The Contribution of Rising School Quality to U.S. Economic Growth

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Abstract

U.S. public school expenditures per pupil increased by a factor of 9 during the 20th century. This paper quantifies how much U.S. labor quality has grown due to the rise in educational spending. A schooling model and cross-sectional earnings variations across cohorts are exploited to identify the effect of the increased school expenditures on labor quality growth. The findings are that (i) U.S. labor quality increased by 0.4% per year between 1967 and 2000, one-fifth of which is attributable to the rise in educational spending; and that (ii) labor quality growth explains one-quarter of the rise in labor productivity.

Keywords: Labor Quality Growth, Rising School Quality, Growth Accounting

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1. Introduction

During the 20th century, the real spending per pupil in U.S. public elementary and secondary schools increased by a factor of 9. This paper explores how much U.S. labor quality has grown due to the rise in school expenditures. The Bureau of Labor Statistics (BLS) currently measures labor quality growth mainly based on increases in the mean years of schooling but fails to capture the impact of changes in the quality of education. If the increased educational expenditures improved school quality, then the BLS underestimates the growth in U.S. labor quality.

This paper proposes a new way of quantifying the rise in the quality of education with a schooling model in which human capital production depends not only on time in school but also on educational spending. This model as well as cross-sectional earnings variations across cohorts is exploited to identify the growth in school quality. Consider cross-sectional earnings differences between younger and older cohorts with the same years of schooling. The earnings variations reflect three components: i) the impact of changing selection into different years of schooling; ii) return to experience; and iii) the growth in the quality of education. Without a model, these three components cannot be identified simultaneously.

To assess the effect of the changing selection in schooling choice, assume that ability distribution stays constant across cohorts. If years of schooling vary only by ability within cohorts, the cohort-invariant ability distribution can be estimated by the schooling distribution of any single cohort. The impact of the changing selection on the cohort-variations in earnings is then measured by accounting for changes in empirical schooling distribution across cohorts.

Once the selection effect is controlled for, a structural restriction derived from the model is used to disentangle the remaining two components, assuming the same return to experience across cohorts. In the model, optimizing agents choose both time in school and educational expenditures so that their relative marginal product in increasing human capital equals their relative costs. Given the data on individual earnings and educational expenditures, foregone earnings due to delayed experience are the key element in the relative cost of time spent in school. If earnings rise with work experience very rapidly, increasing time in school is relatively more costly than raising educational expenditures. Thus, agents substitute expenditure for time in school until the relative marginal product of expenditure equals its low relative cost. According to the model, the relative marginal product of expenditure for the last year in school equals the expenditure elasticity of human capital. Thus, the low relative marginal product of expenditure represents a low value for the elasticity. This implies little increase in the quality of education, given the rise in school expenditures. By the same mechanism, very flat experience-earnings profiles suggest a substantial rise in education quality, given the same increase in educational spending. This model implication on how the return to experience relates to the rise in school quality provides an additional condition, which identifies the growth in quality of education from the observed earnings variations across cohorts.

The main finding is that U.S. labor quality increased by 0.4% per year between 1967 and 2000, with one-fifth of this explained by the growth in school quality. Given the increased school expenditures per pupil, their contribution to U.S. labor quality growth has been fairly modest. The total labor quality growth explains one-quarter of the growth in U.S. labor productivity for the same period. The estimated rise in labor quality reduces the growth rate of total factor productivity (TFP) measured as a residual. The contribution of growth in TFP to U.S. labor productivity growth is about a quarter, whereas the BLS estimates it to be 40% by ignoring the growth in the quality of education. The estimated impact of the rise in school expenditures on labor quality growth is larger among men, while the baseline estimate changes little with a sample of full-time, full-year (FTFY) workers. I also find that the growth in school quality explains only 10% of the increases in empirical returns to schooling and that a rising skill premium explains the rest.

This paper is related to two strands of literature. One branch includes papers that estimate the effects of various measures of school quality, including school expenditures on student achievement and labor market outcomes at the micro-level. Although the estimates vary depending on the data and method used, most papers did not find strong effects of measured school quality.[1] My study differs from these studies in two ways: (i) it suggests an aggregate measure of labor quality growth due to increased school expenditures; and (ii) it focuses on cohort variations in the quality of education instead of cross-sectional or geographical variations. To this aim, the biggest challenge is to identify the growth in education quality from other earnings variations across cohorts such as return to experience and changing selection in schooling choice. This paper proposes a way of overcoming this difficulty using a schooling model and measures the average impact of increased school expenditures on growth in human capital for cohorts born from the early 20th century to the early 1980s. The estimated impact of school expenditures is modest in line with this micro-literature.

Another related strand of literature is on the role of human capital in economic growth and development. The most widely used method to measure country-level human capital stocks is to multiply the mean years of schooling of the population by the estimated Mincerian return to schooling.[2] However, this method does not allow for differences in the quality of education across countries. To correct this, Bils and Klenow (2000) add teachers' human capital to the standard Mincer-type human capital specification, yet they ignore the role of expenditure in human capital production. Manuelli and Seshadri (2007) and Erosa et al. (2010) explicitly incorporate expenditure as well as time as inputs for human capital production to account for cross-country income differences. The contribution of human capital growth to U.S. real income growth implied by Manuelli and Seshadri (2007) is more than twice my estimate, whereas that suggested by Erosa et al. (2010) is only slightly

[1] See, for example, Hanushek (1986), Hanushek et al. (1996), Heckman et al. (1996), and Betts (1995). Dearden et al. (2002) present a survey of previous results.

[2] See, among others, Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999).

greater than mine. One explanation is that Manuelli and Seshadri (2007) view that earnings growth with work experience is solely due to human capital investments, excluding the effects of learning-by-doing or technological progress. This framework tends to amplify the differences in human capital accumulated after leaving school across cohorts, overstating the role of human capital in explaining real income growth. In addition, both Manuelli and Seshadri (2007) and Erosa et al. (2010) assume a common wage per unit of labor regardless of education, whereas my study considers different skill prices by education; failing to do so overestimates the impact of rising school spending on labor quality growth. This paper also relates to Rangazas (2002), who examines the impact of the quantity and quality of schooling on U.S. labor productivity growth. A key difference is that my paper proposes a new way of estimating the expenditure elasticity of human capital, instead of taking it from micro-study estimates that vary by the data and method used. Moreover, I control for the rise in skill premium and unobserved heterogeneity correlated with schooling choice to remove upward bias in the estimated growth in U.S. labor quality.

The remainder of this paper is organized as follows. Section 2 describes the growth accounting framework this paper suggests and discusses the BLS's measure of labor quality growth. In section 3, a schooling model with a Ben-Porath-type human capital production function is introduced. The identification scheme and the estimation procedure are described in section 4, and the main findings are reported in section 5. Section 6 concludes the paper.

2. Measuring Labor Quality Growth

This study suggests that the traditional growth accounting framework should be extended by incorporating labor quality growth. Consider a production function in which economic output Y depends on m types of physical capital inputs k_1, $k_2, \ldots, k_m$; n types of labor inputs $h_1 l_1, h_2 l_2, \ldots, h_n l_n$; and a time-specific factor t.

$$Y = f(k_1, \ldots, k_m, h_1 l_1, \ldots, h_n l_n, t)$$

In this formula, l_j is raw hours provided by type j workers and h_j is its quality per hour.

Assuming a constant returns to scale technology, perfectly competitive factor markets, and the cost-minimizing behavior of firms, growth in labor productivity measured in output per hour of labor, denoted as $\frac{\dot{\overline{Y/L}}}{Y/L}$, is attributed to growth in the physical capital per hour K/L, labor quality H of the economy, and the residual TFP as follows:

$$\frac{\dot{\overline{Y/L}}}{Y/L} = \frac{\dot{\overline{TFP}}}{TFP} + \overbrace{s_K \left(\sum_{i=1}^{m} s_{k_i} \frac{\dot{k}_i}{k_i} - \frac{\dot{L}}{L} \right)}^{\text{Physical Capital Growth } (\frac{\dot{\overline{K/L}}}{K/L})} + \overbrace{\underbrace{s_L \left(\sum_{j=1}^{n} s_{l_j} \frac{\dot{l}_j}{l_j} - \frac{\dot{L}}{L} \right)}_{\substack{\text{Labor Composition } (\frac{\dot{H_c}}{H_c}) \\ \text{(BLS Correction)}}} + \underbrace{s_L \sum_{j=1}^{n} s_{l_j} \frac{\dot{h}_j}{h_j}}_{\text{Human Capital Quality } (\frac{\dot{H_q}}{H_q})}}^{\text{Labor Quality Growth } (\frac{\dot{H}}{H})},$$

where

$$L = \sum\nolimits_{j=1}^{n} l_j,$$
$$s_{k_i} = \frac{P_{k_i} k_i}{\sum_{i=1}^{m} P_{k_i} k_i} \text{ and } s_{l_j} = \frac{P_{l_j} l_j}{\sum_{j=1}^{n} P_{l_j} l_j},$$
$$s_K = \frac{\sum_{i=1}^{m} P_{k_i} k_i}{\sum_{i=1}^{m} P_{k_i} k_i + \sum_{j=1}^{n} P_{l_j} l_j} \text{ and } s_L = \frac{\sum_{j=1}^{n} P_{l_j} l_j}{\sum_{i=1}^{m} P_{k_i} k_i + \sum_{j=1}^{n} P_{l_j} l_j}.$$

Every variable with a dot above it stands for the derivative of the variable with respect to time, and P_{k_i} and P_{l_j} are the unit prices of the ith type of physical capital input and the jth type of labor input, respectively. Note that the price P_{l_j} represents the price for the hours worked by a type j worker and is decomposed into j type hour quality h_j and price P_{h_j} per quality, where $P_{l_j} = P_{h_j} h_j$. The growth rate $\frac{\dot{k}_i}{k_i}$ of type i capital input is weighted by its total physical capital input cost share s_{k_j}, and the weighted average of different capital input growth rates is itself weighted by the share s_K of total capital input costs relative to total factor input costs. The growth rate of type j labor input is similarly weighted by its total cost of labor input share s_{l_j}. As in the case of capital input, the weighted average of different labor input growth is multiplied by the cost share s_L of total labor input costs relative to total factor input costs, before accounting for its contribution to labor productivity growth.

Labor quality growth $\frac{\dot{H}}{H}$ is represented by the last two terms on the right-hand side in the above formula. It includes both labor composition growth $\frac{\dot{H}_c}{H_c}$ and human capital quality growth $\frac{\dot{H}_q}{H_q}$. A simple example clarifies what each component captures. Suppose that there are two types of workers, high school and college graduates, and they work the same hours in the market. If the fraction of college graduates rose from one period to the next, $\frac{\dot{H}_c}{H_c}$ would respond by multiplying the change in the labor composition by the wage differences between worker types. Suppose instead that school quality improved from one period to another while labor composition stayed the same. One would then expect some growth in labor quality because workers in the second period on average acquired a better quality of education. Labor composition growth would remain unchanged ($\frac{\dot{H}_c}{H_c} = 0$), and the response will be reflected through an adjustment in $\frac{\dot{H}_q}{H_q}$.

Since 1983, the BLS has extended the traditional growth accounting framework following Denison (1962) and published its measure of labor quality growth. To construct a labor input measure, the BLS cross-classifies workers according to their education, experience, and gender and considers each cell a different labor input. The BLS then runs Mincer-type regressions and exploits the predicted wages from the regressions to compute the cost shares of different labor inputs. The BLS measure of labor quality growth, obtained in this manner, is determined by labor composition growth but fails to capture any changes in human capital quality. The BLS reports that U.S. labor quality grew 0.22% per year, and this explains about 13% of the growth in U.S. labor productivity between 1967 and 2000.

Data on public educational expenditures, however, suggest that the BLS approach may miss out on a significant part of labor quality growth. As shown in Figure 1, U.S. real public educational expenditures per pupil in elementary and secondary schools increased drastically during the 20th century;[3] the real spending per pupil in U.S. public elementary and secondary schools increased by a factor of 9 between 1908 and 2000. Note that a part of the increased nominal school spending per pupil may be attributable to factors that are not closely related to school quality (e.g.,raises in teachers' pay due to an increase in union power). In order to avoid overstating the real expenditure growth by ignoring these factors, the time series is deflated by an education sector price index, which increases more rapidly than an overall price index.[4]

Considering that increased expenditures tend to improve school quality by reducing the pupil-teacher ratio, raising teacher quality, or upgrading to state-of-the-art educational equipment, it is conceivable that newer cohorts have accumulated more human capital stocks through rising school expenditures than older cohorts. If school quality indeed improved due to the increased educational spending, growth in the quality of human capital should capture its impact. This paper quantifies this component, which the BLS has not addressed.

[3] Hanushek and Rivkin (1997) decompose the rise in school spending over the 20th century and find that it resulted from declining pupil-teacher ratios, increasing real wages for instructional staff, and rising expenditures outside of the classroom. In contrast to the first two types of expenditures, it is not clear whether expenditures outside of the classroom are related to human capital accumulation of students. Unfortunately, detailed data on the basic components of expenditures outside of the classroom are not available. Since expenditures outside of the classroom actually include a variety of items that can be considered part of instructional spending, such as learning materials, I use a times series of total school expenditures as inputs for the estimation.

[4] The price index for personal consumption expenditures (PCE) on education is used to deflate educational expenditures. Between 1929 and 2005, the consumer price index (CPI) city average and the PCE price index rose by 3.3% and 3.1% per annum, respectively, whereas the price index for PCE on education increased by 4.3% per year.

3. The Model

This paper develops a schooling model with a Ben-Porath-type human capital production function.[5] Individuals born in period T choose the optimal level of schooling and goods investment associated with each year in school to maximize the present value of their net lifetime income.

$$\max_{d(a),\, s} \int_s^R e^{-ra} w_{T+a}(s) H(s,a) da - \int_0^s e^{-ra} p_{T+a} d(a) da + \xi_T h(s)$$

$$s.t.\ H(s,a) = h(s)\phi(a-s) \quad \text{for } a \geq s$$

$$\dot{h}(a) = \gamma_0 h(a)^{\gamma_1} d(a)^{\gamma_2} \text{ for } a < s$$

$$0 < \gamma_1, \gamma_2 < 1 \text{ and } h(0) = 1$$

Here, r is the market interest rate; $w_t(s)$ is the wage associated with s years of schooling at time t; $H(s,a)$ is human capital with s years of schooling at age a; p_t is the price of educational goods relative to consumption goods at time t; $d(a)$ is educational goods investment at age a; $\xi_T h(s)$ is utility in money terms from human capital stock accumulated through schooling for agents born in period T; and $\dot{h}(a)$ is the time derivative of human capital at age a. Individuals go to school for s years and enter the market at the age of s with a human capital stock $h(s)$ accumulated through schooling. After completion of schooling, they earn wage income, which is a product of their human capital stock $H(s,a)$ at age a and a skill price $w_{T+a}(s)$. While in school, they purchase educational goods. I also assume that they derive utility from their human capital stock accumulated through schooling. The parameter ξ_T governing this utility from education is cohort-specific, which allows the model to match the mean years of schooling of each cohort.

Individual human capital stock accumulates according to two separate processes during the schooling and postschooling period. Individuals begin accumulating their human capital

[5] See Ben-Porath (1967) for more details.

when they start school. While in school, they are full-time students and cannot take part in market work. During this period, they produce human capital using their entire stock of human capital and educational goods, and their human capital stocks do not depreciate. Given the same investments in both time and goods, agents can produce different amounts of human capital depending on the initial human capital stock $h(0)$ and learning ability γ_0. The initial human capital $h(0)$ is normalized to 1 for every cohort with no variations within cohorts, but individuals within cohorts are heterogeneous in their learning ability γ_0.[6] The distribution of learning ability γ_0 is assumed to stay the same across cohorts. Goods investment in the production function captures school quality for a given year of schooling. Individuals freely choose the length of schooling, but they do not have complete freedom in determining school expenditures. The amount of expenditures is assumed to be optimal for the median ability person in each cohort.[7] I restrict each input in the human capital production function to exhibit diminishing returns by assuming human capital elasticities γ_1 and γ_2 with respect to each input to be between 0 and 1. If $\gamma_1 = 1$ and $\gamma_2 = 0$, then human capital grows exogenously throughout the schooling period at the rate of γ_0, which collapses to the usual Mincer specification ($\ln h(s) = \gamma_0 s$). According to this human capital production technology, an individual's human capital stock when he leaves school is written as

$$h(s) = \left[1 + \gamma_0(1-\gamma_1)\int_0^s d(a)^{\gamma_2} da\right]^{\frac{1}{1-\gamma_1}}.$$

Once individuals leave school, they never go back to school; they work in the market to earn wage income until they retire at age R. Individual human capital is assumed to grow exogenously with work experience through learning-by-doing. How fast it grows is governed by the function $\phi(a-s)$. Wage $w_t(s)$ per unit of human capital (or skill price) varies by

[6] Even if the initial human capital stock $h(0)$ is also a potential source of individual heterogeneity, I focus on heterogeneity in learning ability γ_0 because i) the empirical evidence suggests that heterogeneity in the return to schooling may be more important and ii) data on input for human capital production for the preschool period are not readily available for the entire 20th century.

[7] This would mimic the trends in school spending in a political equilibrium based on a median voter model.

educational attainment. When individuals decide how many years to stay in school, they recognize the present skill prices, but do not have perfect foresight about the evolution of the future skill prices. They anticipate the present skill prices to stay constant over time, i.e., they have static expectations of the skill prices. If skill prices change over time at different rates by educational attainment, younger cohorts face different skill premia when making a schooling choice than do older cohorts.

Assuming interior solutions, first-order conditions with respect to the two choice variables are sufficient to characterize optimal levels $d^*(a)$ for $0 \le a \le s^*$ and s^* of educational goods investments and years of schooling. For notational convenience, define $\widetilde{T} = T + s^*$. The following first-order condition represents the quality margin of schooling on which an individual born at time T is optimizing:

$$\overbrace{\gamma_0\gamma_2 d^*(a)^{\gamma_2-1}h(s^*)^{\gamma_1}\int_{s^*}^{R} e^{-r\tau+\phi(\tau-s^*)}w_{T+\tau}(s^*)d\tau}^{\text{Human Capital Increment}} + \overbrace{\xi_T\gamma_0\gamma_2 d^*(a)^{\gamma_2-1}h(s^*)^{\gamma_1}}^{\text{Utility Gain}} = \underbrace{e^{-ra}p_{T+a}}_{\text{Unit Cost}},\ \forall a \le s^* \tag{1}$$

The left-hand side of equation (1) indicates the marginal benefit of investing one more unit of educational goods at the age of a, which includes a human capital increment that promises higher wage income throughout the individual's working life and utility from the increase in human capital. The right-hand side is the educational goods' marginal cost, or the unit price of educational goods. At the optimum, investment in educational goods for each year in school is determined so that the marginal benefit and cost of an additional unit of educational goods are equal. Since school expenditure is assumed to be optimal for the median ability person, this first-order condition applies only to the median ability person.

The first-order condition on the quantity margin of schooling, which holds for everyone, is given by

$$\overbrace{\gamma_0 h(s^*)^{\gamma_1} d^*(s^*)^{\gamma_2} \int_0^{R-s^*} e^{-r\tau+\phi(\tau)} w_{\widetilde{T}+\tau}(s^*) d\tau}^{\text{Human Capital Increment}} + \overbrace{\int_0^{R-s^*} e^{-r\tau+\phi(\tau)} h(s^*) \frac{\partial w_{\widetilde{T}+\tau}(s^*)}{\partial s} d\tau}^{\text{Gain from the Skill Premium}} + \overbrace{e^{rs^*} \xi_T \gamma_0 h(s^*)^{\gamma_1} d^*(s^*)^{\gamma_2}}^{\text{Utility Gain}}$$
$$= \underbrace{w_{\widetilde{T}}(s^*) h(s^*)}_{\text{Foregone Earnings}} + \underbrace{p_{\widetilde{T}} d^*(s^*)}_{\text{Expenditure}} + \underbrace{\int_0^{R-s^*} e^{-r\tau+\phi(\tau)} w_{\widetilde{T}+\tau}(s^*) h(s^*) \phi'(\tau) d\tau d^*}_{\text{Cost of Delayed Experience}} \tag{2}$$

Equation (2) relates the marginal benefit of staying one more year in school to its marginal cost. Suppose that individuals stay in school for one more year. The left-hand side of equation (2) presents three distinct benefits associated with this additional year of education. Firstly, they accumulate more human capital, which promises a permanent increase in their lifetime wage income. In addition, after completion of schooling, they receive higher wages per unit of human capital stock in the presence of the skill premium. Lastly, they gain from additional utility due to the human capital increment. On the other hand, they bear costs by delaying their labor market entry. As the right-hand side of equation (2) indicates, they forego earnings for another year, make additional educational expenditures, and incur a cost of delaying the returns to work experience. Individuals choose optimal years of schooling by equating the marginal benefit of an additional year of education to its marginal cost. Equation (2) implies that individuals with higher learning ability stay in school longer, i.e., there would be ability sorting in schooling choice within cohorts.[8]

Plugging equation (1) evaluated at $a = s^*$ into equation (2) yields

$$\gamma_2 = \frac{p_{\widetilde{T}} d^*(s^*)}{w_{\widetilde{T}}(s^*) h(s^*) + p_{\widetilde{T}} d^*(s^*) + \int_0^{R-s^*} e^{-r\tau+\phi(\tau)} h(s^*) \left[w_{\widetilde{T}+\tau}(s^*) \phi'(\tau) - \frac{\partial w_{\widetilde{T}+\tau}(s^*)}{\partial s} \right] d\tau} \tag{3}$$

Note that the denominator of the right-hand side of equation (3) represents the marginal cost of obtaining the last year of schooling net wage gain in the presence of the skill premium

[8] See the Online Appendix for a proof.

("net marginal cost of schooling," hereafter). According to equation (3), the relative cost of educational expenditure for the last year in school reflects how effective expenditure is in human capital production, that is, the expenditure elasticity γ_2 of human capital. This expenditure share of the net marginal cost of schooling is exploited as an important moment to estimate the impact of rising school spending on growth in the human capital of the workforce in section 4.

4. Identification and Estimation

In this section, how to identify the growth in school quality from other sources of earnings variations across cohorts is addressed. The estimation procedure then follows.

4.1. Identification

This study identifies the rise in school quality by using the schooling model as well as cross-sectional earnings variations across cohorts. In cross-sectional data, earnings differences between younger and older cohorts with the same years of schooling capture three components: i) the impact of changing selection in schooling choice; ii) return to experience; and iii) changes in school quality. To control for the impact of the changing selection across cohorts, assume that ability distribution stays constant across cohorts. According to the model, more able agents stay in school longer within cohorts, i.e., there would be ability sorting in schooling choice. To be consistent with both the ability sorting and the increases in mean years of schooling across cohorts, it must be that given years of schooling, the average ability level is lower for younger cohorts than for older cohorts. If ability is the only source of variations in educational attainment, the ability distribution can be estimated by schooling distribution of any single cohort. Changes in the empirical schooling distribution across cohorts then quantify the impact of the selection effect on the cohort variations in earnings.

If the changing selection in educational choice is removed this way, then the earnings variations reflect the difference between the return to experience and the growth in school quality, assuming the same return to experience across cohorts. In order to disentangle the two components, the optimality condition from the model is used on both quantity and quality margins of schooling. In the model, optimizing agents choose both time and expenditures so that their relative marginal product in increasing human capital equals their relative costs. If human capital rises with work experience very rapidly, spending more time in school is relatively more costly than raising educational expenditures. Thus, agents substitute educational expenditure for length of schooling until the relative marginal product of expenditure declines to its low relative cost. According to the model, the relative marginal product of expenditure for the last year in school equals the expenditure elasticity of human capital (equation (3)). Thus, the low relative marginal product of expenditure represents a low value for the elasticity. It suggests little rise in human capital of the workforce given the rise in school expenditures, i.e., little improvement in the quality of education. Conversely, very flat postschooling human capital profiles imply a substantial rise in education quality, given the same increase in educational spending. This model implication on how the return to experience is connected to the rise in school quality provides an additional condition, which identifies the growth in school quality from the observed earnings variations across cohorts.

The rise in school quality identified this way simultaneously uncovers the rise in skill premium. Skill prices are not directly observable in the data because agents receive the product of their human capital stocks and skill prices as their wage income. If one tracks wages of the same cohort with the same years of schooling over time, their wage growth includes both return to another year of experience and the changes in relevant skill prices. Given the return to postschooling experience, changes in the skill prices are obtained as residuals.[9]

4.2. ***Estimation***

Before implementing the estimation procedure, the values of a few variables are preset based on a priori information. The retirement age R and the interest rate r are 59[10] and 0.05, respectively. The relative price of educational goods is assumed to increase over time with a continuous growth rate denoted by $g_{p.}$ The growth rate g_p is set to 0.0098 by fitting an exponential trend to the relative price of educational goods over the period of 1908 to 2004. The price of educational goods in 1982 is normalized to one. I also normalize the parameter ξ_{1961} for utility from education of 1961 birth cohort to zero. Neither normalization affects the quantitative results in section 5. The curvature parameter γ_1 for human capital production through schooling is not estimated here. The parameter γ_1 determines the curvature of individual human capital profile across grades while in school. Without data on premarket human capital stocks, it is hard to identify γ_1. The value of γ_1 is set to 0.85 following Heckman et al. (1998).[11] These values are summarized in the first two rows of Table 1.

Given these values, remaining parameters are estimated. I begin by introducing functional forms for the ability distribution and the human capital accumulation process after completion of schooling. Individual learning ability γ_0 is log-normally distributed with mean μ_{γ_0} and standard deviation σ_{γ_0}. The process of human capital accumulation during the postschooling period is given by

$$\phi(a-s) = \phi_0(a-s) + \phi_1(a-s)^2 \quad for\ a \geq s$$

[9] See the Online Appendix for more details on how to compute the skill prices.

[10] This corresponds to a real life age of 65.

[11] There is little literature that estimates the curvature parameter using data on premarket human capital stocks, which is comparable to γ_1 in this study. Heckman et al. (1998) consider a Ben-Porath-type lifetime human capital production technology and estimate the curvature γ_1 using wage data. Their estimates are 0.83 for high school graduates and 0.87 for college graduates. I use the average for my estimation.

With these functional forms, I have five parameters $\{\mu_{\gamma_0}, \sigma_{\gamma_0}, \gamma_2, \phi_0, \phi_1\}$ to estimate for the human capital production function, where γ_2 is the elasticity of human capital with respect to expenditure. The estimation also involves 82 parameters $\{\xi_{1902}, \ldots, \xi_{1960}, \xi_{1962,} \ldots, \xi_{1984}\}$ for cohort-specific utility from education. These 87 parameters are estimated by the generalized method of moments (GMM) method, minimizing the weighted distance between a total of 88 data moments and their model counterparts. The moments include the following three sets: i) the estimated return to schooling and quadratic return to experience from a pooled sample Mincer regression (3 moments); ii) the mean years of schooling of 1902 through 1984 birth cohorts[12] and the variance of educational attainment of the 1961 birth cohort (84 moments); and iii) the expenditure share of the net marginal cost of schooling (equation (3), 1 moment).

The first set of moments are Mincer coefficients from the data and from the model. Using a CPS pooled sample, I regress individual log hourly wages on years of schooling, potential experience and its square, and year dummies along with other individual characteristics.[13] The estimated coefficients on years of schooling and potential experience and its square from this Mincer regression are the first set of data moments. Their model counterparts are computed from a model-based Mincer regression. Since education levels are discrete in the data in contrast with the model, individuals in each cohort are collected in 18 education bins (0 to 17 years of schooling) in the model, based on their proportions in the data. Given the model parameters, the mean log human capital stock of every bin is computed. The model moments in the first category are the corresponding coefficients from a Mincer regression with the sum of the mean log human capital stock and the log skill price as a dependent variable.[14]

The second set of data moments are the mean years of schooling of 1902 through 1984

[12] See Figure 3.

[13] The control variables include gender, race, marital status, part-time status, census division of residence, and standard metropolitan statistical area (SMSA) status.

[14] Running a Mincer regression based on the mean log human capital stocks yields the same coefficients as what I would obtain with individual human capital stocks. See the Online Appendix for a proof.

birth cohorts and the variance of educational attainment of the 1961 birth cohort in the CPS sample. The corresponding model moments are computed by solving the model.

The last moment or the expenditure share in the net marginal cost of schooling is based on equation (3). Unlike the first two sets of data moments, the expenditure share is constructed for a given set of parameters. Since school expenditure is chosen by the median ability person in each cohort, equation (3) holds only for the median ability person. I first solve the optimal educational attainment of the median ability person (with learning ability $e^{\mu_{\gamma_0}}$) in each cohort. Given this level of education, the time path of skill prices and cohort-level educational expenditures[15] are used to compute the expenditure share of the net marginal cost of schooling for each cohort. The mean expenditure share over all cohorts is the third set of data moment. As equation (3) indicates, its model counterpart is the expenditure elasticity γ_2 of human capital.

Having constructed the data and the model moments this way, I estimate the parameters using the GMM. In implementing the estimation, the parameters are divided into two groups: i) $\theta_1 = \{\mu_{\gamma_0}, \sigma_{\gamma_0}, \gamma_2, \phi_0, \phi_1\}$ for the human capital production function; and ii) $\theta_2 = \{\xi_{1902}, \ldots, \xi_{1960}, \xi_{1962,} \ldots, \xi_{1984}\}$ for cohort-specific utility from education. First, find θ_2 that exactly replicates the relevant cohort mean years of schooling (82 moments), for any given θ_1. Then, minimize the weighted distance between the remaining six data moments[16] and their model counterparts over θ_1. The parameter estimates $\widehat{\theta}_1$ for the human capital production function can be written as

$$\widehat{\theta}_1 = \arg\min_{\theta_1} g(\theta_1)' W g(\theta_1),$$

where $g(\theta_1) = m^d - m(\theta_1)$, m^d is the vector of data moments, $m(\theta_1)$ is the vector of model

[15] See the Online Appendix for more details on how to compute cohort-level educational expenditure.

[16] The moments include the Mincer coefficients on years of schooling, potential experience and its square, the mean and the variance of educational attainment of the 1961 birth cohort, and the expenditure share of the net marginal cost of schooling.

moments evaluated at a given set θ_1 of parameters, and W is the weighting matrix. Regardless of the choice of the weighting matrix W, the estimator is consistent. The weighting matrix used for the estimation is the inverse of a diagonal matrix, whose elements are the variances of the data moments. Since the last data moment (or the expenditure share of the net marginal cost of schooling) depends on the model parameters, its variance is computed based on the parameter estimates from a model without utility from education. Standard errors for the estimates are calculated based on numerical differentiation.

5. Results

This section starts with a discussion of the estimates for the human capital production function. It then presents the main growth accounting results, followed by a sensitivity analysis.

5.1. Parameter Estimates and the Fit of the Model

Parameter estimates for the distribution of learning ability and the human capital production function are reported in the last row of Table 1. The baseline model estimates the expenditure elasticity γ_2 of human capital, which is key to understanding the impact of rising school spending on labor quality growth, to be 0.06. This implies that school expenditures explain about 6% of the net marginal cost of schooling as represented by equation (3). Parameter estimates for ϕ_0 and ϕ_1 confirm that the postschooling evolution of human capital with work experience is steeper than the cross-sectional experience-earnings profiles due to the rise in school quality. According to the estimates, individual human capital increases by 63% with 30 years of work experience and the cross-sectional return to experience understates this actual return by more than 7%.

The model matches empirical Mincer coefficients well as shown in Table 2. Both return to schooling and quadratic return to experience from the model-based Mincer regression are very close to those in the data. The model is also consistent with the rise in the estimated Mincer returns to schooling over time in the CPS data. Figure 4 plots the trends in the Mincer return to schooling from the baseline model together with those in the data. Even if the Mincer return to schooling from the pooled sample is targeted, the model is well in line with the rise in the year-by-year Mincerian returns to schooling in the CPS data over the period 1967 to 2000.[17]

Can we let the rise in school quality take all the credit for this rapid increase in the estimated returns to schooling? A vast literature on wage inequality in the U.S. for the past few decades[18] suggests that the increases in relative wages of more educated workers for the period is largely due to a rising demand for them. In order to quantify how much of the rise in the estimated return to schooling in the data is attributable to the growth in school quality and a rising skill premium, respectively, a counterfactual exercise is implemented. The gray solid line in Figure 4 represents the time path of Mincer return to schooling implied by the model, assuming that the skill premium stayed constant for the sample period at its 1967 level. Without the rise in the skill premium, the Mincerian return to schooling increases by less than 1 percentage point between 1967 and 2000, which explains only 12% of the total increase in the Mincer return to schooling in the baseline model. This confirms that a significant part of the rise in the estimated returns to schooling results from an increased skill premium, not from better quality of schooling for more recent cohorts.

The model can replicate the mean and the variance of educational attainment of the 1961 birth cohort as Table 2 presents. By introducing cohort-specific parameters for utility from schooling, the model exactly matches the time series of the cohort mean years of schooling. This enables the model to generate the evolution of mean educational attainment in the

[17] The model slightly overstates the increase in the Mincer returns to schooling, which is attributable to the fact that I use skill prices for four education windows instead of 18 discrete levels of schooling. However, this is inevitable because the numbers of observations in some education groups are small.

[18] Figure 2 presents the trends in wage gap between college graduates and high school graduates in the U.S.

CPS data between 1967 and 2000 as shown in Figure 5.[19] How important is the rise in skill premium in explaining the increases in mean years of schooling of the U.S. workforce? The gray solid line in Figure 5 plots the time path of mean years of schooling predicted by the model, assuming that all skill prices grew at the same rate without a rise in the skill premium. The mean level of educational attainment of the workforce increases initially as the average wages rise. However, it turns to a declining trend since the mid-1970s because the relative price of educational goods grows more rapidly than the average wages. Without the rise in the skill premium, the model cannot generate a secular rise in the mean years of schooling in the data.

5.2. ***Growth Accounting***

This subsection discusses the main quantitative results based on the estimated parameters. Following the growth accounting framework proposed in section 2, two components of labor quality growth (labor composition growth (H_c) and human capital quality growth (H_q)) are computed for any two consecutive years.

Table 3 presents my growth accounting results with those from the BLS's approach. The growth rates of labor productivity and physical capital inputs in all panels are taken from the BLS. The TFP growth is obtained as a residual after accounting for growth in physical capital and labor quality. The contributions of both physical capital growth and labor quality growth presented in Table 3 are adjusted for their cost shares.

As the second panel in Table 3 shows, human capital of the U.S. workforce increased by 0.4% per year between 1967 and 2000, with 20% of this explained by the growth in school quality.[20] This implies that rising educational spending is about one-fourth as important

[19] The mean years of schooling for each year are calculated as a weighted average of cohort mean years of schooling in the pooled sample with year-specific cohort weights.

[20] The BLS labor composition growth is smaller than my estimate. This is because my growth accounting framework views workers with different education and potential experience as different labor inputs, while the BLS additionally considers gender in classifying workers. Since women on average earn less than men, increased female labor force participation in the past decades lowers the BLS measure of labor composition

as increases in mean years of schooling for U.S. labor productivity growth for the period.[21] Given the drastic rise in real school expenditures per pupil during the 20th century, U.S. labor quality growth has been fairly modest. The total labor quality growth due to rises in both the quantity and quality of schooling explains about one-quarter of the U.S. labor productivity growth between 1967 and 2000. With this new measure of labor quality growth, the TFP growth rate declines. I find that the contribution of growth in TFP to U.S. labor productivity growth is about a quarter, compared with the 40% reported by the BLS.

5.3. Sensitivity Analysis

A couple of subsamples are considered for sensitivity analysis. First, the model parameters are reestimated with data on males to remove any effect of significant changes in women's selection into the labor force in recent decades on the estimate. The estimation is also repeated using a sample of FTFY workers since the model rules out part-time workers included in the baseline estimation. Since data on educational expenditures are not available separately for these subsamples, the same data on educational expenditures are used for both exercises. The growth accounting results with these two subsamples are summarized in the bottom two panels of Table 3.

Using the male sample, the estimated labor composition growth is reduced to 0.29% from 0.32% in the baseline model. Recall that labor composition growth is mainly determined by increases in educational attainment. The smaller estimate for labor composition growth among men implies that the female workforce composition has changed toward more educated and more experienced workers relative to the male workforce.

However, this did not accompany better quality of schooling for women relative to men. Human capital quality growth among men is 0.10%, larger than the baseline estimate. One

growth relative to my estimate.

[21] Labor composition growth also includes the impact of changes in the experience composition of the workforce on labor quality growth. Since the mean years of experience of the U.S. workforce do not show any secular trend, their quantitative impact on labor composition growth is small.

explanation is related to changing selection in schooling choice. Given a cohort-invariant distribution of learning ability, increases in mean years of schooling are associated with a lower mean ability for any given years of schooling among recent cohorts. Thus, a greater increase in the mean educational attainment among women lowers human capital quality growth in the baseline model, relative to that with the male sample. In addition, a narrowing gender gap may affect the estimated human capital quality growth. As the gender gap declines, women have greater incentives to spend more while in school because they anticipate a higher rate of return to educational expenditure than men. Given this incentive, expenditures are estimated to be less effective in increasing human capital among women than among men because the same school expenditures are assumed for both men and women.

The last panel of Table 3 shows that the estimated labor quality growth among FTFY workers is little different from that in the baseline model. Both labor composition growth and human capital quality growth are 0.01 percentage point lower with FTFY workers than with the whole sample. The baseline quantitative results are robust to excluding part-time, part-year workers from the sample.

6. Conclusion

Building upon Denison (1962), the BLS incorporates labor quality growth as a source of U.S. labor productivity growth. Although the BLS measure of labor quality growth adjusts for the increases in mean years of schooling of the workforce, it fails to capture any impact of the rise in school quality. Public school spending per pupil in the U.S. increased drastically during the 20th century. If this contributed to the quality of U.S. education, then the BLS approach underestimates labor quality growth.

This paper measures how much U.S. labor quality has risen in response to the increase in public school expenditures per pupil. To this aim, it is critical to identify the productivity of educational spending in human capital production. This paper proposes a new way of estimating this productivity by exploiting a schooling model as well as cross-sectional earnings differences across cohorts.

The main finding is that U.S. labor quality increased by 0.4% per year between 1967 and 2000, one-fifth of which is attributable to the rise in school expenditure. This implies that about a quarter of U.S. labor productivity growth can be accounted for by labor quality growth for the same period. The estimated impact of the increased educational spending on growth in U.S. labor quality is greater among men, whereas the baseline result is similar to that with FTFY workers. I also find that the growth in school quality explains only 10% of the rise in empirical Mincer return to schooling for the sample period, while the remainder is due to a rising skill premium.

This study abstracts from the causes of the increase in school expenditures and focuses on its impact on labor quality growth. The modest impact of the increased educational expenditure on the growth in human capital estimated in this paper raises a question of what has driven such a drastic rise in spending on schooling. Exploring this may help us better understand the role of education in U.S. economic growth.

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Table 1. Key Parameters

Preset Values	$R = 59$, $r = 0.05$, $g_p = 0.0098$, $\gamma_1 = 0.85$				
Normalization	$P_{1982} = 1$, $\xi_{1961} = 0$				
Estimates	μ_{γ_0}	σ_{γ_0}	γ_2	ϕ_0	ϕ_1
	-2.6887	0.0510	0.0605	0.0336	-0.0006
	(0.0301)	(0.0008)	(0.0041)	(0.0002)	(0.0000)

Note: Numbers in parentheses stand for standard errors.

Table 2. Goodness of Fit

Variable	Data	Model
Mincer Regression Coefficients		
S	0.0833	0.0835
Exp	0.0317	0.0315
Exp^2	−0.0005	−0.0005
Schooling Distribution of 1961 Birth Cohort		
Mean Years of Schooling	13.0	13.0
Variance of Year of Schooling	5.2	5.2

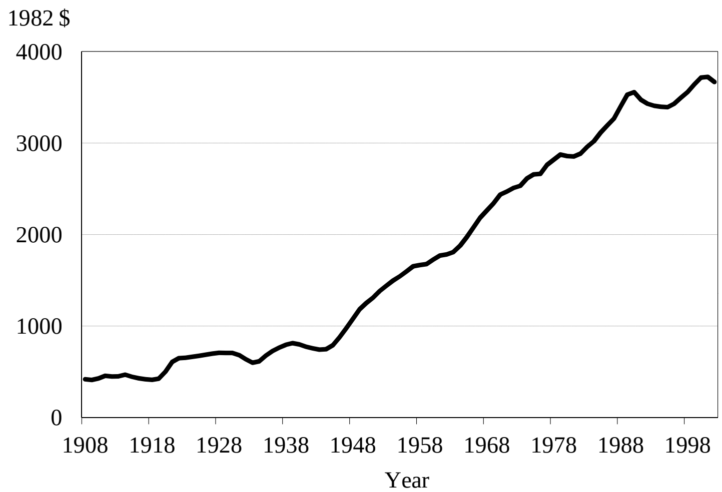
Note: The data source is CPS March Supplements 1968 through 2001. Mincer coefficients from the data are based on a pooled-sample regression of individual log hourly wages on years of schooling, potential experience and its square, gender, race, marital status, part-time status, census division of residence, SMSA status, and year dummies. The mean and the variance of years of schooling are based on the data of 1961 birth cohorts in the pooled sample of 1968 through 2001 surveys.

Table 3. Decomposition of Labor Productivity Growth Between 1967 and 2000

Y/L	TFP	K/L	H (Labor Quality)	
			H_c (Labor Composition)	H_q (Human Capital Quality)
BLS (Private Business Sector)				
1.66	0.67	0.77	0.22	..
Baseline Model				
1.66	0.49	0.77	0.32	0.08
			(0.00)	(0.01)
Men only				
1.66	0.50	0.77	0.29	0.10
			(0.00)	(0.01)
FTFY only				
1.66	0.51	0.77	0.31	0.07
			(0.00)	(0.01)

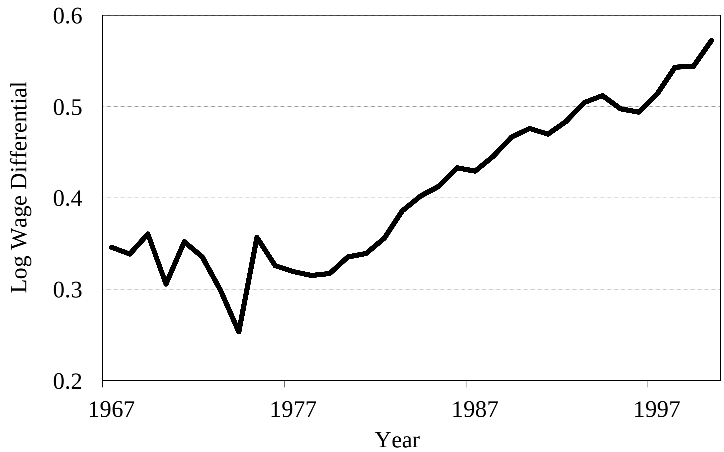
Note: The unit is percent. Numbers in parentheses stand for standard errors. Growth rates of labor productivity (Y/L) and capital-labor ratio (K/L) are from the BLS multifactor productivity tables. Growth rates of total factor productivity (TFP) are obtained as residuals.

Figure 1: U.S. Real Expenditures Per Pupil in Public Elementary and Secondary Schools



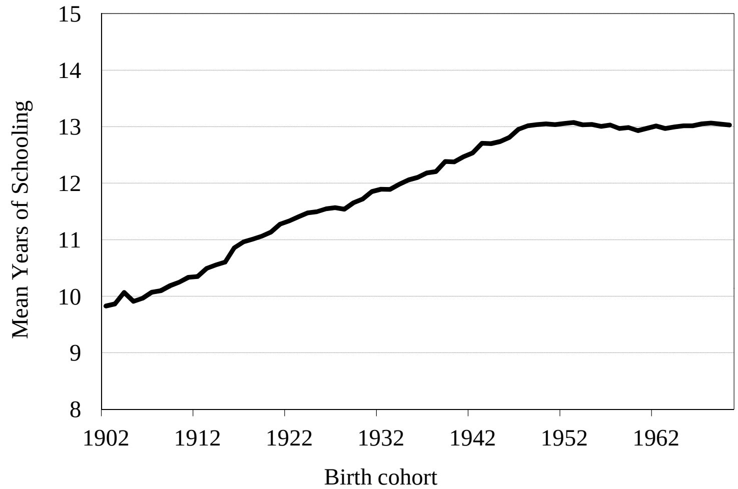
Note: Data sources include the National Center for Education Statistics (1993) and the National Center for Education Statistics (2004). The time series is the yearly total expenditure per pupil in public elementary and secondary schools. For the period during which the data were collected biennially, a cubic spline is used to interpolate the series. The series is deflated by the price index for PCE on education services where the data permit. Since the deflator is not available before 1929, I use the projection of the price index for PCE on education on the CPI by splicing it to actual data since 1929. For the years before 1913, during which the CPI was unavailable, the price index in Warren and Pearson (1935) is used.

Figure 2: Trends in Wage Gap Between College Graduates and High School Graduates in the U.S.



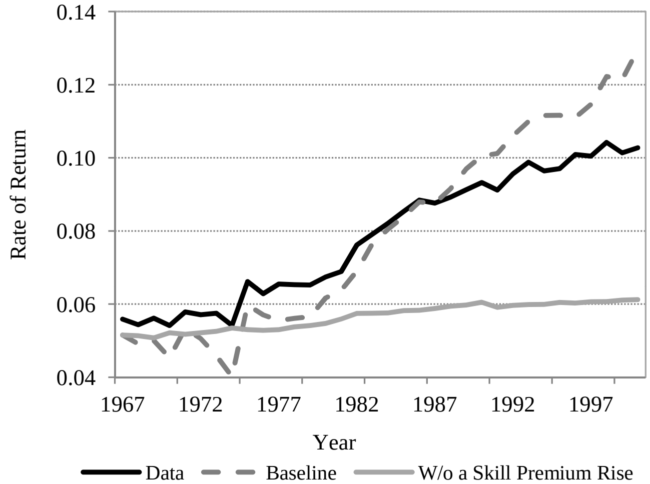
Note: The data source is CPS March Supplements 1968 through 2001. Since wages in the survey data are for the previous calendar year, the figure covers the period 1967 through 2000 even if the survey years are 1968 through 2001. Wage gap is defined as the mean log wage differential. College graduates are those with 16 years of schooling or a college degree, and high school graduates are those with 12 years of schooling or a high school diploma.

Figure 3: The Mean Years of Schooling Across Cohorts



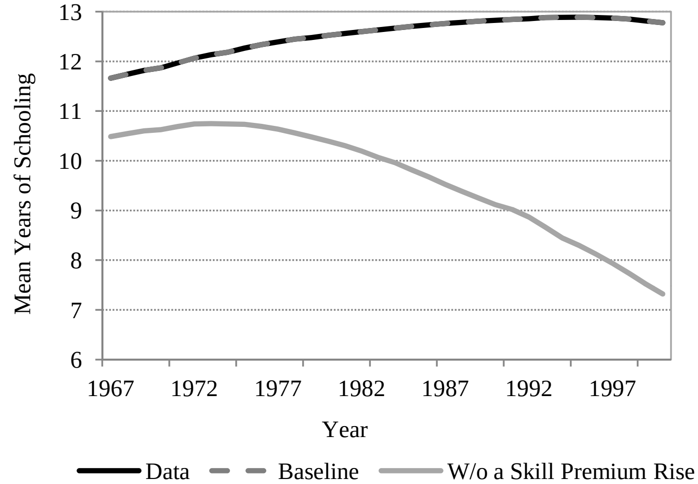
Note: The data source is CPS March Supplements 1968 to 2001. The pooled sample of 1968 to 2001 surveys is used to compute the mean years of schooling of each cohort.

Figure 4: Trends in the Estimated Mincerian Returns to Schooling: Data vs. Model



Note: The data source is CPS March Supplements 1968 through 2001. Since wages in the survey data are for the previous calendar year, the figure covers the period 1967 through 2000 even if the survey years are 1968 through 2001. The black solid line represents the trends in the estimated coefficient on years of schooling from year-by-year Mincer regressions of individual log hourly wages on years of schooling, potential experience and its square, gender, race, marital status, part-time status, census division of residence, and SMSA status. The gray dashed line indicates the time series of the estimated return to schooling from a model-based Mincer regression for each year. The gray solid line represents a counterfactual trend in the Mincerian return to schooling assuming that the skill prices stay constant at their 1967 levels.

Figure 5: Trends in the Mean Educational Attainment



Note: The data source is CPS March Supplements 1968 through 2001. The mean years of schooling for each year are calculated as a weighted average of cohort mean years of schooling in the pooled sample with year-specific cohort weights. The black solid line and the gray dashed line represent the trends in mean years of schooling from the data and from the model, respectively. The gray solid line indicates the mean years of schooling predicted by the model under the assumption that the skill prices have stayed constant since the earliest cohort went to school in 1908.