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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? Using a simple model of schooling decisions, we assess the quantitative contribution of changes in the return to schooling in explaining the evolution of education. We restrict changes in the returns to schooling to match data on earnings across educational groups and growth in aggregate labor productivity. These restrictions imply modest increases in returns that nevertheless generate a substantial increase in educational attainment: average years of schooling increase by 37 percent in the model compared to 23 percent in the data. This strong quantitative effect is robust to relevant variations of the model including allowing for changes in the relative cost of acquiring education. We also find that the substantial increase in life expectancy observed during the period contributed to only 7 percent of the change in educational attainment in the model.

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 8 percent of white males aged 25 to 29 had completed a college education, 31 percent had a high-school degree but did not finish college, and 61 percent did not even complete high-school.[1] The picture is remarkably different in 2000 when 28 percent completed college, 62 percent completed high-school, and 11 percent did not complete high-school. Although our focus in this paper is on white males, Figure 1 shows that these trends are broadly shared across genders and races. The question we address in this paper is: What caused this substantial and systematic rise of 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 and developing countries.

There are several potential explanations for the trends in educational attainment. Changes in the direct or indirect costs of schooling, changes in credit constraints for schooling investment that operate from the relationship between family income and education of children, changes in social norms, changes in life expectancy which increase the effective return of schooling investment, changes in earnings uncertainty, and changes in the returns to schooling. Although we think that each and every one of these explanations are important and deserve a quantitative exploration, in this paper, we focus on assessing the quantitative effect of changes in the returns to schooling. This focus is motivated by empirical evidence that has identified systematic changes in the returns to education between 1940 and 2000 in the United States and by quantitative research showing a substantial response of educational attainment to long-run changes in the returns to schooling.[2] To illustrate the changes in the returns to schooling, we use the IPUMS samples for the 1940 to 2000 U.S. Census to compute earnings of full-time employed white males workers of a given cohort across three educational groups: less than high-school, high-school, and college.[3] Relative earnings among educational groups exhibit noticeable changes. For instance, earnings of college relative to high-school increased by 5 percent between 1940 and 2000 (from 1.30 in 1940 to 1.37 in 2000), while the relative earnings of high-school to less than high-school increased by 10 percent (from 1.31 in 1940 to 1.43 in 2000).[4]

We develop a model of human capital accumulation that builds upon Becker

[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] See for instance Heckman, Lochner and Todd (2003) for empirical evidence and Keane and Wolpin (1997), Restuccia and Urrutia (2004), and the references therein for quantitative analysis.

[3] We will refer to earnings, wages, and income interchangeably.

[4] For a related documentation of these facts see Acemoglu (2002).Heckman, Lochner and Todd (2003) summarize empirical estimates of changes in the returns to schooling using Mincer regressions.

(1964) and Ben-Porath (1967). The model features discrete schooling choices, heterogeneity in schooling utility, a standard human capital production function that requires the inputs of time and goods, and exogenous driving forces that take the form of neutral and skill-biased productivity parameters in the production function. Discrete schooling choice allows the model to better match the distribution of people across years of schooling in the data which is strongly concentrated around years of degree completion. Hence, discrete schooling choice allows the model to match distribution statistics such as those presented in Figure 1 as opposed to just averages for a representative agent. The assumption that agents are heterogeneous in the marginal utility from schooling time 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).[5] 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.

We implement a quantitative experiment to assess the importance of changes in relative earnings on the rise of educational attainment. We discipline the exogenous variables in the model –the pace of technical change– by using data on relative earnings among workers of different schooling groups. More generally, the parameters of the model are chosen to match a set of key statistics, including educational attainment in 2000, earnings differentials across schooling levels from 1940 to 2000, and the average growth rate of gross domestic product (GDP) per worker between 1940 and 2000. This quantitative strategy follows the approach advocated by Kydland and Prescott (1996). In particular, we emphasize that the parameter values are not chosen to fit the data on educational attainment from 1940 to 2000, instead they are chosen to mimic the trends in relative earnings. The answer to the quantitative importance of changes in relative earnings over time is measured by the capacity of the model to generate substantial trends in educational attainment as observed in the data.

Our findings can be summarized as follows. First, changes in relative earnings across schooling groups generate a substantial increase in educational attainment. As a summary statistic, the model generates a 37 percent increase in average years of schooling between 1940 and 2000 compared to a corresponding 23 percent increase in the U.S. data. The bulk of this increase in the model is generated by the change in high-school relative earnings. Second, we show that the quantitative effects of changes in the returns to schooling are remarkably robust to relevant variations of model specification and calibration targets. The main quantitative results are also robust to model extensions that incorporate alternative explanations for the increase in education such as changes in the effective cost of acquiring education.

Our paper is closely related to Heckman, Lochner, and Taber (1998) which

[5] 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.

focus on explaining the increase in the U.S. college wage premium in the recent past.[6] Our emphasis instead is on understanding the rise in educational attainment, both at the college and high-school level, conditional on matching the changes in the returns to schooling. This distinction is critical since we find that the increase in the relative high-school earnings is crucial in generating a substantial increase in educational attainment. Moreover, the exercise in Heckman, Lochner, and Taber (1998) is not designed to decompose the forces that explain the increase in educational attainment over time. Our work also contributes to a literature in macroeconomics assessing the role of technical progress on a variety of trends.[7] Our paper is also related to the labor literature emphasizing the connection between technology and education such as Goldin and Katz (2008) and the literature on wage inequality emphasizing skill-biased technical change.[8] We recognize that changes in the returns to education may not be the only explanation for rising education during this period. For instance Glomm and Ravikumar (2001) emphasize the rise in public-sector provision of education. We also recognize that educational attainment was rising well before 1940 and that changes in the returns to education may not be a contributing factor during the earlier period. Our focus on the period between 1940 and 2000 follows from data restrictions and the emphasis in the labor literature on rising returns to education as the likely cause of rising wage inequality. In the broader historical context, other factors may be more important such as the development of educational institutions and declines in schooling costs.[9]

The paper proceeds as follows. In the next section we describe the model. In Section 3 we conduct the main quantitative experiments. Section 4 extends the model to allow for changes in life expectancy, returns to experience, TFP-level effects, and changes in costs of education not modeled in our baseline version. In Section 5 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 6.

2 Model

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 con-

[6] See also Topel (1997), He (2006), and He and Liu (2008).
[7] See Greenwood and Seshadri (2005) and the references therein.
[8] See for instance Juhn, Murphy, and Pierce (1993) and Katz and Author (1999).
[9] See for instance Goldin and Katz (2008) and Kaboski (2004).

sumption decisions are made. We also assume that there is no uncertainty.

The human capital of an individual is denoted by $h(s, e)$ where s represents the number of periods spent in school and e represents services affecting the quality of education. We denote by q the relative price of education services. 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 $s_i \in \{s_1, s_2, s_3\}$ periods in school and, therefore, is not able to work before reaching 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 category discussed previously. Similarly, level 2 corresponds to the high-school category and level 3 to college. Aggregate human capital results from the proper aggregation of individual's human capital across generations and educational attainment. Human capital is the only input in 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. This is to allow for the possibility that technological progress affects the relative returns across schooling groups. Credit markets are perfect and r denotes the gross rate of interest.

2.2 Technology

At each date, there is one good produced with a constant-returns-to-scale technology. This technology is linear in the aggregate human capital input,

$$Y_t = z_t H_t,$$

where z_t is total factor productivity. The stock of aggregate human capital, H_t, is also linear

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

where H_{it} is the stock of human capital supplied by agents with schooling s_i, and z_{it} is a skill-specific productivity parameter. These linearity assumptions do not affect the main quantitative results of the paper but simplify the exposition and computation of the model. In Section 5 we discuss the implications of the model with different assumptions on the elasticities of substitution across schooling groups.

The technical parameters z_t and z_{it} are the only exogenous variables in the economy. Since our focus is on long-run trends, we assume constant growth rates:

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

Equation (1) implies that the following normalization is innocuous: $z_{1t} = 1$ for 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.

We consider a market arrangement where there is a large number of competitive firms in both product and factor markets that have access to the production technology. Taking the output good as the numéraire, the wage rate per unit of human capital is given by

$$w_t(s_i) = z_t z_i.$$

The youngest worker of type i at date t is of age $s_i + 1$ and thus, was "born" in period $t - s_i$, i.e. of age 1 at date $t - s_i$. The oldest worker is T-period old and was born in period $t - T + 1$. Thus,

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

where $p_{i\tau}$ is the fraction of cohort τ that has attained the ith level of education, and $e_\tau(s_i)$ is the optimal schooling quality of this cohort. The discussions of $e_\tau(s_i)$ and $p_{i\tau}$ are postponed to Sections 2.3 and 2.4.

2.3 Households

Preferences are defined over consumption sequences and time spent in school. They are represented by the following utility function, for an agent of cohort τ:

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

where $\beta \in (0, 1)$ is the subjective discount factor, $c_{\tau,t}$ is the period-t consumption of an agent of generation τ and, finally, $s \in \{s_1, s_2, s_3\}$ represents 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. While the shape of this distribution is important for assessing the quantitative role of changes in relative earnings on educational attainment, the normal distribution fits our calibration targets very well. In addition, in Section 5 we show that, in order to fit the same data, the calibration of a more general distribution function essentially renders back a normal distribution. As a result, a more general 2-parameter distribution yields the same quantitative results in terms of the elasticity of educational attainment to relative earnings.

The optimization problem of a cohort-τ individual with cost of schooling a, conditional on going to school for s periods, is

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

subject to

$$\begin{aligned}
\sum_{t=\tau}^{\tau+T-1}\left(\frac{1}{r}\right)^{t-\tau} c_{\tau,t} &= h(s,e_\tau)W_\tau(s) - qe_\tau, \\
W_\tau(s) &= \sum_{t=\tau+s}^{\tau+T-1} w_t(s)\left(\frac{1}{r}\right)^{t-\tau}, \\
h(s,e) &= s^\eta e^{1-\eta}
\end{aligned}$$

where $\eta \in (0,1)$. The maximization is with respect to sequences of consumption and the quality of education e_τ. The budget constraint equates the date-τ value of consumption to the date-τ value of labor earnings, $h(s,e_\tau)W_\tau(s)$, net of investment in quality, qe_τ. The function $W_\tau(s)$ indicates the date-τ value of labor earnings per unit of human capital. This program summarizes the various costs associated with acquiring education: the utility cost a, the time cost embodied in the definition of $W_\tau(s)$, and the resource cost qe_τ.

An agent of generation τ chooses s to solve

$$\max_{s\in\{s_1,s_2,s_3\}} \tilde{V}_\tau(a,s). \tag{2}$$

This problem can be solved in steps. First, given s, the individual chooses e_τ to maximizes net lifetime earnings. Then, given net lifetime earnings, the individual allocates consumption through time using the credit markets. Finally, the individual chooses s. Hence, conditional on s, the optimal investment in quality, for an agent of cohort τ is

$$e_\tau(s) = \arg\max_e\{h(s,e)W_\tau(s) - qe\},$$

which yields

$$e_\tau(s) = s[q^{-1}W_\tau(s)(1-\eta)]^{1/\eta}.$$

The optimal amount of human capital is

$$h(s,e_\tau(s)) = s[q^{-1}W_\tau(s)(1-\eta)]^{(1-\eta)/\eta}. \tag{3}$$

For later reference, we define the period t labor income of an agent of cohort τ with education s_i as

$$L_{i,\tau,t} = h\left(s_i, e_\tau(s_i)\right) w_t(s_i),$$

for $t \geq \tau + s_i$. The net lifetime income of an agent of cohort τ is $I_\tau(s) = h(s,e_\tau(s))W_\tau(s) - qe_\tau(s)$ or

$$I_\tau(s) = \kappa s W_\tau(s)^{1/\eta} q^{1-1/\eta}, \tag{4}$$

where $\kappa = (1-\eta)^{(1-\eta)/\eta} - (1-\eta)^{1/\eta}$. The optimal allocation of consumption over time, given $I_\tau(s)$, is dictated by the Euler equation, $c_{\tau,t+1} = \beta r c_{\tau,t}$, and the lifetime budget constraint. It is convenient to define $V_\tau(s) \equiv \tilde{V}_\tau(a,s) + as$.

The function $V_\tau(s)$ is the lifetime utility derived from consumption only, for an agent of cohort τ with s periods of schooling, and is not a function of a. The optimal schooling choice described in (2) can then be written as

$$\max_{s \in \{s_1, s_2, s_3\}} \{V_\tau(s) - as\}. \tag{5}$$

2.4 Equilibrium

An equilibrium is a sequence of prices $\{w_t(s_i)\}$ and an allocation of households across schooling levels such that, for all t, $w_t(s_i) = z_t z_{it}$ and households of any cohort τ solve problem (2) given prices.

In equilibrium each cohort is partitioned between the three levels of schooling. The determination of this partition is described in Figures 2 and 3. Figure 2 describes an individual's optimal schooling choice by comparing the value functions $V_\tau(s) - as$ across the three levels s_1, s_2 and s_3. Each pair of value functions has one intersection.[10] An individual of type a chooses the schooling level which delivers the highest value. Specifically, consider an individual choosing between s_i and s_j, with $i > j$ and $i, j \in \{1, 2, 3\}$. The individual chooses s_i over s_j whenever the individual's utility cost of schooling is low enough, that is whenever $a < a_{ij,\tau}$ where $a_{ij,\tau}$ is a threshold utility cost for which an individual with such utility cost of schooling is indifferent between level i and j:[11]

$$V_\tau(s_i) - a_{ij,\tau} s_i = V_\tau(s_j) - a_{ij,\tau} s_j.$$

The educational attainment rates of cohort τ, denoted by $p_{i\tau}$, are then

$$\begin{aligned} p_{1\tau} &= 1 - A(a_{21,\tau}), & (6)\\ p_{2\tau} &= A(a_{21,\tau}) - A(a_{32,\tau}), & (7)\\ p_{3\tau} &= A(a_{32,\tau}), & (8) \end{aligned}$$

as illustrated in Figure 3.[12]

It is possible to characterize the threshold utility costs as functions of the fundamentals. First, we can show that

$$a_{ij,\tau} = \frac{1 - \beta^T}{1 - \beta} \times \frac{1}{s_i - s_j} \times \ln\left(\frac{I_\tau(s_i)}{I_\tau(s_j)}\right). \tag{9}$$

[10] The implication that there exist one intersection between each pair of value functions is a result of the infinite support for a and the fact that $s_3 > s_2 > s_1$.

[11] Since individuals are indexed by their utility cost of schooling we also refer to the threshold a_{ij} as the critical agent.

[12] The infinite support for a ensures that there is always a non-empty set of individuals choosing the first level of schooling and another non-empty set of individuals choosing the third level. It is possible, however, that no individual finds it optimal to choose the second level. In such case, there is only one critical agent, $a_{31,\tau}$, defined by $V_\tau(s_3) - a_{31,\tau} s_3 = V_\tau(s_1) - a_{31,\tau} s_1$. We do not emphasize this case since it does not arise in our main quantitative work.

Furthermore, given the assumption of constant growth, we obtain from Equation (4) that

$$\frac{I_\tau(s_i)}{I_\tau(s_j)} = \chi \left(\frac{z_{i\tau}}{z_{j\tau}}\right)^{1/\eta} \tag{10}$$

where χ is a constant given by

$$\chi = \frac{s_i}{s_j}\left(\frac{1-gg_j/r}{1-gg_i/r} \times \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{(gg_j/r)^{s_j} - (gg_j/r)^T}\right)^{1/\eta}.$$

Equations (9) and (10) indicate the forces that determine the level of educational attainment at a point in time and its evolution over time. We emphasize the following properties of the determination of educational attainment.

Remark 1 Equation (9) establishes that the threshold utility costs are proportional to the semi-elasticity of net lifetime income across educational attainment levels. For instance, an increase in the lifetime income of college relative to high-school raises the threshold utility cost for entering college and, given a distribution of people across schooling-utility costs, more individuals choose to attend college. The change in college attainment depends on the magnitude of the change in the threshold as well as the shape of the distribution A of schooling-utility cost.

Remark 2 Equation (10) establishes that changes in relative lifetime income are driven only by the change in the ratio $z_{i\tau}/z_{j\tau}$. Combining (6) and (7) with (9) and (10), we obtain expressions for the change in the distribution of educational attainment over time for college and less than high school,

$$\frac{dp_{3\tau}}{d\tau} = A'(a_{32,\tau}) \times \frac{1-\beta^T}{1-\beta} \times \frac{1}{s_3 - s_2} \times \frac{\ln(g_3) - \ln(g_2)}{\eta},$$

and

$$\frac{dp_{1\tau}}{d\tau} = -A'(a_{21,\tau}) \times \frac{1-\beta^T}{1-\beta} \times \frac{1}{s_2 - s_1} \times \frac{\ln(g_2) - \ln(g_1)}{\eta}.$$

When there is no skill biased technical progress (i.e., $g_1 = g_2 = g_3$), the ratio of lifetime incomes are constant across education groups and, therefore, as indicated by the above expressions, there are no changes in educational attainment across generations. When $g_1 < g_2 < g_3$, there are changes in the returns to schooling and therefore educational attainment changes: more individuals choose to attend college and less choose less than high-school. The pace of these changes is not constant, and the magnitude of change depends critically on the distribution A of schooling-utility cost.

Remark 3 Constant growth in total factor productivity z_t generates growth in output per capita but no changes in educational attainment. Individuals accumulate more human capital as the economy grows, however, by purchasing more educational services e, a fact that transpires from Equation (3). In Section 4.3, we consider an extension of the model to allow for TFP-level effects and show that our main results still hold under this more general specification.

Remark 4 The relative price of education q does not affect educational attainment because it is assumed constant across education groups. In Section 4.4 we discuss the quantitative implications of allowing for time-varying and skill-dependent prices for educational services.

Remark 5 The threshold schooling-utility costs in equation (9) are not directly affected by the distribution A of schooling-utility costs in the population. This property has two important implications. First, the distribution A of schooling-utility costs can be disciplined by data on the distribution of educational attainment at a point in time and we use this implication in our calibration strategy. Second, changes in the returns to education have a direct impact on the schooling-cost thresholds but their effect on educational attainment hinges critically on the shape of the distribution A. This will explain why our main quantitative results are so robust to relevant variations in the model and to modeling alternative economic forces.

3 Quantitative Analysis

In this section we discuss the calibration and main quantitative results. The calibration strategy 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 GDP 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 measures of the main driving forces. These measures are derived by having the model match the changes in relative earnings. We then assess the quantitative contribution of changes in returns to education in explaining the rise in educational attainment in the U.S. economy.

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. Thus, the generation reaching age 25 in 2000 makes decision in 1981. The length of model life is set to $T = 67$, which corresponds to the life expectancy at age 5, for white males in 1981. We set the gross interest rate to $r = 1.04$, and the subjective discount factor to $\beta = 1/r$.

The number of years spent in school for the average member of each of our three groups has not been constant between 1940 and 2000. Using the IPUMS samples for the 1940 and 2000 U.S. Census, we find that the average number of years spent in school, by an individual of the first group, was 8.5 in 1940 and 9.4 in 2000. For and individual of the second group, we find an increase from 12.5 to 13, between 1940 and 2000. We allow years of schooling to vary in line with these findings. Namely, we set $s_{1,1921} = 8.5$ and $s_{1,1981} = 9.4$, and allow for a constant rate of growth between the two dates. Similarly, we set $s_{2,1921} = 12.5$ and $s_{2,1981} = 13$. We set $s_3 = 16$ for all years.

The list of remaining parameters is

$$\theta = (\mu, \sigma, \eta, q, g, g_{z_2}, g_{z_3}, z_{2,2000}, z_{3,2000})$$

which consists of the distribution parameters for the utility cost of schooling, the human capital technology, the relative price of education services and growth rates and levels for productivity variables. We build a measure of the distance between statistics in the model and the corresponding statistics in the U.S. data. The procedure targets the following statistics: (i) the educational attainment of the 25-29 years old in the 2000 Census which are 10.9 percent less than high-school and 61.5 percent high-school;[13] (ii) a share of time in the total cost of education in 2000 of 90 percent – see for instance Bils and Klenow (2000); (iii) the ratio of the cost of education to output in 2000 which is 7.2 percent – see Snyder, Dillow, and Hoffman (2009); (iv) the time path of relative earnings from 1940 to 2000; and (v) the growth rate of GDP per worker from 1940 to 2000 which was on average 2 percent. We then choose each element of θ simultaneously to minimize this function.

Even though parameter values are chosen simultaneously to match the data targets in (i) to (v), each parameter has a first-order effect on some target. For instance, the levels of skill-biased technology, $z_{i,2000}$, and their growth rates, g_i, are important in matching the time path of relative earnings across schooling groups. The growth of Total Factor Productivity, g, is important in matching growth in average labor productivity. The time share η is important for the share of time in human capital accumulation.[14] The utility cost of schooling parameters, μ and σ, are crucial in matching the distribution of educational attainment in 2000. Finally, the relative price of education services, q, determines the cost-of-education to output ratio.

The calibration procedure can be described formally as follows. Given a value for θ we compute an equilibrium and define the following objects. First,

$$\hat{E}_{ij,t}(\theta) = \frac{\sum_{k=20}^{24} L_{i,t-k,t}}{\sum_{k=20}^{24} L_{j,t-k,t}}$$

[13] The model counterpart to these statistics is educational attainment of the 1981 generation which is 20 years old in 2000 in the model and corresponds to age 25 in the U.S. data.

[14] It turns out that because the model abstracts from TFP-level effects, the shares of time and goods in the production of human capital are irrelevant for the quantitative properties of the baseline model. They do affect the earnings of a given schooling group across cohorts.

is the ratio of earnings between members of group i and j, between the age of 25 and 29 (that is 25-29 in the data) at date t. The empirical counterpart of $\hat{E}_{32,t}(\theta)$ is the relative earnings between college and high-school, for white males between the age of 25 and 29, denoted by $E_{32,t}$. Similarly, $\hat{E}_{21,t}(\theta)$ is the model counterpart of $E_{21,t}$, the relative earnings of high-school to less than high-school. Second, we define

$$M(\theta) = \begin{bmatrix} p_{1,81} - 0.109 \\ p_{2,81} - 0.615 \\ x_{81} - 0.90 \\ Y_{00}/Y_{40} - 1.02^{60} \\ \sum_i p_{i,00} e_{00}(s_i)/s_i/Y_{00} - 0.072 \end{bmatrix}$$

where x_t is the average share of time in the total cost of education and $\sum_i p_{i,00} e_{00}(s_i)/s_i$ is a measure of the annual cost of education.[15] Then, to assign a value to θ we solve the following minimization problem

$$\min_{\theta} \sum_{t \in \mathcal{T}} \left(\hat{E}_{32,t}(\theta)/E_{32,t} - 1 \right)^2 + \left(\hat{E}_{21,t}(\theta)/E_{21,t} - 1 \right)^2 + M(\theta)^\top M(\theta)$$

where $\mathcal{T} \equiv \{1940, 1950, \ldots, 2000\}$.

The second column of Table 1 indicates the value of the calibrated parameters. The model is able to match exactly the calibration targets in terms of the moments summarized in $M(\theta)$. Also, the model implies a smooth path of relative earnings that captures the trend observed in the data as illustrated in Figure 4.[16]

3.2 Baseline Experiment

The main quantitative implications of the model are the time paths for the distribution of educational attainment for the three categories considered: less than high-school, high-school, and college. Figure 5 reports these implications of the model. The model implies a substantial increase in educational attainment. The fraction of 25 to 29 year-olds with college education increases in the model by 25 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 11 to 61.5 percent between 1940 and 2000 whereas, in the data, the increase is from 31 to 61.5 percent.

[15] We compute x_t as

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

[16] Our specification of skill bias has 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 on educational attainment so the exact parametrization matters for the quantitative results. In Section 3.3 we discuss the results in light of different assumptions regarding skill-biased technology.

To summarize the quantitative findings of the model, we calculate average years of schooling of a given generation as the years of schooling required in 2000 in each educational category, multiplied by the distribution of educational attainment of the generation. We calculate average years of schooling for the model and the data as follows:

$$\sum_{i=1,2,3} s_{i,2000} p_{i\tau}$$

where p is the distribution of educational attainment. We refer to this statistic as average years of schooling. In the U.S. data average years of schooling increased by 23 percent, from 10.8 in 1940 to 13.3 in 2000. The model reproduces the average years of schooling in 2000 as it is a calibration target. The model implies an average years of schooling in 1940 of 9.7. Thus, by this measure, average years of schooling increase by a factor 1.37 in the model versus 1.23 in the U.S. data.

We chose the year 2000 for most of 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. Given this alternative calibration, the quantitative results are fairly similar, for instance, the increase in average years of schooling from 1940 to 2000 is 38 percent, close to the 37 percent increase in the baseline model calibrated to data in 2000.

3.3 Decomposing the Forces

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, we decompose the importance of the exogenous forces leading to labor productivity and earnings growth by running a sequence of counterfactual experiments. These experiments are reported in Table 2.

The first experiment is designed to assess the importance of the high-school bias in earnings. That is, we seek an answer to the question: what would educational attainment look like if the earnings of a member of group 2 grew at the same rate as those of a member of group 1, while the premium for a member of group 3 still behave as in the baseline case? In our model there are two sources of school-specific earnings bias: skill-biased technical change and within-group length of schooling. Denote by $\tilde{g}_{z_i}$ the growth rate of skill-biased technical change in the counterfactual experiment. Likewise, let $\tilde{g}_{s_i}$ be the growth rate of the length of schooling. To "shut down" the high-school bias in earnings we set: $\tilde{g}_{z_2} = \tilde{g}_{z_1} = 1$; $\tilde{g}_{z_3}/\tilde{g}_{z_2} = g_{z_3}/g_{z_2}$; $\tilde{g}_{s_2} = \tilde{g}_{s_1} = g_{s_1}$; and $\tilde{g}_{s_3}/\tilde{g}_{s_2} = g_{s_3}/g_{s_2}$. Measured by average years of schooling, the change in educational attainment falls to 2 percent from 37 percent in the baseline. Lower educational attainment growth leads to substantially lower labor productivity growth (1.7 vs 2 percent in the baseline).

The second experiment assesses the role of the college bias. We choose the growth rate of exogenous forces such that: $\tilde{g}_{z_2} = g_{z_2}$; $\tilde{g}_{z_3} = g_{z_2}$; $\tilde{g}_{s_2} = g_{s_2}$; and $\tilde{g}_{s_3} = g_{s_2}$. In this case the earnings of college relative to high-school does not change over time. The departure in this experiment, in terms of average educational attainment, is much less than in the previous experiment: average years of schooling increase by 27 percent instead of 37 percent in the baseline. Also, we note that the college bias does not contribute much to overall productivity growth since it grows at slightly less than 2 percent. In a third experiment, we shut down skill bias all together by imposing $g_{z_i} = g_{s_i} = 1$ for all levels. As discussed previously, the model without skill-biased technical change does not generate any change in educational attainment and relative earnings. As a consequence, labor productivity growth is slightly above the value of g. Given the results from these experiments, we conclude that, in terms of skill-biased 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).

We emphasize that the educational attainment implications of the model are sensitive to the calibration of skill-biased technical change. The baseline calibration captures the overall trend in relative earnings over the 1940 to 2000 period. However, this trend is calculated only over 7 Census years and there is substantial decade-to-decade variation in relative earnings. We illustrate the quantitative importance of the trends in relative earnings by conducting a fourth experiment were we reduce by one half the growth rate of relative earnings between 1940 and 2000. We set $\tilde{g}_{z_i} = 1 + (g_{z_i} - 1)/2$ for $i = 2, 3$ and $\tilde{g}_{s_i} = 1 + (g_{s_i} - 1)/2$ for $i = 1, 2, 3$. In this experiment, average years of schooling between 1940 to 2000 increase by 19 percent (versus 37 percent in the baseline), while average growth in GDP per worker is 1.86 percent (2 percent in the baseline).

4 Extensions

In this section we consider four extensions of the model mechanisms that can potentially affect the importance of relative earnings on educational attainment. First, we study a simulation of the model that allows for life expectancy to change according to data. Since there has been a substantial change in life expectancy for the relevant cohorts in the sample period we ask whether this can provide an important source of changes in educational attainment. Second, we incorporate on-the-job human capital accumulation into the model. Human capital accumulated on the job affects lifetime income and therefore can affect educational attainment. Third, in the spirit of Ben-Porath (1967), Manuelli and Seshadri (2006) and Erosa, Koreshkova, and Restuccia (2009), we extend the model to allow for TFP-level changes to affect schooling decisions. Finally, we allow for changes in the cost of education over time. In all these extensions, we find that the main conclusion that changes in the returns to education imply a substantial increase in educational attainment remains unaltered.

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 in promoting human capital investment. In this section we ask whether the increase in life expectancy is quantitatively important in explaining the increase in educational attainment and whether it dampens the contribution of relative earnings in our baseline model.

We proceed by simulating the model using the changes in life expectancy as observed in the data.[17] 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 relative to the baseline involve parameters pertaining to the distribution of utility cost of schooling and the growth rates of technology. Overall, 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. We make this assessment by comparing the implications on educational attainment of the model calibrated to the changes in life expectancy with the model keeping life expectancy constant at its 2000 level. The model with changes in life expectancy generates an increase of 42 percent in average years of schooling. Holding life expectancy constant reduces this increase to 39 percent, close to the baseline model. Hence, the change in life expectancy during this period explains 7 percent of the increase in educational attainment (3 percentage points out of 42). We conclude that while changes in life expectancy are substantial during this period, their effect on educational attainment are not quantitatively important. Moreover, the change in life expectancy does not affect the quantitative importance of returns to schooling.

[17] 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.)

4.2 On-the-job Human Capital Accumulation

The baseline model abstracts from human capital accumulated on the job. The data suggest that there are considerable returns to experience. The age profile of earnings, for example, are increasing in the data while our baseline model implies that they are decreasing. Returns to experience may affect educational decisions. First, if they 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-biased 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 whether on-the-job human capital accumulation affects the evolution of educational attainment over time.

We extend the model to consider the following human capital accumulation equation:

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

where $x = a - s$ measures years of experience and $\gamma(s)$ 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. This feature is motivated by the age profile of earnings observed in the year 2000. Namely, the ratios of earnings between a 55- and a 25-year old are 1.6, 1.9, and 2.1 for less than high-school, high-school, and college.

In our first pass at assessing the importance of returns to experience, we choose the three $\gamma(s_i)$'s to match the age profile of earnings in 2000.[18] In terms of educational attainment, the calibrated model with on-the-job human capital accumulation reduces the incentives to remain in school created by skill-biased technical progress. The average number of years of schooling increases from 10.4 in 1940 to 13.3 in 2000 – an increase of 27 percent which compares to 23 percent in the U.S. data and 37 percent in the baseline model. The calibrated returns to experience in this extension of the model dampen the incentives for schooling investment.

We note, however, that 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). To try and capture the effect of this decrease in returns to experience, we compare the life-profile of earnings of a 25 year old in 1940 versus a 25 year old in 1970 – see Table 3. A 25-year-old in 1940 can expect annual earnings to increase by a factor of at least 3.19 when reaching 55 years of age. In sharp contrast, a 25-year-old in 1970 should not expect earnings to increase by a factor of more than 2.25 when reaching 55. This "flattening" of the age profile of earnings does not affect equally all educational groups. In fact, the

[18] We recalibrate the model as described in Section 3.1, with three additional targets: the ratios of earnings between a 55- and a 25-year old in 2000 in each group. The calibrated parameters g, g_2, and g_3 are 1.014, 1.003, and 1.005. We find $\gamma(s_1) = 0.38$, $\gamma(s_2) = 0.44$ and $\gamma(s_3) = 0.33$ for the human capital elasticity of experience. The model matches the age profile of earnings in 2000 by construction.

increase in earnings throughout the life cycle is enhanced more by education for the 1970 cohort than for the 1940 cohort: A 25-year old in 1940 would see earnings increase 6 percent faster choosing high-school versus less than high-school. In 1970, the same individual would see earnings increase 30 percent faster by choosing high-school. The same result holds, qualitatively, for college versus high-school: for the 1940 generation, moving from high-school to college entails a 13 percent increase in earnings. In 1970 this move would entail a 52 percent increase.

We conclude that the flattening of the life profiles of earnings across generations is conducive to attracting recent generations into more schooling. We use the model to compute educational attainment for the 1940 and 1970 cohorts. Adjusting the $\gamma(s_i)$'s to allow for the flattening of the life profiles of earnings, we find that the implied increase in educational attainment is slightly above that of the baseline experiment that abstracts from returns to experience (37 percent). Hence, changes in relative earnings generate a substantial increase in educational attainment and this effect is robust to the incorporation of reasonable returns to experience in the data.

4.3 TFP-Level Effects

The baseline model abstracts from TFP-level effects. Since there is a literature that emphasizes TFP-level effects in explaining schooling differences across countries, we extend the model to allow for these effects. We follow Ben-Porath (1967) in allowing for TFP-level effects by extending our production function for human capital to include stages in human capital accumulation, where the human capital from previous schooling levels enters as an input in the production of human capital of the next level. In particular, we assume the following human capital technology:

$$h_i = (s_i h_{i-1})^{\eta} e_i^{1-\eta},$$

where $i \in \{1, 2, 3\}$ denotes the schooling stage and $h_0 = 1$. The lifetime net income of an agent of generation τ is then

$$I_\tau(s_i) = \max_{e_1, e_2, e_3 \geq 0} \{h_i W_\tau(s_i) - qe_1 - qe_2 - qe_3\}.$$

In this formulation, the efficiency units of labor of an agent are used either for producing goods in the market or for producing next stage human capital in school. This differs from the previous formulation where efficiency units of labor where used only in producing goods. The agent decides how much to spend at each level of schooling e_i. An implication of this extension is that a unit of spending in high-school quality increases the marginal productivity of spending in college. Thus, when the level of income rises because of TFP, a one percent increase in education quality affects income proportionately more at the highest level of education. Formally, we can show that $d \ln I(s_i)/d \ln z = \eta^{-i}$ while in the baseline model this elasticity is $1/\eta$ at each schooling level i.

We calibrate this version of the model exactly as described in Section 3.1. We find that the increase in average years of schooling in the model is 41 percent, slightly above the baseline model that abstracts from TFP-level effects where it is 37 percent. We then use this calibrated version of the model to compute the evolution of educational attainment predicted when skill-biased technical change is set to zero, that is when $g_{z_i} = g_{s_i} = 1.0$ for $i = 1, 2, 3$. Thus, TFP alone drives the results of this experiment. We find that average years of schooling increase by 13 percent and conclude that 31 percent (13/41) of the rise in average years of schooling is due to the increase in the TFP level.

4.4 The Cost of Education

In our baseline model the relative price of education services q is the same across education groups and constant over time. We assess how these assumptions may affect our results by considering two broad alternative specifications for the costs of education.

4.4.1 Schooling-Specific Technical Progress

We consider an extension of our baseline model where the relative price of education is different across schooling groups and is growing at different rates. Hence, the relative price of education is indexed by time τ and schooling level s_i: $q_{i\tau}$. Under this assumption, the optimal choice of the level of education services is characterized as the solution to

$$e_\tau(s_i) = \arg\max_e \{h(s_i, e) W_\tau(s_i) - q_{i\tau} e\}.$$

We note that the solution to this program is the same for the case where the human capital production function features investment-specific technical progress in the spirit of Greenwood, Hercowitz and Krusell (1997), e.g., $h\left(z_{i\tau}^h, s_i, e\right) = z_{i\tau}^h s_i^\eta e^{1-\eta}$ where $z_{i\tau}^h \equiv 1/q_{i\tau}$. Thus, in this extension of the model, changes in the relative price of education services are related to skill-biased technical progress.

As noted earlier, a critical determinant for the evolution of educational attainment in the model is the behavior of relative lifetime income, net of education costs. In this extension of the model, the equivalent to equation (10) is

$$\frac{I_\tau(s_i)}{I_\tau(s_j)} = \chi \left(\frac{z_{i\tau}}{z_{j\tau}}\right)^{1/\eta} \left(\frac{q_{i\tau}}{q_{j\tau}}\right)^{1-1/\eta}. \tag{11}$$

Observe that the relative price of schooling affects the returns to schooling. Thus, unlike in the preceding exercises, we cannot determine the effect of the returns to education independently of changes in the cost of education. We assume that the relative price of education changes at a constant rate g_{q_i} so that the price of education is characterized by a level and growth parameter:

$$q_{i\tau} = q_{i0} \times g_{q_i}^{\tau}.$$

We can establish the following results. First, when relative prices grow at the same rate across schooling groups, that is when $g_{q_1} = g_{q_2} = g_{q_3}$, it is possible to just adjust the levels of z_i's to match the same levels of relative earnings in the calibration. These adjustments would leave relative net lifetime income unchanged. As a result, in this case educational attainment would evolve exactly as in the baseline economy. Second, when relative prices grow at different rates, $g_{q_1} \neq g_{q_2} \neq g_{q_3}$, in order to calibrate the model to the same targets for relative earnings in the data, an adjustment to the levels and growth rates of the z_i's is necessary. In this case, relative net lifetime income will change. How does this affect our evaluation of the elasticity of educational attainment to changes in the returns to schooling? We assume that $q_{1\tau} = q_{2\tau}$ and as a result we have only four more parameters in the model: q_{20}, q_{30}, g_{q_2} and g_{q_3}. To discipline the level parameters, q_{20} and q_{30}, we use the ratio of the cost of education to output, as in our baseline calibration and the ratio of higher education expenditures to elementary and secondary expenditures that in 2000 was 0.60 for the U.S. economy. To restrict the growth parameters, we calculate using the Higher Education Price Index from Snyder, Dillow, and Hoffman (2009), that the cost of higher education has risen at a rate 1 percentage point above that of the GDP implicit price deflator. Hence, we set $g_{q_3} = 1.01$.[19] There is no price index for elementary and secondary education. Thus, we report the implications of two alternative values for g_{q_2}. In the first case, we set $g_{q_2} = 1.02$ and find that the model predicts an increase in average years of schooling of 34 percent. In the second case, we set $g_{q_2} = 0.98$ and find an increase in average years of schooling of 44 percent. We consider the second experiment more in line with the evidence since it implies that the cost of education to GDP in 1940 is 2.5 percent (3 percent in the U.S. data in 1949) whereas the alternative assumption implies a cost of education to GDP in 1940 of 25.5 percent.

We conclude that incorporating changes in the relative price of education, in line with empirical evidence, does not alter our main conclusion that observed changes in the returns to schooling generate large changes in educational attainment. Furthermore, our finding suggests that reasonably calibrated changes in the relative price of education strengthen the elasticity of educational attainment to returns to schooling.

4.4.2 Fixed Costs

In the preceding formulation, we have assumed that individuals choose the magnitude of all pecuniary costs associated with attaining an educational level. We consider an alternative formulation where some pecuniary costs of education might be beyond the control of individuals.

[19] See Snyder, Dillow, and Hoffman (2009), Tables 25 and 31. The Higher Education Price Index was computed only from 1960.

We start from our baseline model and assume that, in addition to education services purchased at price q, individuals must also pay a fixed cost in order to complete an educational level. Thus, the income maximization problem writes

$$e_\tau(s_i) = \arg\max_e \{h(s_i, e)W_\tau(s) - qe - k_{i\tau}\}.$$

We model fixed costs that vary across skill groups and over time as

$$k_{i\tau} = k_{i0} \times g_{k_i}^\tau$$

so that we have a level and growth parameter for each educational level. We assume $k_{1\tau} = k_{2\tau}$. We choose the levels k_{20} and k_{30} to match the cost of education to output ratio, and the the ratio of higher education expenditures to elementary and secondary expenditures. Since we interpret these fixed costs broadly, we do not have direct observations of them. Our objective is to evaluate their potential importance in biasing the quantitative assessment of the role of changes in returns to education. Therefore, we choose to discipline the growth parameters g_{k_2} and g_{k_3} such that our model is as close as possible to replicating the growth in observed educational attainment. This implies $g_{k_2} = 1.028$ and $g_{k_3} = 1.03$. A possible interpretation of these changes in schooling costs is that there are factors that have made education effectively more costly, specially for college. This interpretation is consistent with both the indirect evidence of a stronger relationship between family income and educational attainment over time in Belley and Lochner (2007) as well as the direct evidence suggesting an increase in tuition costs and an overall erosion of borrowing limits as summarized by Kane (2007). The model implies that average years of schooling increase by 24 percent (versus 23 percent in the U.S. data.) Figure 6 displays the model's predicted path for educational attainment with the U.S. data.[20]

We can now ask how these costs affect our evaluation of the effect of the returns to schooling on educational attainment. We do this by computing the path implied for educational attainment under the counterfactual assumption that the fixed costs of education remain constant (i.e., $g_{k_1} = g_{k_2} = g_{k_3} = 1.0$). Thus, this exercise measures the effect of changes in relative earnings alone. We find that average years of schooling increase by 40 percent. Recall that the baseline model implied an increase in average years of schooling of 37 percent.

We conclude that, although some explicit or implicit costs to education may be important for matching the evolution of educational attainment in the data, their abstraction does not alter our measure of the elasticity of educational attainment to changes in the returns to schooling. Assessing the specific forces such as borrowing constraints, earnings uncertainty, and direct costs among others, that have lead to an increase in the effective cost of education is an interesting question that we leave for future research.

[20]The calibrated parameters are $\mu = 0.62$, $\sigma = 0.69$, $\eta = 0.93$, $g_z = 1.01$, $g_{z_2} = 1.003$ and $g_{z_3} = 1.005$.

5 Discussion

In this section we evaluate the robustness of our main quantitative results to relevant variations in functional-form specifications. Namely, we introduce imperfect substitution across schooling groups in the output technology and we consider alternative distributions for the marginal utility of schooling. We find that the importance of changes in relative earnings in explaining the increase in educational attainment is remarkably robust to these variations.

5.1 Substitution across Schooling Groups

We emphasize that the technology for aggregate human capital allows perfect substitution between skill groups. This assumption is less problematic than it may first appear. The reason is that our results do not emphasize a particular quantitative elasticity of educational attainment to skill-biased technical change. Neither do they emphasize a tight measurement of skill-biased 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 changes in the returns to schooling – as measured by changes in relative earnings – on educational attainment. Our results do not hinge on what the sources of changes in returns to education are. Alternative technology specifications, for example, would require different measurements of the z_i's to match the same relative earnings paths. The discipline imposed on the quantitative results of the paper hinges on the relative earnings paths observed in the U.S. data.

The following exercise illustrates this 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 the baseline specification, and an increase in any given z_{it} affects the wage rate of all skill groups. The assumption that the elasticity of substitution is the same between any pair of skill groups may seem restrictive. Goldin and Katz (2008), for example, use different elasticity of substitution between pairs of skill groups. But again, once the model is restricted to match the relative earnings observed in the U.S. data, differences in technologies only imply different measurements for the z_i's, but do not affect educational attainment.

For simplicity, we consider a steady-state situation in levels, that is a situation where z_t and the z_{it}'s are constant through time.[21] An equilibrium is a set of prices, $w(s_i)$, and an allocation of individuals across schooling levels such

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

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

$$H_i = (T - s_i)h(s_i, e(s_i)),$$

for $i \in \{1, 2, 3\}$, and individuals solve problem (2) given prices. The first condition above equates the marginal product of human capital for skill group i to its wage rate. The second equation is the labor market clearing condition for skill group i.

The nature of the exercise is similar to that of Section 3.1. We proceed in two steps. First, we calibrate the steady state of the model to match the U.S. economy in 2000. We set the s_i to their corresponding values and r, β and T to their values in Table 1. We set z_1 and z to one. We have two targets for educational attainment rates, two for relative earnings and one for the share of time in the total cost of education. We pick five parameters to match these targets: $(\mu, \sigma, \eta, z_2, z_3)$. In a second step, we set the s_i's to their values for the 1940 generation and 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, this exercise uses the evolution of relative earnings to measure skill-specific technical change. We then ask by how much educational attainment is changing. We repeat this exercise for different values of ρ. This procedure delivers the equivalent of the baseline experiment described earlier.

Table 4 reports the results. For selected values for ρ, the table shows educational attainment in 1940, as well as the calibrated values of key parameters. By comparing across steady-state economies with different values for ρ, Table 4 shows that the elasticity of substitution does not affect the main conclusions. Once skill-biased technical parameters are calibrated to match the evolution of relative earnings, changes in educational attainment across different calibrations for ρ are 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-biased 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.

5.2 Distribution of Marginal Utility of Schooling

The model assumes a Normal distribution to represent heterogeneity in preferences. Are the results robust to this choice? Alternative distributional assumptions may deliver different implications for the evolution of educational attainment. In fact, changes in educational attainment depend on the distribution of the marginal cost of schooling time, as can be seen from Equations (6) to (8). To address this issue, we consider a more general distribution function: the Beta distribution. This distribution is defined on the unit interval and characterized by two parameters. Depending on the parameters, its density can be uniform, bell-shaped or u-shaped and it is not necessarily symmetric. Our question is whether the calibration described in Section 3.1 imposes enough discipline on the distribution of schooling utility so as to identify the elasticity of educational attainment to relative earnings.

We use the Beta distribution because it has two parameters and, therefore, we can keep our calibration strategy while allowing the distribution of schooling utility to be potentially different from a Normal. To make comparisons with the baseline case, where the marginal utility of schooling can take any value on the real line, we write the utility function of an agent born at τ as

$$\sum_{t=\tau}^{\tau+T-1} \beta^{t-\tau} \ln\left(c_{\tau,t}\right) - \left(Mb - \frac{M}{2}\right) s_{\tau}, \tag{12}$$

where b is distributed according to a Beta distribution and M is a positive number. Hence, the marginal utility of schooling time is $(Mb - M/2)$. The role of M is to map the domain of b into the interval $[-M/2, M/2]$, therefore allowing an arbitrarily large range for the marginal utility of schooling time.

We calibrate this version of the model as described in Section 3.1, for different values of M.[22] Thus, the distribution of a is subject to the same discipline as in our baseline exercise. We describe our findings in two steps. First, we find that for large enough values of M the mean and variance of the marginal utility of schooling are the same (up to the fifth digit) than in our baseline calibration. When we increase M, these number gets even closer. Second,

[22] Remark 5 of Section 2 plays a role here. Since the thresholds utility costs do not depend on the distribution, the same thresholds must hold under the current (Beta) model than under the baseline (Normal) model, for the 1981 generation. Hence, the parameters of the Beta distribution can be found by solving a system of two equations in two unknowns: given the thresholds, what is the Beta distribution which delivers the actual distribution of educational attainment for the 1981 generation?

we compute the sum of squared differences between the path of educational attainment obtained from the baseline (Normal) model and from the current (Beta) model. We find that the difference can be arbitrary small. For example, if $M = 500$, the difference is of the order of $2.5 \times 1.0e^{-9}$.[23] We conclude that our calibration strategy imposes sufficient discipline on the distribution of a so that the normality assumption used in the baseline is not critical per se in determining the elasticity of educational attainment to relative earnings.

6 Conclusion

We developed a model of schooling decisions to address the role of changes in the returns to education on the rise of educational attainment in the United States between 1940 and 2000. The model features discrete schooling choices and individual heterogeneity so that people sort themselves into the different schooling groups. In the model, skill-biased technical change increases the returns to schooling thereby creating an incentive for more people to attain higher levels of schooling. We find that changes in the returns to education generate a substantial increase in educational attainment and that this quantitative importance is robust to relevant variations in the model. We also found that the substantial changes in life expectancy in the data turn out to explain almost none of the change in educational attainment in the model.

There are several issues that would be worth exploring further. First, we have only slightly touched on the factors that can contribute to the slowdown in educational attainment since the late 70s. Assessing the contribution of rising college costs together with tighter borrowing constraints is important in addressing educational policy questions. Second, it would be interesting to assess the role of changes in the returns to education on educational attainment in other contexts such as across genders, races, and countries. For instance, it would be relevant to investigate changes in the returns to schooling in countries with different labor-market institutions. Institutions that compress wages may reduce the incentives for schooling investment and perhaps, holding other institutional aspects constant, this wage compression may explain the lower educational attainment in some European countries compared to the United States. Similarly, it is relevant to explore the changes in the returns to education for women in conjunction with the observed increase in labor market participation and the reduction in the gender wage gap. A quick look at the data suggests that changes in the returns to schooling for women have been similar than that of men. Hence, together with faster overall wage growth and an increase in labor market hours for women may explain the larger increase in educational

[23]We also compare the density functions obtained for the marginal utility of schooling in the baseline (Normal) model and the current (Beta) model. We do that by constructing a vector of $1,000$ equally spaced points within ± 5 standard deviations from the mean. At each point we calculate the density function for each model and compute the norm of the difference. We find differences of the order of $1.0e^{-5}$.

attainment observed for women between 1940 and 2000. Third, our analysis has taken the direction of technical change as given. It would be interesting to study quantitatively the process of human capital accumulation allowing for endogenous technical change in the spirit of Galor and Moav (2000). We leave all these relevant explorations for future research.

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Table 1: Calibrated Parameters

Interpretation	Parameters 2000 Calibration	Parmeters 1940 Calibration
Length of schooling		
s_1	$g_{s_1} = 1.0017$	
s_2	$g_{s_2} = 1.0007$	
s_3	$g_{s_3} = 1.0$	
Length of life	$T = 67$	
Interest rate	$r = 1.04$	
Subjective discount factor	$\beta = 1/r$	
Human capital technology	$\eta = 0.94$, $q = 0.46$	$\eta = 0.94$, $q = 0.95$
Distribution of a	$\mu = 0.94$, $\sigma = 0.48$	$\mu = 0.49$, $\sigma = 0.34$
Growth rates		
Neutral technology	$g \quad = 1.0150$	$g \quad = 1.0133$
HS biased technology	$g_{z_2} = 1.0033$	$g_{z_2} = 1.0033$
College biased technology	$g_{z_3} = 1.0049$	$g_{z_3} = 1.0049$

Table 2: Decomposing the Role of Skill-Biased Technology and TFP

	Baseline	Exp. 1	Exp. 2	Exp. 3	Exp. 4
Years of Schooling					
2000	13.30	12.34	12.82	12.07	12.71
1940	9.74	12.14	10.11	12.07	10.69
Ratio	1.37	1.02	1.27	1.00	1.19
Ratio of Relative Earnings 2000/1940					
College/HS	**1.07**	1.07	1.00	1.00	1.03
HS/Less HS	1.16	1.00	1.16	1.00	1.08
Average Growth (%)					
GDP per Worker	2.00	1.67	2.00	1.59	1.86

Note – Exp. 1: No high-school bias; Exp. 2: No college bias; Exp. 3: No skill biased technical change bias; Exp 4: Half the skill biases.
The figure 1.07 means that the ratio of earnings between college and high school is 7 percent higher in 2000 than in 1940.

Table 3: Ratio of Earnings Age 55 to Age 25

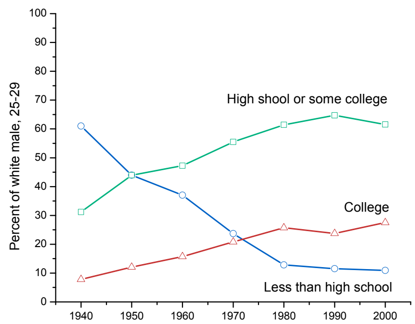
	Less than high-school	high-school	College
25 in 1940	3.19	3.39	3.86
		(= 3.19 × 1.06)	(= 3.39 × 1.13)
25 in 1970	1.14	1.48	2.25
		(= 1.14 × 1.30)	(= 1.48 × 1.52)

Note – The figures are the ratio of real annual earnings of a person at age 55 versus age 25, by educational groups and generations.

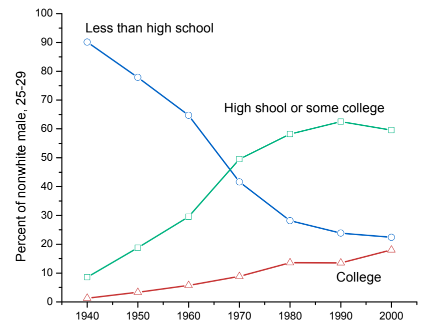
Table 4: Sensitivity Analysis – Elasticity of Substitution across Education Groups (ρ)

						1940		2000	
	$p_{2,1940}$	$p_{3,1940}$	μ	σ	η	z_2	z_3	z_2	z_3
$\rho = 0.8$	0.21	0.02	0.38	0.54	0.89	0.87	0.69	1.07	1.06
$\rho = 0.6$	0.21	0.02	0.38	0.54	0.89	0.91	0.72	1.19	1.25
$\rho = 0.4$	0.21	0.02	0.38	0.54	0.89	0.99	0.77	1.47	1.73

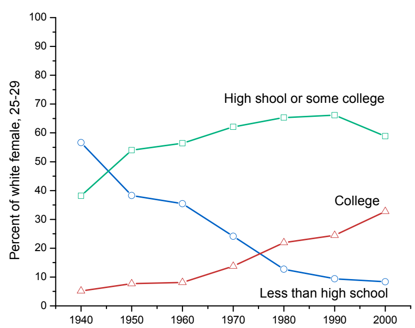
Figure 1: The Evolution of Educational Attainment



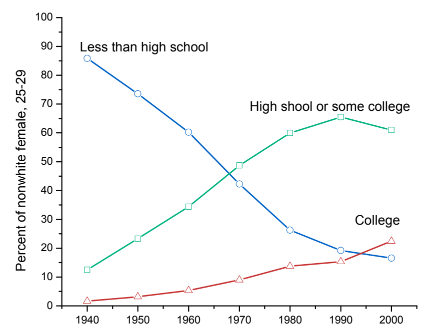
A – White men



B – Black men



C – White women



D – Black women

Note – See the appendix for the source of data.

Figure 2: Value Functions

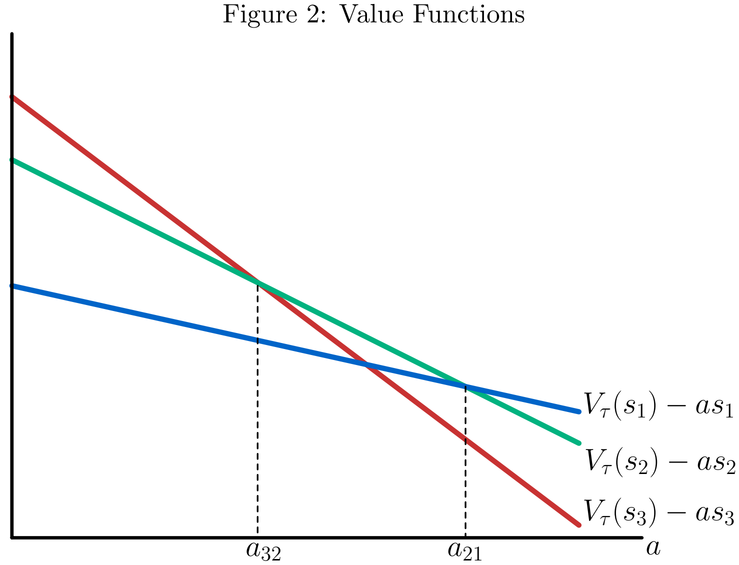


Figure 3: Distribution of Educational Attainment

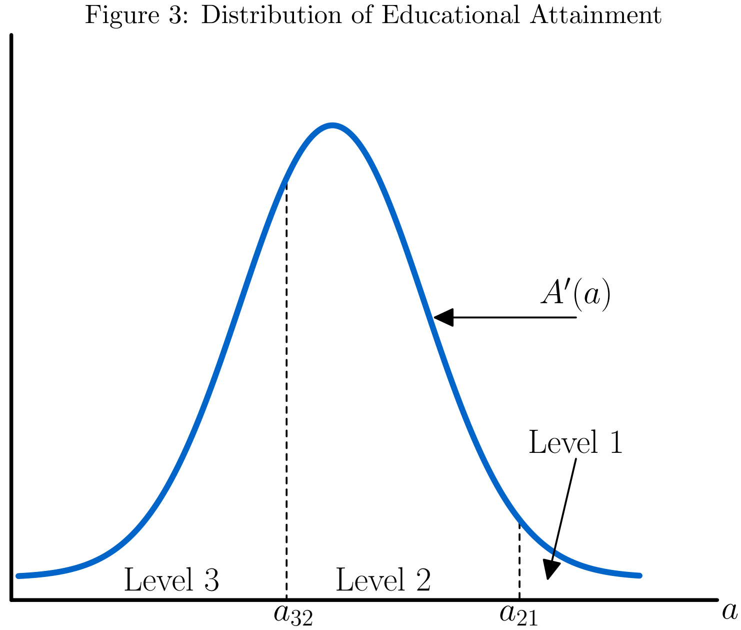
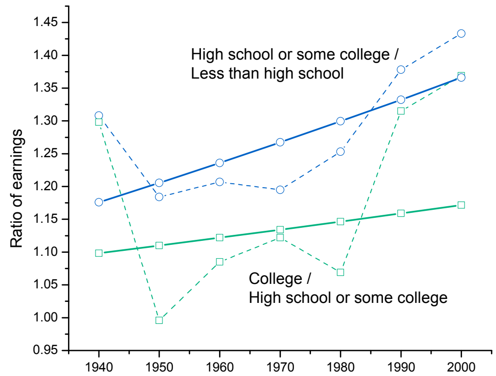
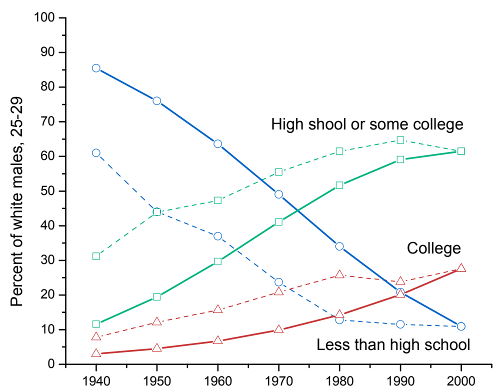


Figure 4: Relative Annual Earnings – Model vs. Data



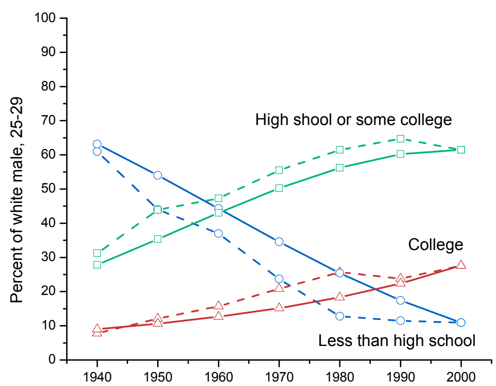
Note – The model data are represented with solid lines. The U.S. data are represented by dotted lines.

Figure 5: Educational Attainment – Model vs. Data



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

Figure 6: Educational Attainment – Model with Fixed Costs vs. Data



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