hence, the model features a time cost of schooling (foregone wages), a resource cost e, and a utility cost a. During period t, the agent chooses s once and for all to solve

$$\max_{s \in \{s_1, s_2, s_3\}} \tilde{V}_t(a,s). \tag{1}$$

This problem can be solved in three steps. First, given s, it simplifies to a utility maximization problem which can, in itself, be divided into two parts. Specifically, the optimal investment in the quality of education, that is e_t, maximizes lifetime net earnings. Then, given lifetime net earnings, the agent optimally allocates consumption through time using the credit markets. Hence, conditional on the choice of s, the optimal investment in quality, for an age-1 agent at time t, is

$$e_t(s) = \arg\max_e \{h(s,e)W_t(s,T) - e\},$$

which yields

$$e_t(s) = s[W_t(s,T)(1-\eta)]^{1/\eta}.$$

The optimal amount of human capital is

$$h(s, e_t(s)) = s[W_t(s,T)(1-\eta)]^{(1-\eta)/\eta}. \tag{2}$$

Then, the net lifetime income of the agent is $I_t(s) = h(s, e_t(s))W_t(s,T) - e_t(s)$ or

$$I_t(s) = \kappa s W_t(s,T)^{1/\eta}, \tag{3}$$

where $\kappa = (1-\eta)^{(1-\eta)/\eta} - (1-\eta)^{1/\eta}$. The optimal allocation of consumption through time, given $I_t(s)$, is dictated by the Euler equation, $c_{\tau+1}^{\tau-t+2} = \beta r c_\tau^{\tau-t+1}$, and the lifetime budget constraint. At this stage, it is convenient to define $V_t(s) \equiv \tilde{V}_t(a,s) + as$. In words, the function $V_t(s)$ is the lifetime utility derived from consumption only, for an agent of cohort t with s periods of schooling. Note that $V_t(s)$ is not a function of a. The optimal schooling choice described in (1) can then be written as

$$\max_{s \in \{s_1, s_2, s_3\}} \{V_t(s) - as\}. \tag{4}$$

2.3 Aggregates

The stock of aggregate human capital is

$$H_t = z_{1t}H_{1t} + z_{2t}H_{2t} + z_{3t}H_{3t}. \tag{5}$$

In this formulation H_{it} is the total stock of human capital supplied by agents with s_i periods of schooling, and z_{it} is a skill-specific productivity parameter. The youngest worker of type i at date t is of age $s_i + 1$ and, therefore, was born at $t - s_i$. The oldest worker is T-periods old and was born at $t - T + 1$. Thus, we have

$$H_{it} = \sum_{\tau=t-T+1}^{t-s_i} p_{i\tau} h(s_i, e_\tau(s_i)),$$

where $p_{i\tau}$ is the fraction of population of τ cohort with i level of education. The production function is linear in the aggregate human capital input with total factor productivity z_t,

$$Y_t = z_t H_t.$$

Since our focus is on long-run trends, we assume constant growth rates for all driving variables:

$$\begin{aligned} z_{t+1} &= g z_t \qquad \forall t \\ z_{i,t+1} &= g_i z_{it}, \quad \text{for } i = 1, 2, 3, \qquad \forall t. \end{aligned}$$

Equation (5) implies that the following normalization is innocuous: $z_{1t} = 1$ at all t – thus $g_1 = 1$. Regarding the level of z_t, we set it to one at an arbitrary date. As it will transpire shortly, this normalization is innocuous too. The determination of the levels of z_{2t} and z_{3t} is discussed in Section 3.

2.4 Equilibrium

An equilibrium is a sequence of prices $\{w_t(s_i)\}$ and an allocation of households across schooling levels such that, at all t, $w_t(s_i) = z_t z_{it}$ and households solve problem (1) given prices.

At an equilibrium, a cohort is partitioned between the three levels of schooling: Agents with low enough utility costs choose level three, while agents with high enough costs choose level one. The rest of the cohort chooses level two. To better understand the determination of this partition consider the function $V_t(s) - as$. Note that it is linear decreasing in a with a slope given by s and an intercept increasing in $I_t(s)$. The ranking of $I_t(s)$ with respect to s depends on opposing effects, as equation (3) suggests. First, higher values of s correspond to higher human capital and, therefore, higher lifetime income. Second, higher values of s tend reduce the work life of the agent and, therefore, lifetime income. This forgone earnings effect transpires through $W_t(s, T)$. Finally, $W_t(s, T)$ also depends on s through the sequence of future wages. When $I_t(s)$ is finite, however, the assumption that $s_3 > s_2 > s_1$ implies that, at all t, there always exists an agent with a low enough value of a, let's denote it by $\underline{a}_t$, such that

$$V_t(s_3) - \underline{a}_t s_3 > V_t(s_2) - \underline{a}_t s_2 > V_t(s_1) - \underline{a}_t s_1.$$

Thus, for $a \geq \underline{a}_t$, there exists a single intersection between each pair of value functions. This implies that they can be represented as in Figure 4. There are two cases. First, consider panel A of Figure 4. Here, an agent chooses s_3 when $a < a_{23,t}$ where $a_{23,t}$ is the marginal agent characterized by

$$V_t(s_3) - a_{23,t} s_3 = V_t(s_2) - a_{23,t} s_2.$$

Similarly, an agent chooses s_1 when $a > a_{12,t}$ where

$$V_t(s_2) - a_{12,t} s_2 = V_t(s_1) - a_{12,t} s_1.$$

Thus,

$$a_{12,t} = \frac{V_t(s_2) - V_t(s_1)}{s_2 - s_1} \quad \text{and} \quad a_{23,t} = \frac{V_t(s_3) - V_t(s_2)}{s_3 - s_2}, \tag{6}$$

and the enrollment rates of cohort t in level i, denoted by p_{it}, are

$$\begin{aligned} p_{1t} &= 1 - A(a_{12,t}), \\ p_{2t} &= A(a_{12,t}) - A(a_{23,t}), \\ p_{3t} &= A(a_{23,t}). \end{aligned}$$

In the case of panel B of Figure 4, there exists only one critical agent:

$$a_{13,t} = \frac{V_t(s_1) - V_t(s_3)}{s_1 - s_3}, \tag{7}$$

and the enrollment rates are $p_{1t} = 1 - A(a_{13,t})$, $p_{2t} = 0$ and $p_{3t} = A(a_{13,t})$. Figure 5 represents, graphically, the determination of enrollment rates in each case.

It is possible to characterize a critical agent as a function of the fundamentals of the model. First, we can show that

$$a_{ij,t} = \frac{1-\beta^T}{1-\beta} \times \frac{1}{s_i - s_j} \times \ln\left(\frac{I_t(s_i)}{I_t(s_j)}\right).$$

Thus, the critical level is proportional to the semi-elasticity of lifetime income with respect to years of schooling. This observation is helpful to understand the difference between the two cases represented in Figure 4. Observe that in the case described in panel A, $a_{13,t}$ is not critical, i.e., $V_t(s_2) - a_{13,t}s_2 > V_t(s_1) - a_{13,t}s_1$ or $a_{23,t} < a_{13,t} < a_{12,t}$. This means that, for an agent contemplating choosing a different level of schooling than s_1, the largest reward comes from choosing s_2, not s_3. The case depicted in panel B is one where $V_t(s_2) - a_{13,t}s_2 < V_t(s_1) - a_{13,t}s_1$, or $a_{12,t} < a_{13,t} < a_{23,t}$. In such case, the largest reward for an agent considering choosing a different level than s_1 comes from choosing s_3. The smallest elasticity is that of a move from s_1 to s_2. This is the reason why enrollment in s_2 is zero in this case.

The assumption that z_t, z_{1t}, z_{2t} and z_{3t} grow at constant rates imply

$$W_t(s_i, T) = \sum_{\tau=t+s_i}^{t+T-1} w_\tau(s_i) \left(\frac{1}{r}\right)^{\tau-t} = z_t z_{it} \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{1 - gg_i/r},$$

so that

$$\frac{I_t(s_i)}{I_t(s_j)} = \frac{s_i}{s_j} \left(\frac{z_{it}}{z_{jt}} \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{(gg_j/r)^{s_j} - (gg_j/r)^T}\right)^{1/\eta}. \tag{8}$$

At this stage, there are a few points worth mentioning. The first is the absence of the level of total factor productivity, z_t, in the determination of the critical agents. The reason for this result is that our model abstracts from any potential asymmetry between the changes in benefits and costs of schooling. A change in z_t affects the lifetime income of agents in the same proportion, regardless of their education. The opportunity cost of education (forgone wages) also changes

proportionally to z_t. Note that the growth rate of total factor productivity, g, appears in Equation (8). However, it does not affect the evolution of educational attainment. The second point is that skill-biased technology affects enrollment rates. Remember that, in our model, skill-biased technology takes place only when the z_{it}'s are growing at uneven rates, implying that z_{it}/z_{jt} is a function of time. Not surprisingly, holding everything else constant, an increase in z_{it}/z_{jt} raises enrollment at level i and reduces it at level j. Observe that life expectancy, T, affects the critical agent too. The lifetime returns on human capital, as measured by $W_t(s,T)$, increases with T, inducing agents to accumulate more human capital. This can be accomplished by attaining higher levels of schooling, or by an increase in the quality of schooling. An increase in T also has an income effect. An agent can maintain educational investment constant and consume more. Hence, theoretically, the effect of T on educational investment is ambiguous and needs to be sorted out quantitatively. One can conjecture, however, that regardless of its direction, the effect of changes in T on educational attainment is quantitatively small due to discounting.

The period τ labor income of an agent of generation t with education s_i is

$$L_{i,t,\tau} = h\left(s_i, e_t(s_i)\right) w_\tau(s_i),\ \tau \geq t + s_i. \tag{9}$$

Note that age matters in the determination of labor income. The reason for this is that an agent's age indicates the year in which schooling decisions are made and, as a result, the year in which human capital is determined.

3 Quantitative Analysis

This section proceeds as follows. In Section 3.1 we discuss the calibration which consists of two stages. First, some parameters are assigned numerical values using a-priori information. Second, the remaining parameters are calibrated to match key statistics of the U.S. economy for the year 2000, as well as overall growth in gross domestic product per worker, and relative earnings across schooling groups during the period 1940 to 2000. Unlike the business cycle literature, where the evolution of productivity is calibrated independently to Solow residuals, we do not have independent measurement of our main driving forces. Our measures are, in fact, derived in the second stage of the calibration. It is important to emphasize that the actual evolution of educational attainment between 1940 and 2000 is not used for calibration. Thus, the quantitative importance of the mechanisms built into the model can be assessed by their ability to generate trends in educational attainment as displayed in Figure 1. In Section 3.2, we use our measures of technical change to assess their quantitative contribution in explaining the rise in educational attainment in the U.S. economy. In Section 3.3 we propose a series of experiments to decompose the role of each components of technical change. Finally, in Section 3.4 we also extend the model to allow for changes in life expectancy and to allow for on-the-job human capital accumulation.

3.1 Calibration

The first stage of our calibration strategy is to assign values to some parameters using a-priori information. We let a period represent one year, and consider that agents are born at age 6. The length of model life is set to $T = 60$, the gross interest rate to $r = 1.05$ and the subjective discount factor to $\beta = 1/r$. The length of schooling, s_1, s_2 and s_3, are set to the average time spent in school at each educational category, for the 25-29 year-old, white males in the 2000 U.S. Census. This restriction dictates $s_1 = 9$, $s_2 = 13$ and $s_3 = 18$ – see appendix.

At this stage, the list of remaining parameters is

$$\theta = (\mu, \sigma, \eta, g, g_2, g_3, z_{2,2000}, z_{3,2000})$$

which consists of the distribution parameters for the utility cost of schooling, the human capital technology, and growth rates and levels for productivity variables. We build a measure of the distance between the model and the U.S. data for: (i) the time path of relative earnings from 1940 to 2000; (ii) the growth rate of gross domestic product per worker from 1940 to 2000; (iii) the share of time in the total cost of education in 2000; and (iv) the educational attainment of the 25-29 years old in the 2000 census. We then choose each element of θ simultaneously to minimize this function.

Our objective function is motivated by the model. More specifically, the fact that the relative z_i's drive the evolution of relative earnings motivates their presence.[6] Note that each element of θ, except μ and σ, matters for the determination of the levels of relative earnings at date t. However, only g_2 and g_3 matter in the determination of their evolution through time. We use the growth rate of the gross domestic product per worker to help pinning down g. The reason is that, as mentioned earlier, g does not affect the evolution of educational attainment or relative earnings. However, it determines, among other things, the growth rate of output per worker. Observe now that μ and σ matter in the determination of the evolution of educational attainment.[7] This, however, is the object of our study. Thus, we restrict ourselves to use only one year of data, namely 2000, to help pinning down these variables. Since this choice is arbitrary we discuss our results in light of an alternative calibration year, such as 1940, and show that the fundamental quantitative forces in the model are not affected. Finally, the elasticity η determines, among other things, the relative importance of time and goods in the production of human capital. This is the reason for the presence of the share of time in the total cost of education in our objective function.

[6] This fact can be seen from Equation (9), which implies

$$\frac{L_{i,t,\tau}}{L_{j,t,\tau}} = \frac{s_i}{s_j} \left(\frac{z_{it}}{z_{jt}} \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{(gg_j/r)^{s_j} - (gg_j/r)^T} \right)^{(1-\eta)/\eta} \frac{z_{i\tau}}{z_{j\tau}}.$$

[7] More precisely, different values of μ and σ imply different paths for p_{it}, given paths for $a_{ij,t}$.

Formally, given a value for θ we compute an equilibrium and define the following objects. First,

$$\hat{E}_{ij,t}(\theta) = \frac{L_{i,t-s_i,t}}{L_{j,t-s_j,t}}$$

is the period-t labor earning of an agent of generation $t-s_i$ and education level i, relative to that of an agent of generation $t-s_j$, with education level j. Observe that at date t both agents are entering the labor force for the first time of their lives. This calculation is justified by the importance of age in determining human capital and, therefore, labor earnings. The empirical counterpart of $\hat{E}_{32,t}(\theta)$ is the relative earnings between the College and High-school groups, described in Figure 3, and denoted by $E_{32,t}$. Similarly, $\hat{E}_{21,t}(\theta)$ is the model counterpart of $E_{21,t}$, the relative earnings of the High-school and Less-than-high-school groups. Then, we define

$$M(\theta) = \begin{bmatrix} p_{1,1981} - 0.134 \\ p_{2,1981} - 0.588 \\ x_{2000} - 0.90 \\ Y_{2000}/Y_{1940} - 1.02^{60} \end{bmatrix}$$

where x_t is the average share of time in the total cost of education.[8] Finally, to assign a value to θ we solve the following minimization problem

$$\min_{\theta} \sum_{t \in \mathcal{T}} \left(\hat{E}_{32,t}(\theta) - E_{32,t}\right)^2 + \left(\hat{E}_{21,t}(\theta) - E_{21,t}\right)^2 + M(\theta)^\top M(\theta)$$

where $\mathcal{T} \equiv \{1940, 1950, \ldots, 2000\}$. The first part of the objective function implies that the model's predicted relative earnings are set to match their empirical counterpart, in a least-square sense. The second part includes four additional restrictions on the parameters. The first two impose that the enrollment rates for the generation born in 1981 match their empirical counterparts. The 1981 generation in the model is 20 years old in 2000, which corresponds to age 25 in the U.S. data. The data displayed in Figure 1 show that, in 2000, 13.4% of the 25-29 year-old group did not finish high school, and 58.8% did or attended some college. The third restriction imposes that the time cost of education, as measured by x_t in 2000, is 90%.[9] Finally, the last restriction imposes that the average annual growth rate of labor productivity between 1940 and 2000 is two percent

The second column of Table 1 indicates the value of the calibrated parameters. The model is able to match the calibration targets very well (see Table 2 and Figure 6.) Notice in Figure 6 that the model implies a smooth path of relative earnings. The reason for this is that our specification of skill bias has

[8] Formally, it is defined as

$$x_t = \frac{\sum_{i=1,2,3} p_{i,2000} L_{i,t,t} s_i}{\sum_{i=1,2,3} p_{i,2000}(L_{i,t,t} s_i + e_{2000}(s_i))}.$$

[9] See for instance Bils and Klenow (2000).

only two parameters per relative skill level, as a result, the best the calibration can do is to fit a trend line through the data points. As we will discuss below, skill bias produces a substantial effect in educational attainment so the parameterizations matters for the quantitative results. In section 3.3 we discuss the results in light of different assumptions regarding skill-bias technology.

3.2 Baseline Experiment

Given the calibration of parameters to 2000 data, and the calibration of the technology growth factors, we feed in technology levels and compute educational attainment for individuals 25 to 29 years of age between 1940 and 2000 which we then compare to data in Figure 1.

The main quantitative implications of the model are with respect to the time path of educational attainment. In particular, the model implies time paths for the distribution of educational attainment for the three categories considered: less than high-school, high-school, and college. Figure 7 reports these implications of the model. The model implies a much sharper increase in educational attainment than what is observed in the data. In particular, the fraction of 25 to 29 year-old with college degree or more increases in the model by 28 percentage points from 1940 to 2000, while in the data the increase is 20 percentage points. For high-school, the model implies an increase from 10 to 60 percent between 1940 and 2000 whereas, in the data, the increase is from 30 to 60 percent. A summary statistic of these implications in educational attainment is the average years of schooling of the 25 to 29 year-old population. We compute the average years of schooling implied by the model as $\sum_i s_i p_i$ at each year. We do the same for the data, i.e., we use the attainment data together with $s_i's$. By construction of our calibration strategy, the model implies an average years of schooling of 13.9 as in the data for 2000. In 1940, the model implies an average years of schooling of 9.4 whereas, in the data, this average is 10.9 years. The model implies a roughly constant share of expenditures in education over GDP around 4 percent which is in the ball park of estimates in Haveman and Wolfe (1995).

We chose the year 2000 for our calibration targets. Given how different the educational attainments are in 1940, the question arises whether the results depend on this choice. We investigate this issue by calibrating the economy to data for 1940 instead. The calibrated parameters are presented in the last column of Table 1. Note that the parameters are reasonably close in each calibration, except for μ and σ, which should not be a surprise.[10] Given this alternative calibration, the quantitative results are fairly similar, for instance, the increase in average years of schooling from 1940 to 2000 is around 50 percent, close to the 48 percent increase in the baseline model calibrated to data in 2000.

[10] Table 1 reports the level of $z_{2,1940}$ and $z_{3,1940}$ which are the calibrated level parameters in this exercise. The paths z_{2t} and z_{3t} are remarkably close, however, in the two exercises. For example, the implied value of $z_{2,2000}$ and $z_{3,2000}$ in the 1940 calibration are 1.37 and 1.78, respectively.

One interesting aspect of the results of the calibration to 1940 data is that, while the underlined quantitative force of technological progress on educational attainment is the same, the results presented in this way emphasize one aspect of the data that the model is not able to capture, namely the slow-down in educational attainment starting in the mid 1970's (see Figure 1 and Figure 8).

3.3 Decomposing the Forces: Skill-Bias vs. TFP

In our model, the increase in educational attainment is the result of skill-biased technical change. Total factor productivity alone does not affect the evolution of education. Other models such, as in Manuelli and Seshadri (2006) and Erosa, Koreshkova and Restuccia (2007), have a nonzero elasticity of schooling to TFP changes. As mentioned in the introduction, the motivation for our approach is to exploit the observed earnings heterogeneity in a parsimonious environment to isolate its contribution on the evolution of educational attainment.

In light of this feature of our model, we decompose the importance of skill-bias technical change by running counterfactual experiments. Remember that skill-bias technical change means that $1 \neq g_2 \neq g_3$. For example, the fact that $g_2 > 1$ in the baseline experiment means that there is a technical bias toward the high-school people, relative to the less-than-high-school group. How important is this bias? To answer this question we set $g_2 = 1$ in our first experiment. We adjust g_3 such that g_3/g_2 remains the same as in the baseline case and we let the rest of the parameters at their baseline values, such as described in the second column of Table 1. The first experiment, therefore, is designed to assess the importance of the high-school technical bias. In a second experiment we ask: how important is the college vs. high-school technical bias? To answer this question, we shut this bias down by assuming $g_3 = g_2 = 1.0045$, where 1.0045 is the growth rate of g_2 in the baseline calibration. Thus, in this experiment, the college bias (relative to high-school) is shut down, while maintaining the high-school bias (relative to primary schooling). In a third experiment, we shut down skill bias completely by imposing $g_2 = g_1 = 1$. Table 3 displays some model statistics for each experiment. Figure 9 shows the change in educational attainment, for college and high-school, for each experiment relative to the baseline.

Observe that in experiments one through three, the increase in educational attainment, as measured by average years of schooling, is less than in the baseline case. The source of this result is different in each experiment. In the first, the relative earnings of the High-school and Less-than-high-school groups are not changing through time because $g_2 = 1$. As a result, the elasticity of lifetime income with respect to an increase in s from s_1 to s_2 is constant and, therefore, the Less-than-high school group remains a constant fraction of the population – see Equation (6). Under this calibration, the model predicts an increase in the proportion of College educated, at the expense of the size of the High-school group. Figure 9 shows that the magnitude by which the proportion of College

educated increases is quite similar to the baseline case, while the number of High-School educated falls. Less human capital is accumulated overall, thus the growth rate of the economy falls noticeably relative to the baseline case.

Let us turn to the second experiment, where the technical bias of college versus high school is shut down. The high-school and college groups retain a technical advantage, relative to the less-than-high-school group, though. Table 3 suggests that the departures from the baseline case, under this experiment, are less than in the previous experiment. The reason is that the College group now is almost constant: college earnings, relative to high-school earnings do not change. The high-school bias attracts agents into high-school hence, unlike the previous case, the High-school group increases and the Less-than-high-school group decreases – a movement similar, in direction, to what is observed in the baseline experiment. Since the College group represents a "small" fraction of the population, the movements of groups one and two are enough to make this experiment closer to the baseline case than the first two experiments. In fact, observe that the growth rate of the economy is less than in the baseline case, because the College group does not increase, but that this difference is small, suggesting that the change in the College group did not contribute much to economic growth.

When we shut down skill bias at both levels, as in experiment three, the model does not generate any change in educational attainment. Income growth is 1.18% in this experiment which is only slightly above the assumed TFP growth (around 1%). The additional growth comes from changes in educational quality.

Given these results, we conclude that, in terms of skill-bias technical change, the high-school bias is the most important force behind the changes in educational attainment. More precisely, shutting down the high-school bias implies the largest departure from the baseline at the aggregate level (average years of schooling and the growth rate of the economy). At a more disaggregated level (the distribution of schooling attainment) high-school and college bias play similar, but different, roles and are of similar quantitative importance – see Figure 9.

We emphasize that the educational attainment implications of the model are sensitive to the calibration of skill-bias technical change. The baseline calibration captures the overall trend in relative earnings over the 1940 to 2000 period. Not only the information captured by these trends is contained in 7 Census years (conducted every 10 years), but also there is substantial decade-to-decade variation in relative earnings. We illustrate the importance of these relative earnings trends by conducting a fourth experiment were we reduce by half the growth rate of relative earnings between 1940 and 2000. We accomplish this by adjusting the growth rates g_2 and g_3 so that the growth in relative technical progress of the two groups is reduced by half relative to the baseline calibration. We leave all other parameters the same. In this experiment, average years of schooling between 1940 to 2000 increase by 24 percent (27 percent in the data), while average growth in GDP per worker is 1.84 percent (2 percent in the data).

(See Table 3.)

Table 3 contains a fifth experiment where TFP growth is shut down, leaving all other parameters the same as in the baseline calibration. As discussed earlier, TFP growth does not affect educational attainment much (notice that without TFP growth the model generates almost the same educational attainment as in the baseline experiment).[11] Notice however that the model would imply much lower aggregate income growth, 0.6% compared to 2% in the baseline. So while in the model the effect of TFP growth on educational attainment is limited, it plays a crucial role in income growth over time.

3.4 Other Potential Forces

We evaluate the potential implications of other features in explaining the rise in educational attainment. First, we study a simulation of the model that allows for life-expectancy to change according to data. Second, we consider an extension of the model that allows for on-the-job human capital accumulation. We calibrate this additional form of human capital to match the observed returns to experience in the data.

3.4.1 Life Expectancy

There has been a substantial increase in life-expectancy in the United States. For males, life expectancy at age 5 increased from around 50 years in 1850 to around 70 years in 2000. Because the return to schooling investment accrues with the working life, this increase can generate an incentive for higher amounts of schooling investment. However, human capital theory also indicates that the returns to human capital investment are higher early in the life cycle rather than later (see for instance Ben-Porath (1967)) and as a result, increases in life expectancy may command a low return given that they extend the latest part of the life cycle of individuals. Whereas the increase in life expectancy is substantial, this life cycle aspect of the increase in life expectancy may dampen the overall contribution of this factor. It is also possible, as mentioned earlier, that the increase in life expectancy reduces the incentive to go to school: an income effect. Since our baseline model predicts an increase in educational attainment larger than observed, we ask whether increasing life expectancy may, through its income effect, dampen the skill-biased technology effect. Hence, we simulate the implications of the model by changing life expectancy as it does in the data.[12] We recalibrate the economy in 2000 to the same targets but taking into account the changes in life expectancy. The main changes in the calibration

[11] The reason why the numbers do not line up exactly with the baseline is that g is different. Although total factor productivity does not matter for the evolution of education, the level of g determines the level of variables in the model – see Equation (8).

[12] Specifically, the life expectancy of the period-t generation is $T_t = g_T T_{t-1}$ given an initial condition T_{1850}. The pair (T_{1850}, g_T) is chosen as to minimize the distance between the U.S. data and $[T_t]$, in a least square sense. (The notation $[\cdot]$ denotes the nearest integer function.)

relative to the baseline involve parameters pertaining to the distribution of utility cost of schooling and the growth rates of technology.

We find that the increase in life-expectancy does not change the implications of the model substantially, in fact, life-expectancy has only modest effects in educational attainment during this period. This can be assessed by comparing the implications for educational attainment of the baseline simulation to the one where life expectancy changes (see Figure 10). Overall, the life expectancy experiment generates an increase of 50 percent in the average years of schooling while the baseline experiment generates a 48 percent increase. We conclude that while changes in life expectancy increase educational attainment the effect is not quantitatively substantial.

3.4.2 On-the-job Human Capital Accumulation

Human capital can be accumulated on the job. Whereas in our baseline model earnings increase only moderately during the life-cycle of an individual (due to TFP and skill-bias technical change), the data shows a high return to experience. A substantial return to experience may in fact affect educational decisions. First, if returns to experience increase with education, as we will show it is the case in the data, then this provides an additional return to schooling, reinforcing the effects of skill-bias technical change. Second, substantial returns to experience implies that, other things equal, individuals would have an incentive to enter the labor market sooner. Because of these opposing effects, it is a quantitative question to assess the role of on-the-job human capital accumulation on the evolution of educational attainment over time.

We extend the model to incorporate on-the-job human capital accumulation. In particular we consider the following human capital accumulation equation:

$$h(s, e) = s^{\eta} e^{1-\eta} x^{\gamma(s)},$$

where x is years of experience and $\gamma(s) \in (0, 1)$ is the human capital elasticity of experience for a worker who has completed s years of schooling. Note that we allow this elasticity to differ across schooling groups. Again, this feature is motivated by data. Using IPUMS Census data we find that the return to experience is systematically higher for higher education groups. Specifically, we construct the age profile of earnings in 2000 as follows. For each educational level, the data point at age a is the average weekly earnings of the $(a-5)-(a+5)$ age group. The resulting age profile is displayed in Figure 11. We then run the following regression: $\log y_i = a_{i0} + a_{i1}x + a_{i2}x^2$ where y_i represents weekly earnings for someone with education level i and $x = \text{age} - s_i$ measures experience. Note that a_{i1} measure the return to 5 years of experience. We find $a_{11} = 0.05$, $a_{21} = 0.07$ and $a_{31} = 0.08$.

We calibrate this economy by, in addition to our baseline targets, targeting the age profile of earnings from 25 to 55 years of age in 2000. The calibration procedure is detailed in Appendix B. The calibrated parameters g, g_2 and g_3

are 1.012, 1.005 and 1.010, respectively. They are comparable to the baseline values displayed in Table 1. The values for $\gamma(s_i)$ are

$$\gamma(s_i) = \begin{cases} 0.38 & \text{for } i = 1, \\ 0.47 & \text{for } i = 2, \\ 0.25 & \text{for } i = 3. \end{cases}$$

Although we have mentioned that the returns to experience are higher for higher education groups, the values of $\gamma(s_i)$ are not monotonic in i. This is due to the fact that the returns to experience are measured, in the spirit of Mincer (1974), by $d \log E/dx$ whereas $\gamma(s)$ measures $d \log E/d \log x$, which is also $x \times d \log E/dx$. Thus, high Mincerian returns for the College group are mitigated, in $\gamma(s_3)$, by a relatively low level of experience. Given this calibration, the model matches the age-earnings profiles well – see Figure 11.

Figure 12 shows the educational attainment implied by the model with on-the-job human capital accumulation, vis à vis the U.S. data. It shows that on-the-job human capital accumulation reduces the incentives to remain in school created by skill-bias technical progress. The average number of years of schooling increase from 11.9 in 1940 to 13.9 in 2000 – a factor of 1.17, which compares with the 1.27 factor in the U.S. data and 1.48 in the baseline. The calibrated returns to experience in this extension of the model dampen the incentives for schooling investment. However, there is strong evidence that the returns to experience have been falling for recent cohorts in the U.S. data – see Manovskii and Kambourov (2005). Hence, even with substantial returns to experience in the model, skill-bias technical change generate about 2/3 of the increase in educational attainment in the data. We conclude that skill-bias technical change is a quantitative importance source of changes in educational attainment in the United States.

4 Discussion

4.1 Substitution across Schooling Groups

We emphasize that the technology for aggregate human capital allows perfect substitutions between skill groups. We view this assumption less problematic as it may first appear. The reason is that our results do not emphasize a particular quantitative elasticity of skill-bias technical change to educational attainment nor it emphasizes a tight measurement of skill-bias technical parameters. Clearly those applications would necessitate tight measurements for the elasticities in the technology for aggregate human capital as well as other sources of labor productivity growth. Instead our emphasis is on the role of skill-bias technical change – as measured by the change in relative earnings – on educational attainment without explicit decomposition of the quantitative source. For instance, an alternative elasticity in aggregate human capital would require a different quantitative source of skill-bias technology to match the same relative earnings

paths. The discipline imposed on the quantitative results of the paper hinge on relative earnings paths. In fact, as we illustrated in experiment 4, section 3.3, the quantitative results are sensitive to the calibration of skill bias from relative earnings in the data.

The following exercise illustrates our point. Consider, a general constant-elasticity-of-substitution technology for aggregate human capital:

$$H_t = \left[(z_{1t}H_{1t})^\rho + (z_{2t}H_{2t})^\rho + (z_{3t}H_{3t})^\rho\right]^{1/\rho},$$

where $\rho < 1$. Output is $Y_t = z_t H_t$. This specification implies an elasticity of substitution of $1/(1-\rho)$ between skill groups. For values of ρ strictly below one different skill groups are more complementary than in our main specification, and an increase in any given z_{it} affects the wage rate of all skill groups.

For simplicity, let us consider a steady-state situation in levels, that is a situation where z_t and the z_{it}'s are constant through time.[13] An equilibrium, is a set of prices: $\{w(s_i)\}$ and an allocation of households across schooling levels such that:

$$w(s_i) = z\left[(z_1H_1)^\rho + (z_2H_2)^\rho + (z_3H_3)^\rho\right]^{1/\rho-1}(z_iH_i)^{\rho-1}z_i,$$

and

$$H_i = (T - s_i)h_i, \qquad i \in \{1, 2, 3\}$$

and households solve problem (1) given prices. The first condition above equates the marginal product of human capital for skill group i to its wage rate. The second equation aggregates individual human capital across generations for group i.

The nature of the exercise is similar to that of Section 3.1. We set s_1, s_2, s_3, T, r and β to their values in Table 1, and we fix z_1 to one. Then we proceed in two steps. First, we calibrate the steady state of the model to match the U.S. economy in 2000. Specifically, we have two targets for enrollment rates, two for relative earnings and one for the share of time in the total cost of education. We impose $z = 1$ and we pick five parameters to match these targets: $(\mu, \sigma, \eta, z_2, z_3)$. In a second step, we re-calibrate z, z_2 and z_3. We choose them to match three targets: the relative earnings in 1940 and the ratio of GDP per capita between 1940 and 2000. Hence, as in the baseline calibration of Section 3.1, our exercise uses the evolution of relative earning to measure skill-specific technological change. We then ask by how much educational attainment is changing. We repeat this exercise for different values of ρ.

Table 4 reports the results. First, we note that there are differences between the steady-state version of the model with $\rho = 1$ and the baseline experiment. The steady-state version of the model implies a lower increase in educational attainment because of the absence of exogenous growth in earnings throughout the lifetime of individuals. Second, by comparing across steady-state economies

[13] Our model does not have a balanced growth path.

with different values for ρ, Table 4 shows that the elasticity of substitution does not affect our main conclusions. Namely, once the skill-bias technical parameters are calibrated to match the evolution of relative earnings, the changes in educational attainment across different calibrations for ρ are almost identical. In addition, it is interesting to note that the calibrated parameters for the human capital technology and the distribution of utility cost of schooling are hardly changing across these calibrations. Thus, the main effect of ρ is to impose different values for the skill-bias technical parameters in levels and rates of change.

We recognize that these results only apply to a steady-state version of the model. However, we expect that the same quantitative effects will carry through in the dynamic version of the model with different elasticities of substitution across skill groups. Data limitations prevent us from carrying through these experiments. When $\rho < 1$, the dynamic version of the model requires much more data than presently available. The reason for this is that in the model with $\rho < 1$, the wage rate at a point in time depends on the educational attainment of all cohorts working. Thus, this will require data on relative earnings going as far back as 1900 or before. And wages are necessary to solve for human capital and earnings in 1940. When $\rho = 1$, wages are only a function of technical parameters at each date.

Assuming perfect substitution across skill groups in the human capital technology not only allows us to assess the role of technical change in educational attainment in a simple and tractable framework, but also gives us a reasonable characterization since the quantitative implications of the model turn out to be insensitive to alternative substitution elasticities after the model is calibrated to match the same relative earnings targets.

4.2 Further Implications

Our theory emphasizes skill-bias technical change as an important source of movements in educational attainment over time. In Figure 2 we emphasized that the evolution of educational attainment was similar for men and women. For our model to be consistent with these trends, skill-bias technical change would have to be about the same magnitude for men and women. Using data from the U.S. Census we decompose relative earnings across schooling groups for men and women. We find that the trend behavior of relative earnings across schooling groups are remarkably similar between men and women – see Figure 13. This process would imply a similar evolution of educational attainment across genders in the model, which is consistent with the data. Whereas the data for relative earnings indicates similar skill-bias technical change for men and women – with comparable evolution of education across genders – there is also a substantial and declining gender wage gap during this period. Hence, it appears that the gender wage gap has not played a major role for schooling investments across genders.

5 Conclusion

We developed a model of schooling decisions to address the role of technological progress in the rise of educational attainment in the United States. The model features discrete schooling choices and individual heterogeneity so that people sort themselves into the different schooling groups. Technological progress takes two forms: neutral and skill-biased. Skill bias technical change increases the returns of schooling thereby creating an incentive for more people to attain higher levels of schooling. We find that this source of technological progress can account for all of the increase in educational attainment in the United States between 1940 and 2000. More specifically, what we labeled the high-school bias (that is the bias which favors high-school graduate over those who did not finish high-school) is quantitatively more important in accounting for the trends than the the college bias (with respect to high-school graduates.) The substantial changes in life expectancy turns out to account for almost none of the change in educational attainment.

We have focused on the long-run trend of educational attainment in the United States. Two issues would be worth exploring further. First, while the model with skill-bias technical change can account for the overall trend in educational attainment, the model fails to capture the sharp slowdown in educational attainment since the late 70's. This slowdown in educational attainment is even more puzzling given the observed decline in the returns to experience for recent cohorts in the United States. Second, in assessing the role of skill-bias technical change in other contexts, it would be relevant to investigate the changes in relative earnings in other countries. For instance, institutions that compress wages may reduce the incentives for schooling investment and it would be interesting to see (holding other institutional aspects constant) whether this wage compression can explain the lower educational attainment in European and other countries compared to the United States. These explorations would require important departures of the model so we leave these for future research.

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A Data

Educational Attainment The source of data for Figures 1 and 2 is the Current Population Survey. The "Less-than-high-school" category corresponds to the percentage of the 25-29 year-old population who has completed less than four years of high school. The "High-school-and-some-college" category is the percentage of the 25-29 year-old population who has completed four years of high school or more, but less than four years of college. Finally, the "College" category corresponds to those who have completed four years of college or more.

Weekly Earnings The source of data is the U.S. Census (1 percent samples from IPUMS, 1940-2000). The income variable is INCWAGE, which reports the respondent's total pre-tax wage and salary income. This variable is available at each census date from 1940 to 2000, and is intended to capture all monetary compensations received for work as an employee. Earnings are divided by the number of weeks worked. This is computed from WKSWORK2, which reports the number of weeks worked, by intervals. (We use the mid-point of the interval). This variable is available at each Census from 1940 to 2000. A variable reporting the exact number of weeks worked exists at some, but not all, Census dates. The education variable is EDUCREC which indicates the highest grade or year of college completed. The categories for EDUCREC are: 1 for N/A or No schooling; 2 for Grades 1 through 4; 3 for Grades 5 through 8; 4 for Grade 9; 5 for Grade 10; 6 for Grade 11; 7 for Grade 12; 8 for 1, 2, or 3 years of college; and 8 for 4 years of college or more. There are no differences between the educational attainment figures implied by these categories and the Current Population Survey numbers displayed in Figure 1 and 2. For each educational level, we focus on a different age group, in order to compare the earnings of agents with similar levels of experience. Furthermore, since our model is about the returns to schooling and not those to experience, we focus on the youngest age groups. More specifically, the Less-than-high-school group is represented by 15-to-21-year-old reporting EDUCREC between 1 and 6, the High-school-or-more group is represented by 18-to-24-year-old reporting 7 or 8. Finally, the College group corresponds to by 21-to-27-year-old reporting 9. We restrict our analysis to white (RACED) males (SEX) working (EMPSTAT) for a wage or salary in the private or public sector (CLASSWKR). For each group, the bottom and top one percent of the distribution is ignored.

Length of Schooling The source of data, to calibrate s_1, s_2 and s_3 is the U.S. Census (1 percent samples from IPUMS, 1940-2000). The first table below shows the proportion of white males, 25-29, at each educational level available in the data set. The second column indicates the number of years spent at each level (on average). The last four lines of the table use the data to compute the average years spent at school overall, and at each of the three levels relevant for the model.

			1940	1950	1960	1970	1980	1990	2000
Less than HS	None or preschool	0 years	0.7	0.8	0.6	0.8	0.5	0.6	0.7
	Grade 1, 2, 3, or 4	4 years	3.3	2.9	2.0	0.7	0.6	0.3	0.3
	Grade 5, 6, 7, or 8	8 years	34.3	18.5	14.9	7.4	3.7	2.1	2.7
	Grade 9	9 years	7.4	6.1	6.2	4.3	2.6	2.0	2.0
	Grade 10	10 years	9.4	8.7	7.1	5.7	3.1	3.1	2.4
	Grade 11	11 years	5.7	6.9	6.2	4.7	3.6	3.2	2.7
HS	Grade 12	12 years	23.8	30.3	33.5	38.2	36.4	35.3	30.4
	1 to 3 years of college	14 years	7.4	13.6	13.7	17.3	24.3	29.4	31.1
	4+ years of college	18 years	7.8	12.1	15.7	20.8	25.1	24.0	27.6
	Avg Years		10.4	11.5	12.0	12.9	13.6	13.7	13.9
	Avg Years before HS		8.5	8.8	8.9	9.2	9.3	9.6	**9.4**
	Avg Years HS		12.5	12.6	12.6	12.6	12.8	12.9	**13.0**
	Avg Year Coll.		18.0	18.0	18.0	18.0	18.0	18.0	**18.0**

B On-the-job Human Capital Accumulation

This section describes how the model with on-the-job human capital accumulation is calibrated. The list of parameters to calibrate is the same as for the baseline model, with the addition of $\gamma(s_i)$ for $i = 1, 2, 3$. Using the notations of Section 3.1, we have

$$\theta = (\mu, \sigma, \eta, g, g_2, g_3, z_{2,2000}, z_{3,2000}, \gamma(s_1), \gamma(s_2), \gamma(s_3)).$$

Others parameters, calibrated a priori, have the same values as in the baseline case. The determination of θ requires to include into the objective function described in Section 3.1 an additional set of conditions that will help in the determination of the three additional parameters. Let

$$\hat{A}_{i,m,t}(\theta) = L_{i,t-m+1,t}$$

denote the date t earnings of an age-m agent with education level i. Let $A_{i,m,t}$ denote its empirical counterpart, measured from IPUMS Census data. The parameters are the solution to:

$$\min_{\theta} \sum_{t \in \mathcal{T}} \left(\hat{E}_{32,t}(\theta) - E_{32,t}\right)^2 + \left(\hat{E}_{21,t}(\theta) - E_{21,t}\right)^2 + \sum_{i=1,2,3} \sum_{m \in \mathcal{M}} \left(\frac{\hat{A}_{i,m,2000}(\theta)}{\hat{A}_{i,m-5,2000}(\theta)} - \frac{A_{i,m,2000}}{A_{i,m-5,2000}} \right)^2 + M(\theta)^\top M(\theta)$$

where $\mathcal{T} \equiv \{1940, 1950, \ldots, 2000\}$, $\mathcal{M} \equiv \{30, 35, \ldots, 55\}$ and $M(\theta)$ is defined in Section 3.1. Observe that the increases along the age profile of earnings are used in the new component of the objective function. The relative levels of these profiles are pinned down by the first set of restrictions on relative earnings.

Table 1: Calibrated Parameters

Interpretation	Parameters 2000 Calibration	Parameters 1940 Calibration
length of schooling	$s_1 = 9$, $s_2 = 13$, $s_3 = 18$	
length of life	$T = 60$	
Subjective discount factor	$\beta = 0.95$	
Interest rate	$r = 1/\beta = 1.05$	
Human capital technology	$\eta = 0.88$	$\eta = 0.89$
Distribution of abilities	$\mu = 2.16$, $\sigma = 0.62$	$\mu = 1.45$, $\sigma = 0.69$
Growth rates		
Neutral technology	$g = 1.0104$	$g = 1.0070$
HS biased technology	$g_2 = 1.0045$	$g_2 = 1.0046$
College biased technology	$g_3 = 1.0092$	$g_3 = 1.0094$
Level conditions		
HS biased technology	$z_{2,2000} = 1.37$	$z_{2,1940} = 1.05$
College biased technology	$z_{3,2000} = 1.78$	$z_{3,1940} = 1.02$

Table 2: Matching Calibration Targets – Model and Data

	Data	Model
Enrollment rates 2000 (%)		
Less than High School	13.4	13.4
High School but less than College	58.8	58.8
College or more	27.8	27.8
Share of time in total		
cost of schooling	90%	90%
Growth rate of GDP per worker	2%	2%
Earnings ratios by schooling level	See Figure 6	

Table 3: Decomposing the Role of Skill-Bias Technology and TFP - I

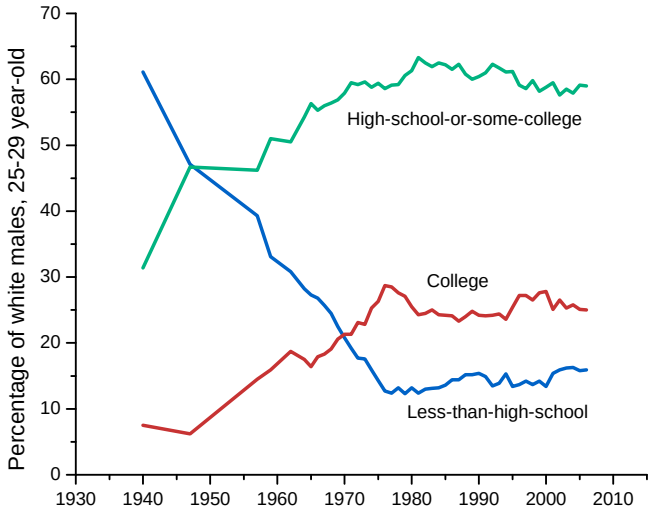
	Baseline	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5
Years of Schooling						
2000	13.85	13.16	13.14	12.55	13.16	12.97
1940	9.38	12.01	10.03	12.55	10.61	9.18
Ratio	1.48	1.10	1.31	1.00	1.24	1.41
Ratio of Relative Earnings 2000/1940						
College/HS (*)	1.38	1.38	1.00	1.00	1.17	1.38
HS/Less HS (**)	1.36	1.00	1.36	1.00	1.16	1.36
Average Growth (%)						
GDP per Worker	2.00	1.26	1.96	1.18	1.84	0.64

Note – Exp. 1: No High-School bias i.e., $g_2 = 1.0$ and g_3 is adjusted such that g_3/g_2 remains as in the baseline case. Exp. 2: No College bias i.e., $g_3 = g_2 = 1.0045$. Exp. 3: No technical bias e.g., $g_2 = g_3 = 1.0$. Exp. 4: Half the High-School bias i.e., the growth rate of z_2 is divided by two and g_3. Exp. 5: No TFP i.e., $g = 1.0$. (*) the ratio is $\hat{E}_{32,2000}(\theta)/\hat{E}_{32,1940}(\theta)$; (**) the ratio is $\hat{E}_{21,2000}(\theta)/\hat{E}_{21,1940}(\theta)$.

Table 4: Sensitivity Analysis – Elasticity of Substitution across Skill Groups (ρ)

Exercise	$p_{2,1940}$	$p_{3,1940}$	$z_2(2000)$ $z_2(1940)$ g_2	$z_3(2000)$ $z_3(1940)$ g_3	$z(2000)$ $z(1940)$ g	μ σ η
$\rho = 1.0$, Baseline	0.0863	0.0043	1.3707	1.7761	1.0000	2.1652
			1.0473	1.0243	0.5384	0.6236
			1.0045	1.0092	1.0104	0.8770
$\rho = 1.0$, Steady State	0.1459	0.0058	1.3620	1.7740	1.0000	1.6354
			1.0663	1.0530	0.5011	0.6690
			1.0041	1.0087	1.0116	0.8507
$\rho = 0.8$, Steady State	0.1459	0.0058	1.5869	2.3278	1.0000	1.6354
			1.1562	1.1854	0.5504	0.6690
			1.0053	1.0113	1.0100	0.8507
$\rho = 0.6$, Steady State	0.1459	0.0058	2.0474	3.6611	1.0000	1.6354
			1.3232	1.4440	0.6437	0.6690
			1.0073	1.0156	1.0074	0.8507
$\rho = 0.4$, Steady State	0.1459	0.0058	3.4080	9.0558	1.0000	1.6354
			1.7330	2.1429	0.8805	0.6690
			1.0113	1.0243	1.0021	0.8507

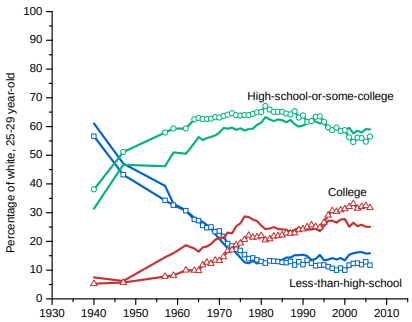
Figure 1: The Evolution of Educational Attainment for White Males, 25-29



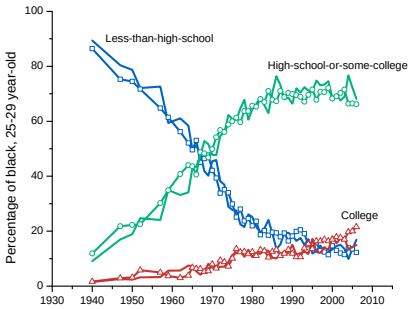
Note – See the appendix for the source of data and definitions.

Figure 2: The Evolution of Educational Attainment

- White -

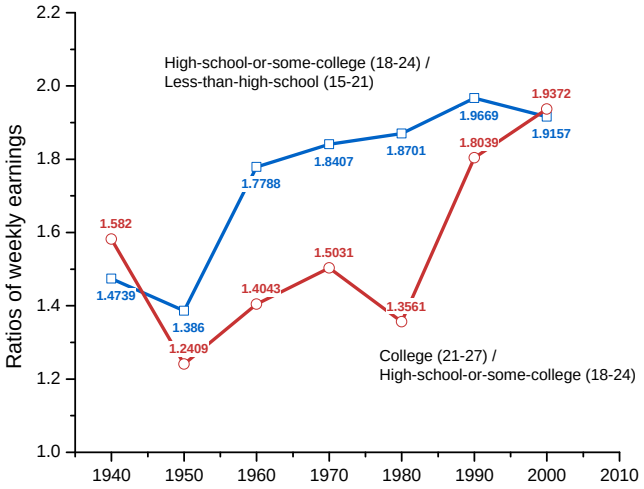


- Black -



Note – See the appendix for the source of data and definitions. Women are represented with markers and men with solid lines.

Figure 3: Ratio of Weekly Earnings for Educational Groups – White Males



Note – See the appendix for the source of data and definitions.

Figure 4: Individual Decision Problem

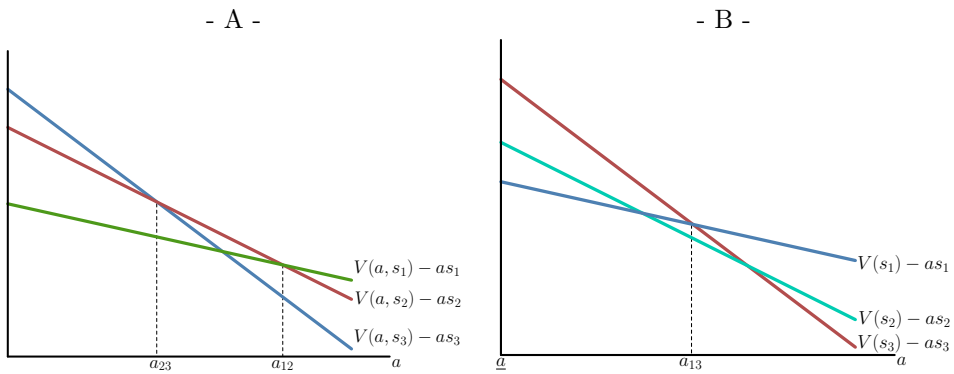


Figure 5: The Distribution of Schooling Attainment

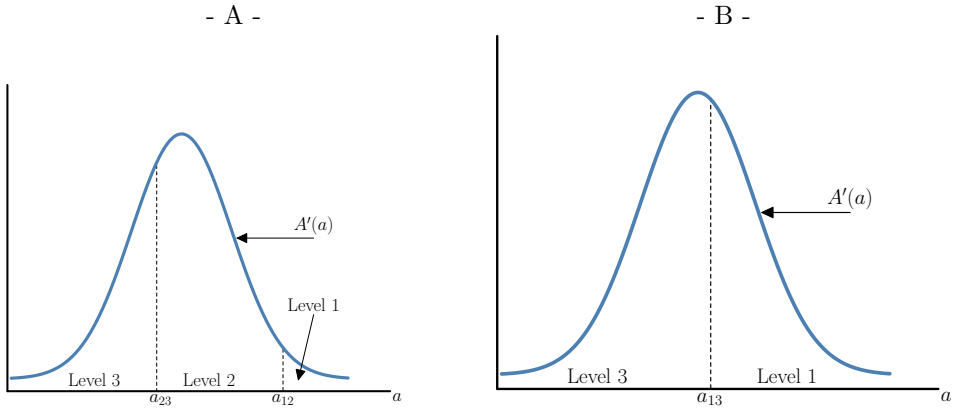
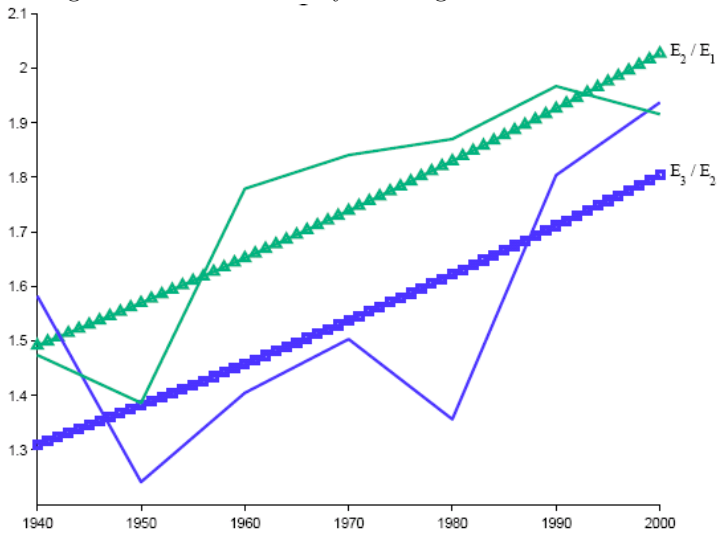
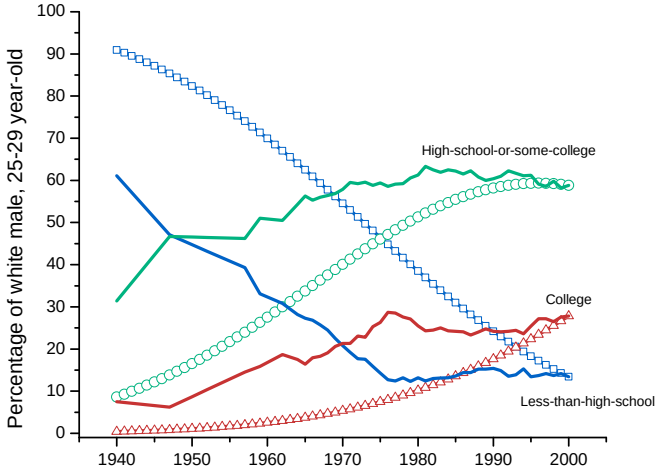


Figure 6: Relative Weekly Earnings – Model vs. Data



Note – The model data are represented with markers. The U.S. data are represented by solid lines.

Figure 7: Educational Attainment – Model vs. Data



Note – The model data are represented with markers. The U.S. data are represented by solid lines.

Figure 8: Average Years of Schooling – Model Calibrated 1940 vs. Data

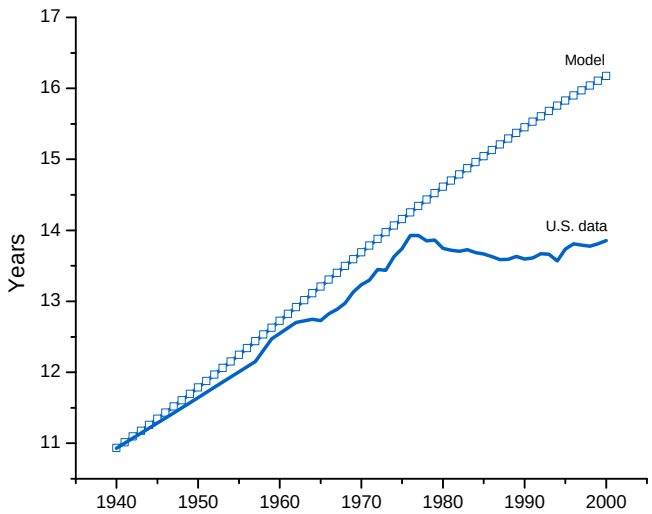
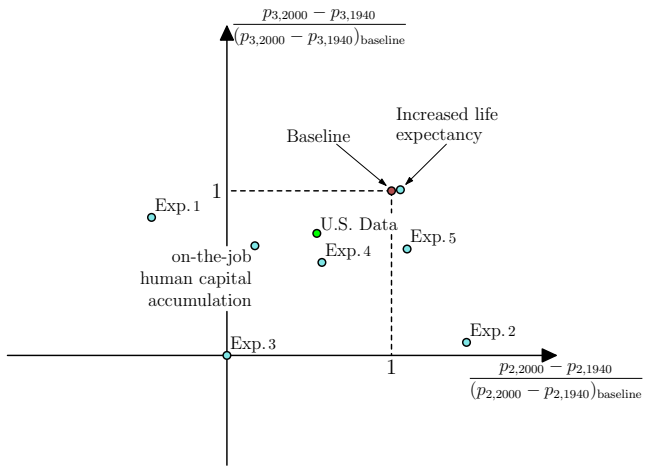
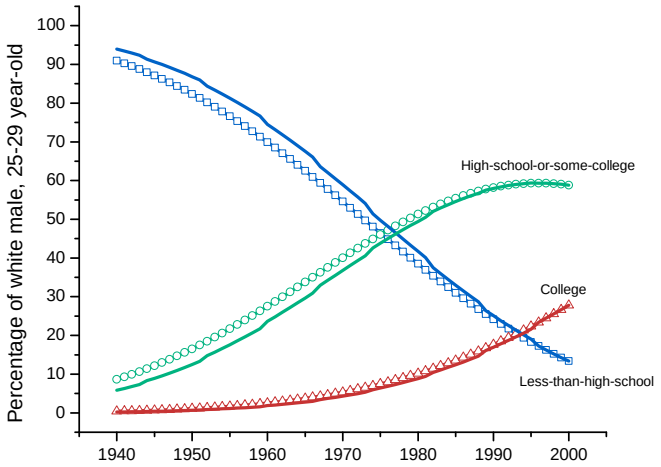


Figure 9: Decomposing the Role of Skill-Bias Technology and TFP - II



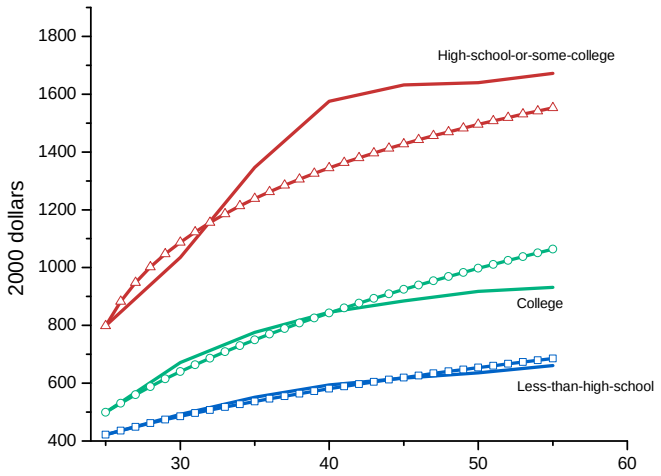
Note – Exp. 1: No High-School bias i.e., $g_2 = 1.0$ and g_3 is adjusted such that g_3/g_2 remains as in the baseline case. Exp. 2: No College bias i.e., $g_3 = g_2 = 1.0045$. Exp. 3: No technical bias e.g., $g_2 = g_3 = 1.0$. Exp. 4: Half the High-School bias i.e., the growth rate of z_2 is divided by two and g_3 is adjusted. Exp. 5: No TFP i.e., $g = 1.0$.

Figure 10: Educational Attainment – Baseline vs. Life Expectancy Change



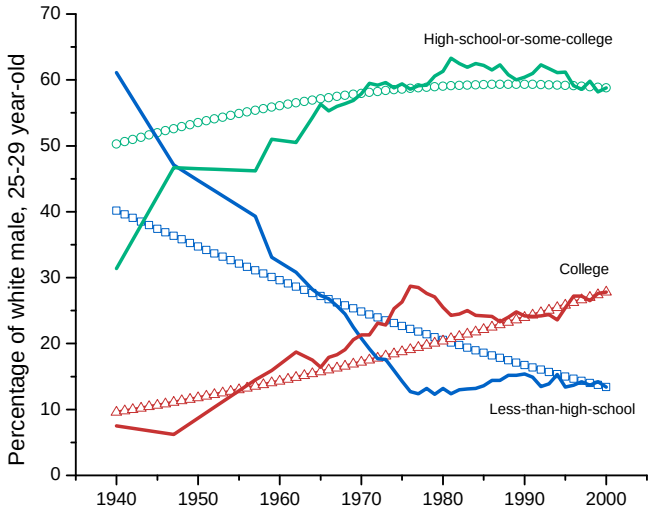
Note – The baseline calibration data are represented with markers. The calibration with increasing life expectancy is represented by solid lines.

Figure 11: Age Profile of Earnings – Model vs. Data



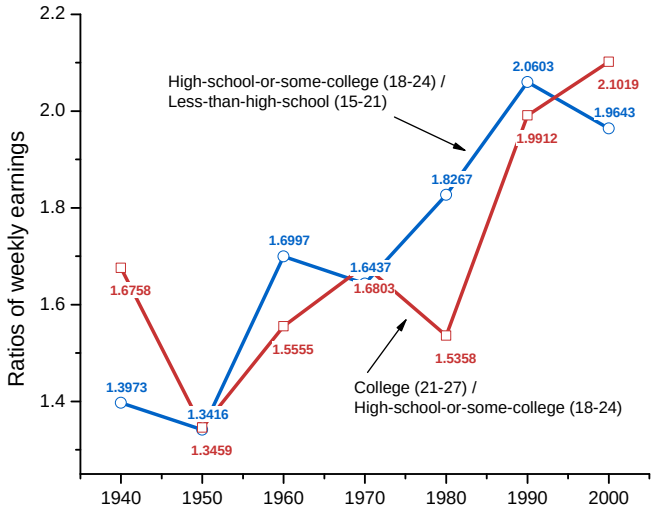
Note – The U.S. data are represented with markers. The model data are represented by solid lines. For each education group the model is normalized to equal the age-25 data point. See appendix B for details.

Figure 12: Educational Attainment with On-the-job Human Capital – Model vs. Data



Note – The model data are represented with markers. The U.S. data are represented by solid lines.

Figure 13: Ratio of Weekly Earnings for Educational Groups – White Women



Note – The source of data is the U.S. Census. We use the exact same approach as the one described in Appendix A to build the series of relative earnings.