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

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December 2, 2009

Abstract

This paper explores how much U.S. labor quality has increased due to rising school spending. Given a drastic increase in the U.S. public school spending per pupil during the 20th century, accounting only for the increases in mean years of schooling of the workforce may miss out on a significant part of labor quality growth. In order to estimate the impact of rising school spending on labor quality growth, I examine how earnings of younger cohorts compare to those of older cohorts, beyond the estimated Mincer return to schooling. My findings are that rising school spending is about half as important as increases in mean years of schooling for U.S. labor quality growth, and that labor quality growth explains about one quarter of the growth in labor productivity between 1967 and 2000. The growth in human capital of the workforce due to rising school spending explains only a quarter of the increases in empirical returns to schooling, and a rising skill premium explains the rest. Controlling for the rise in skill premium is important–failing to do so would double the estimated importance of the increased expenditure to growth in human capital.

Keywords: Rising School Quality, Labor Quality Growth, Growth Accounting
JEL Classifications: J24, O47, O51

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* This is a revised version of chapter 1 of my Ph.D. dissertation submitted to the University of Rochester. I am deeply indebted to Mark Bils for his generous support and encouragement. I also thank Mark Aguiar, Yongsung Chang, Jay H. Hong, and seminar participants at the University of Rochester, the State University of New York at Buffalo, the Federal Reserve Bank of Richmond, Korea Development Institute, Far Eastern Meeting of the Econometric Society 2008, and Midwest Macro Meetings 2007 for their valuable comments. All errors are mine.

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1 Introduction

This paper explores how much U.S. labor quality has increased due to rising school spending. Schooling investments in the U.S. increased drastically during the 20th century. According to the Current Population Survey March Supplement, the mean years of schooling for the U.S. workforce rose from about 11 years in 1967 to more than 13 years in 2000. On top of that, the public school spending per pupil in elementary and secondary schools for the cohorts appearing in either survey more than tripled on average. While both of these are potential sources of human capital growth of the U.S. workforce, the measure of labor quality growth used by the Bureau of Labor Statistics (BLS) is determined mainly by increases in the mean years of schooling, and fails to capture changes in education quality. The BLS reports that labor quality grew by 0.22 percent per year between 1967 and 2000; if the increased school spending improved school quality, then the BLS may miss a significant part of the contribution of labor quality growth to U.S. real income growth.

In order to understand the role of school spending in human capital accumulation, I develop a simple schooling model. An important characteristic of the model is that human capital depends not only on the amount of time spent in school, but also on the level of expenditures while in attendance. The productivity of school spending is governed by the elasticity of human capital production with respect to school spending. In this study, I propose a new way of estimating this elasticity, and quantify the impact of the increased school spending per pupil on U.S. labor productivity growth.

To estimate the productivity of school spending in increasing the human capital of the workforce, I examine how earnings of younger cohorts compare to those of older cohorts who received their schooling at earlier dates. I also examine how the estimated Mincer return to schooling has evolved across cohorts. Empirical returns to schooling more than doubled for 1970 birth cohorts, compared to 1912 birth cohorts, while mean years of schooling increased. If we allow for the marginal return to schooling to decline with the level of education, then increased returns to schooling can only be explained by a rise either in school quality or in skill premiums. For illustration, suppose that individual human capital does not increase with experience at all. If school quality had indeed improved due to rising school spending, then in cross-sectional data we should observe higher earnings for younger cohorts than for older cohorts. Since experience has no effect on human capital, rising school quality could be quantified by accounting for earnings differences across cohorts in cross-sectional data, conditioned on years of schooling. The increases in returns to schooling unexplained by the estimated increases in school quality could then be attributed to a rising skill premium.

Earnings, however, do increase with work experience, because individuals accumulate human capital through work experience in addition to schooling, but the above logic is still valid. To be consistent both with rising school quality and with increasing experience-earnings profiles in cross-sectional data, it must be that individual human capital stocks increase very rapidly with work experience. Individual human capital profiles cannot be too steep after completion of schooling, however, or else individuals would leave school earlier than we observe, substituting expenditure on schooling for time in school. Individual post-schooling human capital profiles, identified in this manner, allow us to estimate the proportion of labor quality growth that is due to rising school expenditures by disentangling the impact of rising school quality and differences in work experience upon cross-sectional earnings differences across cohorts.

My findings are that rising school spending is about half as important as increases in mean years of schooling for U.S. labor quality growth, and that total labor quality growth explains about one quarter of the growth in labor productivity between 1967 and 2000. The growth in human capital of the workforce in response to rising school spending explains only a quarter of the increases in empirical returns to schooling, and a rising skill premium explains the rest. Given the increased school spending per pupil, U.S. labor quality growth has been fairly modest. Controlling for the rise in skill premium is important – failing to do so would double the estimated importance of the increased expenditure to growth in human capital.

There is a vast literature that seeks to quantify the role of human capital in economic growth and development. The most widely used methodology to measure country-level human capital stocks in the literature is to multiply the mean years of schooling of the population by the estimated Mincer return to schooling as in Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999). Since this method does not allow for differences in education quality across countries, however, Bils and Klenow (2000) add teacher human capital to the standard Mincer-type human capital specification. Bils and Klenow (2000) consider only time inputs for human capital production and ignore goods inputs, which can potentially generate remarkable differences in education quality. Manuelli and Seshadri (2005) and Erosa, Koreshkova, and Restuccia (2006) explicitly incorporate education goods as well as time as inputs for human capital production and attempt to quantify the role of human capital in explaining cross-country income differences. Their approaches are not applicable to the growth accounting presented later in the paper, however, because their calibration is based on a steady state, which excludes the possibility that different cohorts may face different levels of quality of education.

This paper most closely relates to Rangazas (2002) by attempting to quantify the impact of quantity and quality of schooling on U.S. labor productivity growth. It differs from Rangazas (2002), however, in that it estimates the productivity of school spending at increasing human capital instead of taking it from micro-study estimates in the literature. When one attempts to measure growth in human capital using inputs for human capital accumulation we observe in the data, critical is finding reasonable parameters governing human capital production function. A significant contribution of this paper is proposing a new way of estimating the elasticity of human capital production with respect to expenditures, which is key to quantifying the impact of rising school spending on labor quality growth. I also control for the rise in skill premium and unobserved heterogeneity correlated with schooling choice – ignoring these may overestimate the role of human capital growth in income growth.

The remainder of this paper is organized as follows. Section 2 describes the BLS measure of labor quality growth and discusses the relation between the estimated return to schooling and school quality. In section 3, I introduce a simple schooling model in which individual human capital depends on expenditures as well as time spent in school, and extend it by considering skill premium and heterogeneous learning ability. I describe the identification scheme and the estimation procedure for relevant parameters in section 4 and report the estimation results and main findings in section 5. Section 6 concludes the paper.

2 Measuring Labor Quality Growth

2.1 The BLS Measure

Since 1983, the Bureau of Labor Statistics (BLS) has extended the traditional growth accounting framework[1] by incorporating labor quality growth into U.S. economic growth accounting following Denison (1962). The BLS considers a production function, in which economic output Y depends on m types of physical capital inputs $k_1,\ k_2,\ ..., k_m$ and raw hours $l_1,\ l_2, ..., l_n$ provided by n types of workers.

$$Y = f(k_1, ...k_m, l_1, ..., l_n, t)$$

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

$$\frac{\dot{\overline{Y/L}}}{Y/L} = \frac{\dot{\overline{TFP}}}{TFP} + s_K \left[\sum_{i=1}^{m} s_{k_i} \frac{\dot{k}_i}{k_i} - \frac{\dot{L}}{L} \right] + s_L \left[\sum_{j=1}^{n} s_{l_j} \frac{\dot{l}_j}{l_j} - \frac{\dot{L}}{L} \right]$$

where

$$L = \sum\nolimits_{j=1}^{n} l_j$$

$$s_{k_i} = \frac{P_{k_i} k_i}{\sum_{i=1}^{m} P_{k_i} k_i} \text{ and } s_{l_j} = \frac{P_{l_j} l_j}{\sum_{j=1}^{n} P_{l_j} l_j},$$

$$s_K = \frac{\sum_{i=1}^{m} P_{k_i} k_i}{\sum_{i=1}^{m} P_{k_i} k_i + \sum_{j=1}^{n} P_{l_j} l_j} \text{ and } s_L = \frac{\sum_{j=1}^{n} P_{l_j} l_j}{\sum_{i=1}^{m} P_{k_i} k_i + \sum_{j=1}^{n} P_{l_j} l_j}$$

[1] The well-known Solow residual is income growth unexplained by physical capital growth only.

Every variable with 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. The growth rate $\frac{\dot{k}_i}{k_i}$ of the type i capital input is weighted by its cost share s_{k_j} in total physical capital input costs and the weighted average of different capital input growth rates is itself weighted by the share s_K of total capital inputs in total factor input costs. The growth rate of type j labor input is weighted by its cost share s_{l_j} in the total cost of labor inputs. As in the case of capital inputs, the weighted average of different labor input growth is multiplied by the cost share s_L of total labor inputs in total factor input costs before accounting for its contribution to labor productivity 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 that include dummies for a few education windows, work experience, and other individual traits as regressors and exploits the predicted wages from the regression to compute cost shares of different labor inputs. The BLS measure $s_L \left[\sum_{j=1}^{n} s_{l_j} \frac{\dot{l}_j}{l_j} - \frac{\dot{L}}{L}\right]$ of labor quality growth, obtained in this manner, is mainly determined by the increases in years of schooling, but fails to capture the impact of changes in education quality on human capital of the workforce.

A simple example makes a point. Suppose 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 increased from one period to the next, the BLS reflects that in its measure of labor quality growth by multiplying the change in the labor composition by the wage differences between the two groups of workers. Suppose instead that school quality improved from one period to another while labor composition stayed the same. We would then expect some growth in labor quality because workers in the second period on average acquired better quality education. The BLS approach, however, yields no labor quality growth between the two periods because labor composition stayed the same. The BLS reports that U.S. labor quality grew by 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, suggests that the BLS measure of human capital may miss out on a significant part of labor quality growth. As shown in Figure 1, real public educational expenditures per pupil in elementary and secondary schools increased drastically during the 20th century, which led the average spending per pupil to more than triple for the cohorts appearing in 2000, compared to the cohorts working in 1967. To avoid overstating the expenditures growth, I deflate the time series using an education sector price index, which increases more rapidly than an overall price index.[2]

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,[3] it is conceivable that newer cohorts have accumulated more human capital stocks through rising school spending and educational attainment than older cohorts.

In this study, I suggest that labor input is expressed as a product of raw hours and its quality.

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

In this formula, l_j is raw hours provided by type j labor input and h_j is its quality per hour. This approach decomposes the changes in the price for the hours worked by j worker types into changes in hour quality h_j provided by j type worker and the price P_{h_j} per quality where $P_{l_j} = P_{h_j} h_j$. Labor productivity growth accounting is then modified as follows.

$$\frac{\dot{\overline{Y/L}}}{Y/L} = \frac{\dot{\overline{TFP}}}{TFP} + s_K \left[\sum_{i=1}^{m} s_{k_i} \frac{\dot{k_i}}{k_i} - \frac{\dot{L}}{L} \right] + s_L \left[\sum_{j=1}^{n} s_{l_j} \frac{\dot{h_j}}{h_j} + \left(\sum_{j=1}^{n} s_{l_j} \frac{\dot{l_j}}{l_j} - \frac{\dot{L}}{L} \right) \right]$$

Labor quality growth now has an additional component $s_L \sum_{j=1}^{n} s_{l_j} \frac{\dot{h_j}}{h_j}$ representing the weighted average of quality growth of different labor inputs. If school quality indeed improved

[2] The price index for Personal Consumption Expenditures (PCE) on education is used to deflate educational expenditures. Using an overall price index as a deflator, the factor by which those data increased almost triples.

[3] Hanushek and Rivkin (1997) decomposed the rise in school spending over the 20th century and found that it resulted from declining pupil-teacher ratio, increasing real wages for instructional staffs, and rising expenditures outside of the classroom.

due to rising school spending, this term should capture its impact. This paper quantifies this component, which the BLS has not treated.

2.2 Rising School Quality and Return to Schooling

Economists have long used the well-known Mincer specification[4] to estimate the impact of schooling on individual earnings. If school quality indeed improved due to rising school expenditures, it should also be reflected in the estimated Mincer return to schooling. One might then argue that accounting for the increases in the estimated Mincer return to schooling over time as presented in Table 3 should be enough to quantify labor quality growth.

Although the estimated Mincer return to schooling contains important information about cross-sectional returns to schooling, it is not well-suited for cohort analysis because it implicitly assumes a constant return to schooling and the absence of cohort effects. For illustration, consider cross-sectional data where younger cohorts on average obtained better quality of education as well as more years of schooling than older cohorts. Figure 2 plots marginal returns to schooling for two cohorts in this case, where mean years of schooling for older and younger cohorts are denoted by $\overline{S}_1$ and $\overline{S}_2$, respectively. While the marginal return to schooling diminishes with the level of schooling within cohort, rising school quality shifts up the marginal return to schooling of the younger cohort over all education levels. This is captured by the curve for the younger cohort (MRS_2), which resides above the curve for the older cohort (MRS_1). The more school quality rises, the more the MRS_2 curve shifts upward from the MRS_1 curve. As a result, the estimated Mincer return to schooling, r_S, approximates the marginal return to schooling for both cohorts fairly well.

If human capital growth between the two cohorts is naively computed by multiplying the estimated Mincer return to schooling by the difference between cohort mean years of schooling, the resulting measure is represented by the shaded area in panel (a) of figure 2.

[4] Mincer (1974) derived an earnings specification, building on life-cycle earnings models developed in Becker (1964) and Ben-Porath (1967) with a few simplifying assumptions. The key assumptions include constant returns to years of schooling and linearly declining post-school investments in human capital. See Heckman, Lochner, and Todd (2003) for more details.

Noting that the human capital stock accumulated for each cohort is obtained by integrating the area below the corresponding marginal return to schooling curve up to the mean schooling level, however, the true growth in human capital between the two cohorts is measured by the bold-lined area in panel (b). This measure of labor quality growth understates true growth in human capital by the amount indicated by the black-lined parallelogram,[5] which is greater, the more the rising school spending shifts up the marginal return to schooling curve for the younger cohort.

Rising school quality is, however, not the only factor that increases the marginal returns to schooling. If different education groups are imperfectly substitutable in the labor market, the market pays different wage rates to different education groups depending on the demand for and the supply of corresponding education groups. When more educated workers get paid higher wage rates per unit of human capital than less-educated workers, the MRS_2 curve shifts upward from the MRS_1 curve as is shown in Figure 2, without much rise in school quality across cohorts. Ignoring the presence of this skill premium, the higher return to schooling for more educated workers that is due to the skill premium is attributed instead to rising school quality, overstating the impact of rising school quality on growth in human capital for a given diminishing return to schooling. Since empirical evidence indeed supports the notion that the skill premium rose drastically from the 1980's on, controlling for this seems to be quantitatively important.

Within-cohort heterogeneity that is positively associated with schooling choice also affects the estimated return to schooling. Card (1994) argues that individuals with a higher return to schooling tend to obtain more education because of the comparative advantage. Assuming that ability distribution stays the same across cohorts, in order to account for the increases in mean years of schooling across cohorts, it must be that average ability level is lower for younger cohorts than for older cohorts at a given number of years of schooling. This implies

[5] Even if we add higher-order polynomials of schooling in the Mincer regression to improve the model fit, the reasoning still applies because the specification mistakes the shift of marginal return to schooling curve due to school quality rise as a small degree of diminishing returns.

that a unit of school spending is relatively less productive for younger cohorts than for older cohorts. Failing to control for heterogeneity correlated with schooling choice then overstates labor quality growth due to increases in school spending.

The discussion in this section confirms that the estimated cross-sectional Mincer return to schooling itself does not provide us with a correct measure for labor quality growth when school spending has risen. In this study, I free up the assumptions behind the Mincer specification by considering factors that affect the schooling-log earnings relation in cross-sectional data. This includes changes in education quality across cohorts, the rise in skill premium, and heterogeneous ability associated with individual schooling choice. I then use the estimated Mincer return to schooling as a guide to pin down the combination of parameters governing each factor along with other data moments.

3 The Model

In this section, I first introduce the baseline model in which human capital production depends on expenditures as well as time inputs. I then extend the model in two directions by introducing either a skill premium or heterogeneous learning ability.

3.1 The Baseline Model

3.1.1 Human Capital Production Function

To consider quality differences in schooling, I introduce a Ben-Porath type human capital production function[6]. Individual human capital stock $h(a)$ at age a, accumulates according

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

to two separate processes during schooling and on-the-job training as follows.

$$\overset{\bullet}{h}(a) = \gamma_0 h(a)^{\gamma_1} D(a)^{\gamma_2} \text{ for } a < S+6$$

$$\overset{\bullet}{h}(a) = \phi'(a-S-6)h(a) \quad \text{for } a \geq S+6$$

$$\phi(a-S-6) = \phi_0(a-S-6) + \phi_1(a-S-6)^2 \quad \forall a > S+6$$

$$0 < \gamma_1, \gamma_2 < 1 \text{ and } h(6) \text{ is given}$$

Here, $\overset{\bullet}{h}(a)$ is the time derivative of human capital at age a, $D(a)$ is education goods investment at age a and S is years of schooling. An individual accumulates his human capital beginning at the age of 6 when he starts schooling. I assume that initial human capital at age 6 stays constant across cohorts. Although this may seem restrictive, I make this assumption because data on input for human capital production for pre-school period are not readily available for the entire twentieth century. Considering this will further refine the measure for school quality improvement estimated in this paper[7]. While in school, he produces human capital using his entire stock of human capital and education goods, and his human capital stock does not depreciate. While in school, an individual is a full-time student and cannot take part in market work. Goods investment in the production function captures school quality for a given year of schooling. 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, but do not impose a restriction on the return to scale represented by $\gamma_1 + \gamma_2$. In Ben-Porath (1967), diminishing returns to scale, or $\gamma_1 + \gamma_2 < 1$, is required because the assumption guarantees partial engagement of individuals in human capital investment after leaving school[8]. Since I assume a separate human capital accumulation process during on-the-job training from during schooling, such a restriction on

[7] To the extent that the initial human capital stock has increased across cohorts, the estimated rise in school quality in this paper is overstated.

[8] In Ben-Porath (1967), the law of motion of individual human capital follows $\dot{h}(a) = \pi[sh(a)]^{\gamma_1} D(a)^{\gamma_2}$ where $\gamma_1 + \gamma_2 < 1$. Diminishing returns to scale guarantees that the marginal cost of producing one unit of human capital increases such that there appears a period during which an individual works in the market and produces human capital at the same time, or $0 < s < 1$. If $\gamma_1 + \gamma_2 = 1$, the fraction s of one's time spent in human capital production is either 0 or 1.

the return to scale is not necessary. The parameter γ_0 governs the scale of human capital stocks and is allowed to vary across individuals in an extended model with heterogeneity, in which it is interpreted as individual learning ability. 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.

Once an individual leaves school, his human capital is assumed to grow exogenously through learning by doing on-the-job. More specifically, log human capital on-the-job accumulates as a quadratic function of experience. I made this assumption because we do not have good data for individual time allocation to human capital production and to the market, nor do we have good data for goods investment after completion of schooling. When staying an additional year in school, an individual incurs the same cost by delaying the return to post-schooling experience, whether human capital accumulates through learning by doing or through Ben-Porath type investments, after completion of schooling. Since what matters to identify the productivity of school spending in increasing human capital is only the quantity of this cost, the learning by doing assumption for on-the-job human capital accumulation is innocuous. If younger cohorts invest more quality goods to increase human capital after completion of schooling as well as while in school than older cohorts, however, I may miss its impact on labor quality growth.

According to the human capital production function described above, an individual's human capital stock when he leaves school is written, given $h(6)$, as

$$h(S+6) = \left[h(6)^{1-\gamma_1} + \gamma_0(1-\gamma_1) \int_6^{S+6} D(a)^{\gamma_2} da \right]^{\frac{1}{1-\gamma_1}}$$

An efficiency unit assumption that differently skilled workers are unequal, but perfect substitutes implies that each individual is paid in proportion to his human capital. Therefore, the logarithm of the observed wage bill of an individual i at time t, denoted by WB_{it} satisfies

$$\ln WB_{it} = \ln w_t + \frac{1}{1-\gamma_1} \ln \left[h(6)^{1-\gamma_1} + \gamma_0(1-\gamma_1) \int_6^{S_i+6} D(a)^{\gamma_2} da \right] + \phi(Exp_{it}) + \varepsilon_{it} \quad (1)$$

The aggregate wage at time t common to every worker is denoted by w_t. In an extended model, individuals with different levels of education are assumed to be imperfectly substitutable and get paid different wages from each other. An individual shock component at time t denoted by ε_{it} is assumed to be exogenous to any known individual characteristics Z_{it} at time t such that

$$E(\varepsilon_{it}|Z_{it}) = 0$$

3.1.2 A Simple Schooling Model

I now introduce a simple schooling model to add a restriction on the relationship between human capital production technology and schooling investment.

An individual born at time 0 chooses the optimal level of schooling and goods investment associated with each year of schooling to maximize the present value of his lifetime income stream.[9]

$$\max_{D(a),\, S} \int_{S+6}^{R} e^{-ra} w(a)h(a)da - \int_{6}^{S+6} e^{-ra} P(a)D(a)da$$

$$s.t.\;\; h(a) = \left[h(6)^{1-\gamma_1} + \gamma_0(1-\gamma_1)\int_{6}^{S+6} D(t)^{\gamma_2}dt\right]^{\frac{1}{1-\gamma_1}} e^{\phi(a-S-6)}$$

The individual goes to school for S years, beginning at age 6, and enters the market with a human capital stock accumulated through schooling at the age of $S+6$. Human capital production technology is the same as described in the previous section. Prices of education goods relative to consumption goods are denoted by $P(a)$[10]. Once he leaves school, he never goes back to school and works till he retires at age R. He discounts his income using the market interest rate r.

Assuming interior solutions, first-order conditions with respect to the two choice variables are sufficient to characterize optimal levels S^* and $D^*(a)$ of schooling and education goods

[9] In the presence of perfect credit markets, the individual optimization problem described here is equivalent to the standard utility maximization problem.

[10] In the data, education goods prices grow more rapidly than overall price levels. Between 1929 and 2005, inflation rates based on the Consumer Price Index (CPI) city average and the Personal Consumption Expenditures (PCE) price index are 3.3% and 3.1% per annum while PCE on the education price index increased by 4.3% per year.

investments for $6 \leq a \leq S^* + 6$. For notational convenience, I define $\widetilde{S}^* = S^* + 6$.

$$\gamma_0 \gamma_2 D^*(a)^{\gamma_2 - 1} h(\widetilde{S}^*)^{\gamma_1} \int_{\widetilde{S}^*}^{R} e^{-rt+\phi(t-\widetilde{S}^*)} w(t) dt = e^{-ra} P(a),\ \forall a \leq \widetilde{S}^* \tag{2}$$

$$\gamma_0 h(\widetilde{S}^*)^{\gamma_1 - 1} D^*(\widetilde{S}^*)^{\gamma_2} \int_0^{R-\widetilde{S}^*} e^{-r\tau+\phi(\tau)} h(\widetilde{S}^*) w(\tau + \widetilde{S}^*) d\tau \tag{3}$$

$$= w(\widetilde{S}^*) h(\widetilde{S}^*) + P(\widetilde{S}^*) D^*(\widetilde{S}^*) + \int_0^{R-\widetilde{S}^*} e^{-r\tau+\phi(\tau)} w(\tau + \widetilde{S}^*) h(\widetilde{S}^*) \phi'(\tau) d\tau$$

The above two first-order conditions represent two margins on which an individual is optimizing: the quality and quantity margins of schooling. Equation (2) implies that at the optimal point, the marginal benefit of investing one more unit of education goods at the age of a, which is a human capital increment promising higher income throughout his working life, equals its marginal cost, or the unit price of education goods. An individual spends more in higher grades because it is a cheaper way to achieve the optimal human capital stock when leaving school, given the optimal number of years of schooling. More specifically, the model predicts that spending for each grade is increasing at the rate of $\frac{g_p - r}{\gamma_2 - 1}$ where g_p is the continuous growth rate of the relative price of education goods[11]. Equation (3) relates the marginal cost of staying one more year in school to its marginal benefit. If an individual decides to stay in school for one more year, he incurs a cost in delaying the returns to post-schooling experience as well as foregone earnings and educational expenditures for that year while he expects a permanent increase in his lifetime income.

[11] When I introduce a heterogeneity in individual ability in an extension, I assume that individuals freely choose the length of schooling, but that they do not have complete freedom in determining school expenditures. I made this assumption because in reality, individuals do not have complete discretionary control over school spending, particularly in primary and secondary schools. The amount of expenditures is assumed to be optimal for the median ability person in each cohort. This would mimic the trends in school spending in a political equilibrium based on a median voter model.

Plugging equation (2) evaluated at $a = \widetilde{S}^*$ into equation (3) yields

$$\gamma_2 = \frac{P(\widetilde{S}^*)D^*(\widetilde{S}^*)}{w(\widetilde{S}^*)h(\widetilde{S}^*) + P(\widetilde{S}^*)D^*(\widetilde{S}^*) + \int_6^{R-\widetilde{S}^*} e^{-r\tau+\phi(\tau)} w(\tau+\widetilde{S}^*)h(\widetilde{S}^*)\phi'(\tau)\} d\tau} \tag{4}$$

Equation (4) indicates that the elasticity of human capital with respect to expenditures is equal to the share of expenditures in the marginal cost of obtaining the last year of schooling by the optimizing individuals. It implies that γ_2 can be estimated by uncovering the fraction of expenditure cost out of the marginal cost of staying one more year in school at the optimal schooling level. I exploit this expenditure share in the marginal cost of schooling represented by equation (4) as an important moment to estimate the impact of rising school spending on growth in the human capital of the workforce.

3.2 Extensions

In this section, I extend the baseline model in two directions. First, I introduce skill-specific wages to the baseline model, the changes of which affect the estimated return to schooling without changing the marginal product of schooling. Second, I allow learning ability to vary across individuals. Learning ability affects individual schooling decisions.

3.2.1 Skill Premium

Beginning in the late 70's, the skill premium represented by the wage gap between college and high school graduates has risen consistently. Autor, Katz, and Kearney (2005) present evidence from the CPS March Supplement that log wage gap between college and high school graduates increased from 0.4 in 1979 to about 0.65 in 2000. In light of the increased supply of college graduates, economists have concluded that demand for high-skilled workers has been rising even more rapidly, thereby raising the skill premium during that period. Since a rising skill premium increases empirical returns to schooling for later cohorts who on average stayed in school longer than earlier cohorts, we may overstate the role of rising school quality if we let it explain the entire increase in the Mincerian return to schooling.

To avoid mistaking a skill premium rise as labor quality growth, I introduce different skill prices associated with different levels of schooling. I assume that when individuals decide how many years to stay in school, they do not recognize the present skill premium[12]. Under this assumption, equation (4) for the expenditure share in the marginal cost of schooling is still valid. I denote by w_S the wage rate per unit of human capital of an individual with S years of schooling. The observed wage bill of an individual i at time t depends on the skill-specific wage instead of the aggregate wage. The logarithm of his wage bill is then expressed as:

$$\ln WB_{it} = \ln w_{St} + \frac{1}{1-\gamma_1} \ln \left[h(6)^{1-\gamma_1} + \gamma_0 (1-\gamma_1) \int_6^{S_i+6} D(a)^{\gamma_2} da \right] + \phi(Exp_{it}) + \varepsilon_{it}$$

When determining skill-specific wages, I follow Katz and Murphy (1992)[13]. I categorize workers into four education groups: i) workers with less than 12 years of schooling, ii) high school graduates, iii) workers with some college, and iv) college graduates. Additionally, I obtain average skill-specific wages for the four groups using CPS data and the parameterized on-the-job human capital production function.[14] For workers with less than 12 years of schooling and workers with some college, I use the linear projections of the time series of their average wages on the wages of high school graduates and college graduates to extract the extent to which their wages move with the wages of high school and college graduates. I then allocate the resulting wages to workers with 0, 12, 14, and 17 years of schooling and linearly interpolate wages for in-between education levels.

[12] Even if individuals recognize the skill premium when they make schooling decisions but do not anticipate it to rise or fall over time, the results do not change much.

[13] When creating a measure of labor supply, Katz and Murphy (1992) allocate workers to two aggregate groups, high school equivalents and college equivalents. High school graduates and college graduates are treated as pure high school equivalents and college equivalents, respectively. For workers with all other education levels, they allocate them based on the extent to which their wages move with the wages of high school and college graduates. For example, they regress the average series for workers with some college on the wages of high school and college graduates and use the estimated coefficients to allocate them to the two aggregate groups. See Katz and Murphy (1992) for more details.

[14] See section 4 for more details.

3.2.2 Heterogeneous Learning Ability

Labor economists have paid attention to the impact of unobserved heterogeneity among individuals, such as innate ability on the estimated return to schooling. More able individuals tend to obtain more education because of comparative advantage, and this systematically biases the OLS estimate for the marginal return to schooling upward. Assuming that the ability distribution stays constant across cohorts, the increases in cohort mean years of schooling imply that the average ability level of younger cohorts is lower than that of older cohorts for any given years of schooling. Without adjusting for this, I may overestimate labor quality growth given rising school spending. In this extension, I introduce individual heterogeneity in learning ability γ_0.[15] This type of heterogeneity affects the individual return to schooling, inducing individuals with higher ability to choose more years of schooling.

Specifically, I assume that individual learning ability is log-normally distributed for every cohort, where the distribution stays the same across cohorts. I set the number of discrete levels of learning ability equal to the number of education levels we observe in the data for each cohort, where higher ability is associated with higher levels of schooling. Given the log-normal learning ability distribution characterized by its mean μ_{γ_0} and standard deviation σ_{γ_0}, I assign learning ability to each schooling level as follows. For instance, if 12 years of schooling covers the 50th to 70th percentiles of the schooling distribution for a certain cohort in the data, I assign the learning ability for the 60th ($60 = (50 + 70)/2$) percentile to high school graduates.

[15] Although individual human capital stock $h(6)$ at the age of 6 is also a potential source of individual heterogeneity, I only consider heterogeneity in learning ability γ_1 in this paper. This is sufficient for the purpose of demonstrating how the correlation between unobserved heterogeneity and schooling affects the estimated labor quality growth. In addition, empirical evidence supports that heterogeneity in the return to schooling may be more important. Many studies that attempt to measure the true return to schooling using instruments find that the ability bias is negative. Card (2001) argues that heterogeneous return to schooling may drive these results because treatment groups affected by those instruments have higher returns to schooling.

4 Identification and Estimation

In this section, I provide insights on how to identify the productivity of school spending in increasing the human capital stocks of the workforce and describe the estimation procedure.

4.1 Identification

As is shown in Table 3, the estimated Mincer return to schooling rose from about 5.6% in 1968 CPS data to about 10.3% in 2001 CPS data, and the mean years of schooling of the U.S. workforce also increased. If the marginal return to additional years of schooling declines with the level of schooling, this increase in the return to schooling requires a rise either in school quality across cohorts or in skill premiums.

To estimate the impact of rising school spending on the growth in labor quality, I examine how earnings of younger cohorts compare to those of older cohorts who acquired schooling at earlier dates in cross-sectional data. To illustrate, suppose that individual human capital does not accumulate with work experience at all. If rising school spending increased school quality, in cross-sectional data, we should observe that younger cohorts earn more than older cohorts for given years of schooling. Since work experience does not increase human capital at all, the earnings differential between younger and older cohorts provides a measure of the growth in human capital due to rising school spending. The increase in the estimated return to schooling unexplained by the rise in school quality can then be attributed to a skill premium rise over time.

Earnings do however increase in cross-sectional data because individuals accumulate human capital through work experience as well as through schooling, but the above logic is still valid. To be consistent both with sharply rising school quality and with increasing experience-earnings profiles in cross-sectional data would require that individual human capital stocks increase even more rapidly with work experience than in the cross-sectional data. Figure 3 contrasts the cross-sectional experience-earnings profile with individual post-schooling human capital profiles when rising school spending indeed improves school quality.

The dotted curve indicates the usual hump-shaped cross-sectional experience-earnings profile, while the black solid curves represent how individual human capital evolves with work experience for different cohorts, controlling for years of schooling. Even though the shape of the post-schooling human capital profile is the same for every cohort, rising school quality shifts the profile for younger cohorts upward. Since earnings differences across cohorts in the cross-sectional data are determined by rising school quality and differences in work experience across cohorts, I can estimate the proportion of labor quality growth that is due to rising school expenditures by understanding how individual human capital increases with work experience.

The relationship between school expenditures and years of schooling imposed by the optimal schooling investments described in section 3 helps unveil the effect of work experience on human capital accumulation. Individuals take into account how their human capital stocks evolve after completion of schooling, when they decide on their education levels and school expenditures. If individual human capital profiles are too steep after leaving school, staying in school is very costly for individuals, inducing them to substitute expenditures on schooling for time in school. We should then observe more school expenditures than we actually observe in the data. If individual human capital profiles are too flat instead, individuals would not spend as much money while in school as we see in the data. In this way, I identify individual post-schooling human capital profiles which satisfy the optimality condition on schooling investments, using data on expenditures and years of schooling. This leads me to quantify the impact of rising school expenditures on growth in the human capital of the workforce, which flattens the cross-sectional relationship of experience and earnings based on different cohorts compared with individual post-schooling human capital profiles.

One thing to note is that with the models without heterogeneous ability, I do not attempt to estimate γ_1 governing the curvature of the human capital production function while in school. Not only do those models not provide a proper moment to estimate γ_1, but the value of γ_1 also hardly affects the estimated labor quality growth due to rising expenditures on schooling. In a model with heterogeneity, however, the mean years of schooling over all samples and the mean schooling dispersion within cohorts are used for identifying the variance of the ability distribution and the curvature parameter γ_1. When more able individuals stay in school longer, the estimated Mincer return to schooling is higher than the mean of individual marginal return to schooling, by the magnitude of the ability bias. The larger the variance of the ability distribution is, the further the mean of individual marginal return to schooling is below the estimated return to schooling. Mean years of schooling, given the curvature of the human capital production function, then determines the mean of individual marginal return to schooling, thereby identifying the variance of the ability distribution. On the other hand, given the variance of ability distribution, a higher curvature of the human capital production function generates more schooling dispersion within cohorts. The degree of curvature of the human capital production function is then identified by the mean dispersion of schooling within cohorts. Therefore, the basic identification scheme of the impact of rising school quality on labor quality growth described above is still valid with the introduction of unobserved heterogeneity.

4.2 Data and Estimation

Before implementing the estimation procedure, I pre-set the values of a few variables. I set the retirement age R and the interest rate r to 65 and 0.05, respectively. Education good prices are assumed to grow at the constant rate of 0.115, which is the average annual growth rate of the PCE on the education price index between 1908 and 2000. I normalize the price of education goods in 1982 to one. I also normalize the initial human capital stock $h(6)$ of an individual at age 6 to one, which is the same for any individual in any cohort. Neither normalization affects anything other than the scale parameter γ_0. I vary the value of the curvature parameter γ_1 from 0.3 to 0.7 for the baseline model and the skill premium model. These values are summarized in Table 4.

Given those variables, I estimate the parameters characterizing the human capital production technology during schooling and on-the-job training using the Generalized Method of Moments (GMM), minimizing the weighted distance between the model moments and data counterparts. I start with a model with an efficiency unit assumption and then introduce the skill premium to investigate its impact on the estimated labor quality growth due to increased school expenditures. The moments I use include the estimated Mincer return to schooling over all samples and for each year and the estimated cross-sectional return to experience (modelled as a quadratic function of potential experience in the pooled sample Mincer regression), and the expenditure share of the marginal cost of schooling represented by equation (4).

I use the Current Population Survey March Supplement from 1968 to 2001 as the representative sample of the U.S. to run Mincer regressions and construct the expenditure share of the marginal cost of schooling for each cohorts. Although the data set is available beginning 1964, I excluded the first four surveys because questions on earnings have changed since 1968. Sample selection criteria follow those of BLS (1993) as closely as possible. To be included in the sample, individuals should have a job when surveyed and report positive weeks and hours worked for the past year. Individuals working for the government or self-employed are excluded. Age restrictions are imposed so that individuals between the ages of 16 and 65 in the year they worked are included in the sample. Relaxing the age restriction appears to have little affect on the results.

All individuals in the sample reported their years of schooling, weeks worked in the past year, usual hours worked (or hours worked in the past week for surveys before 1976), wage or salary income in the past year and other individual characteristics such as gender, race, marital status, census division of residence and SMSA status. Since weeks worked were separated into intervals through 1975, mean weeks worked in the 1976 survey were substituted for previous surveys. Annual hours are obtained by the product of weeks worked and hours worked per week. Top-coded earnings before 1996 were multiplied by 1.5, following Katz and Murphy (1992). Earnings equations are based on hourly wages obtained from annual earnings and annual hours worked. The BLS started to code years of schooling in intervals since 1992. I assigned 0, 3, 6, 8, 9, 10, 11, 12, 14, 16, and 17 for the categories of none, 1-4, 5-6, 7-8, and 9-11 years of schooling, 12 years with no diploma, 12 years and some college with no degree or an associate degree, bachelor degree, master and Ph.D. degree. Throughout the survey, the highest years of schooling was recoded as 17 years.

I run Mincer regressions using pooled sample of 1968 to 2001 surveys and use coefficients on years of schooling, potential experience and its square along with year-by-year Mincer returns to schooling as data moments for estimation. I also compute the expenditure share in the marginal cost of schooling for each cohort, as represented by equation 4, using the cohort mean years of schooling and data on school expenditures. Computing the expenditure share in the marginal cost of schooling requires the evolution of aggregate wages for the entire period during which any of the cohorts was working in the market. Since I assume that individuals do not recognize the skill premium when they decide on schooling, I use the mean of the skill-specific wages obtained above, between 1967 and 2000. I assume that wage growth rates before 1967 and after 2000 are the same as the growth rates for the first and last decades of the sample period $(1967-2000)$, respectively.

Ideally, individual data on school expenditures at different grade levels for all cohorts I consider are needed for the analysis in this paper. Unfortunately, school spending per pupil is available only as a time series for public elementary and secondary schools and for all degree-granting institutions. As an alternative, I assume that there is no difference in school expenditures within cohorts and infer school spending for each cohort using the schooling choice model in section 3. As mentioned in section 3, school spending grows at the rate of $\dfrac{g_p - r}{\gamma_2 - 1}$ as one proceeds to a higher grade. I assume that school expenditures for the first grade increase at a constant rate across cohorts and set its growth rate and the level of first grade spending of the earliest cohort I consider such that it generates a time series of school expenditures consistent with what we observe in the data. More specifically, I have the time series match the level of school expenditures per pupil in public elementary and secondary schools in the 1908 data as well as its average growth rate between 1908 and 2000.

The time series of educational expenditure data were taken from the *Digest of Education Statistics 2004* by the National Center for Education Statistics (NCES) and *120 years of American education: A statistical Portrait* by the U.S. Department of Education. Specifically, yearly total expenditure per pupil in public elementary and secondary schools were used for the analysis in this paper. Since the data were collected biennially in the mid-20th century, I used a cubic spline to interpolate the series.

To obtain a time series of real spending per pupil, I needed to be careful about what deflator to use. Since education goods prices rose much faster than the average commodity prices, deflating educational expenditures by an overall price index would overstate the growth of real expenditures on education. Therefore, I used the price index for Personal Consumption Expenditures (PCE) on education to deflate educational expenditures. Since the data are not available before 1929 yet, the earliest cohort I considered in this paper started to go to school in 1908, I used the projection of the price index for PCE on education on the Consumer Price Index (CPI) and spliced it to the actual data since 1929. Since CPI has been published by the BLS beginning 1913, the price index in Warren and Pearson (1935) was used for years before 1913. All other goods and wages were deflated using the PCE. Using the CPI instead changes the results little.

In order to estimate relevant parameters usign the GMM, I should construct model moments corresponding to data counterparts. For Mincer regression coefficients from the model, I construct individual human capital stocks accumulated through schooling and through learning-by-doing on the job. Since the aggregate wage is common to every individual and the error terms are assumed to be strongly exogenous, running regressions using logged human capital stocks of individuals as dependent variables should be sufficient to obtain Mincer conefficients from the baseline model. Since individual human capital stocks vary in the model only by cohort, years of schooling and work experience, I construct human capital stocks for each schooling-potential experience[16] cell for each survey year between 1968 and 2001 for a given set of parameters. Constructed this way, cell-specific human capital stocks are then logged, and regressed on years of schooling, potential experience and its square, and time dummies, using cell sizes as weights over the whole samples and for each survey year.

[16]Since individual experience is not available in the CPS, I use potential experience defined as age minus years of schooling minus 6 for the analysis.

When I consider the skill premium, skill specific wages should also be considered for Mincer regressions as they affect the estimated coefficients for the returns to schooling. Skill specific wages are estimated non-parametrically from wage data in the repeated cross-sections of CPS. For cohort c with s years of schooling, changes in their mean wage bills between the two consecutive years, t and $t+1$, include changes in the skill-specific wage associated with schooling level s, return to accumulated experience, and a difference in mean errors (because their human capital stocks accumulated from schooling cancel out) as follows:

$$\ln \overline{WB}_{cst+1} - \ln \overline{WB}_{cst} = \ln w_{st+1} - \ln w_{st} + \phi(Exp_{cst+1}) - \phi(Exp_{cst}) + \overline{\varepsilon}_{cst+1} - \overline{\varepsilon}_{cst}$$

Here variables with an upper bar are group means. Assuming that the error term ε_{icst} in the wage bill of an individual i with s years of schooling in cohort c at time t is $i.i.d.$, a difference in mean errors approaches 0 for a large sample. Given parameters governing the experience function ϕ, taking the average of log changes in mean group wage bills for schooling level s over all cohorts determines changes in the skill-specific wage associated with that schooling level as residuals. The levels of skill-specific wages in earliest year in the sample are obtained as residuals from the mean hourly wages of different skill groups in 1968 CPS after taking out what is explained by human capital stocks.

Having constructed Mincer coefficients from the model this way, I estimate the model parameters using the GMM. Note that γ_2 is the model moment corresponding to the mean expenditure share in the marginal cost of schooling across cohorts as shown in equation 4. The parameter estimates denoted by $\widehat{\theta}$ minimize the weighted distance between the model moments and data counterparts, represented by the following objective function.

$$\widehat{\theta} = \arg\min\nolimits_{\theta} g(\theta)' W g(\theta)$$

where $\theta = (\gamma_0, \gamma_2, \phi_0, \phi_1)$. The vector of moment conditions and the weighting matrix are denoted by $g(\theta)$ and W, respectively. It is well-known that the optimal weighting matrix is determined by the inverse of the variance-covariance matrix of data moments. For Mincer regression coefficients, estimated variances are used where covariances between moment conditions are ignored, except that covariances between coefficients of the pooled sample regressions are allowed. Since the variances of the expenditure share in the marginal cost of schooling depend on the parameters, I implement a two-step estimation. The optimal weighting matrix is the inverse of the variance-covariance matrix estimated in the first-stage. I present standard errors for the estimates using numerical differentiation.

For the extended model with heterogeneous learning ability, I have two more parameters to estimate: the curvature parameter γ_1 and the variance σ_{γ_0} of the ability distribution such that $\theta = (\mu_{\gamma_0}, \gamma_1, \gamma_2, \phi_0, \phi_1, \sigma_{\gamma_0})$. I solve the income maximization problem to obtain the optimal years of schooling for each level of ability and cohort. I then compute the mean years of schooling over all cohorts and the mean dispersion in schooling attainment within cohorts, to match data counterparts.

5 Results

In this section, I report parameter estimates and, using those estimates, the estimated impact of rising school spending on labor quality growth.

5.1 Parameter Estimates and Growth Accounting

I report parameter estimates for all three model specifications in Table 5. For all three models, the elasticity γ_2 of human capital production with respect to expenditures is estimated to be between 0.12 and 0.13. This means that school expenditures explain between 12% and 13% of the marginal cost of schooling[17] as represented by equation (4). For the models without heterogeneity, the estimated value of this share is insensitive to the curvature γ_1 of the human capital production function for a given schooling period. The model with heterogeneous learning ability estimates the return to scale $\gamma_1 + \gamma_2$ of the schooling human capital production function to be about 0.87. Parameter estimates for ϕ_0 and ϕ_1 governing individual post-schooling human capital profiles confirm that the evolution of individual

[17] Foregone earnings form about 60% of the marginal cost of schooling, and the rest is attributed to the cost one incurs by delaying the return to work experience.

human capital with work experience is steeper than the cross-sectional relationship between experience and earnings when school quality rises over time. When the skill premium or heterogeneous learning ability are considered, however, the post-schooling human capital profile is estimated to be flatter than in the baseline model, which implies that ignoring a skill premium or the heterogeneity associated with schooling choice may overstate the impact of rising school quality on labor quality growth.

Table 6 presents growth accounting for U.S. labor productivity between 1967 and 2000 using the estimated parameters. The growth rates of labor productivity and physical capital inputs are taken from the BLS. I estimate the two components of labor quality growth – pure quality growth H_q and labor composition growth H_c – using the model, and obtain the TFP growth as a residual. Pure quality growth and labor composition growth measure labor quality growth due to increases in school quality and in mean years of schooling[18], respectively, where the latter corresponds to the BLS measure of labor quality growth. Physical capital growth and labor quality growth presented in Table 6 are adjusted for their cost shares. For comparison purposes, the BLS measure of labor quality growth is reported in the first panel.

As a starting point to examine the role of rising school spending in labor quality growth, I proceed with a baseline setup that allows quality investments in schooling, but ignores a skill premium or heterogeneous ability. The second panel of Table 6 presents the estimated labor quality growth in this setup. I find that the human capital of the U.S. workforce increased by 0.5% per year between 1967 and 2000, with about two fifths of this explained by the growth in school quality. Labor composition growth in this model differs from what the BLS reports because the BLS additionally considers changes in the gender composition of the U.S. workforce and adopts time-varying weights for each experience group using year-by-year Mincer regression results. Instead, labor composition growth in this model focuses on changes in the education composition of the U.S. workforce. The estimated labor quality

[18] Labor composition growth also includes the impact of changes in experience composition of the workforce on labor quality growth. Since the mean years of experience of the U.S. workfoce does not show any secular trend, however, its quantitative impact on labor compostition growth is small.

growth due to the rise both in school spending and in educational attainment explains about 30% of the U.S. labor productivity growth between 1967 and 2000.

With this new measure of labor quality growth, the growth rate of total factor productivity declines. The contribution of the growth in total factor productivity to U.S. labor productivity growth is a little less than a quarter, instead of 40% as the BLS reports. For the first subperiod($1967-1984$), during which a recession hit the U.S. economy, the total factor productivity is estimated to have been fairly small.

The assumption that the skill premium does not affect the estimated Mincer return to schooling is, however, too restrictive. A vast literature on the rise of U.S. college premiums for the last two decades of the 20th century suggests that later cohorts work while the skill premium is higher, and hence some part of their higher return to schooling is due to the rise in skill premium, instead of rising school quality. Without considering a skill premium, we may incorrectly attribute the increases in the Mincer return to schooling across cohorts resulting from the rise in school premium to rising school quality. The third panel in Table 6 indeed confirms this argument. Controlling for a skill premium reduces the estimated pure quality growth almost by half from the estimate in the model without a skill premium.

The importance of considering the rise in skill premium is reinforced by Figure 4. It decomposes the driving forces behind the rise in the estimated Mincer return to schooling over time. I plot the trends in the Mincer return to schooling from the model, and compare them with the trajectory of the Mincer return to schooling, holding the skill premium fixed at its 1967 level. Without the rise in skill premium, the model explains only about a quarter of the total increase in the Mincer return to schooling between 1967 and 2000. This confirms that a significant part of higher returns to schooling for more recent cohorts results from the fact that they work in the market when the skill premium is higher, not from better quality schooling. Ignoring the rise in skill premium and letting the rise in school quality take all the credit for a higher return to schooling for later cohorts substantially overstates the impact of rising school spending on labor quality growth. Accordingly, I use this model with a skill premium as a benchmark for the counterfactual exercises and for the comparison with related literature later in this paper.

Even though controlling for the skill premium is important for correctly measuring the impact of rising school spending on labor quality growth, it rarely affects the estimated labor composition growth. Weights used to compute labor composition growth do not require distinguishing skill prices from quality (both reflected in individual wages). Examining labor composition growth for two subperiods divided at 1984, however, reveals that failing to control for the skill premium overstates labor composition growth for the first subperiod and understates it for the second. The skill premium is estimated to have risen more rapidly in the early 1980s, and this is not fully captured by the baseline model.[19]

Adjusting for the skill premium, the contribution of labor quality growth and total factor productivity growth to U.S. labor productivity growth is estimated equally to be 27%. I report sensitivity analysis results for the baseline and skill premium models in which I preset the value of γ_1 in Table 7. The estimated labor quality growth changes little as the value of γ_1 varies.

The last panel of Table 6 presents the growth accounting for the heterogeneous agent model. Controlling for heterogeneous learning ability (holding the distribution constant across cohorts) decreases the estimated impact of rising school spending on labor quality growth. A single value of γ_0 in the models without heterogeneity implicitly assumes that schooling is as productive for younger cohorts as for older cohorts, for given investments of time and goods. Considering that more able individuals tend to stay in school longer, accounting for both the constant ability distribution across cohorts and the increases in cohort mean years of schooling requires the average ability of younger cohorts to be lower than that of older cohorts, for any given level of education. This implies that schooling is less productive for younger cohorts than for older cohorts when the same amount of time and goods are invested. Adjusting for this effect reduces the baseline estimate of pure quality growth, particularly for the first subperiod when the mean years of schooling increased more

[19] Holding the skill premium fixed at its 1967 level reduces labor composition growth in the latter subperiod by a quarter.

rapidly. The impact of heterogeneity on the estimated labor quality growth should, however, be interpreted with caution. Without considering the skill premium at the same time, the variance of heterogeneous learning ability may be overstated to match the mean years of schooling in the data. If agents anticipate a fraction of the rise in skill premium in advance, the ex-ante return to schooling that agents take into account when making schooling decisions is on average lower than the Mincer return to schooling. If this is the case, the mean years of schooling over all samples can be matched without a large ability bias. I interpret the quantitative result for this specification to be suggestive, rather than conclusive.

5.2 Counterfactual exercises

In this subsection, I implement two counterfactual exercises to provide some insights on the identification of labor quality growth due to rising school spending. First, I examine how robust the estimated proportion of labor quality growth that is due to rising school expenditures is, using the consistency of the estimate with observed school spending per pupil. For illustration, suppose labor quality has actually grown more rapidly due to rising school spending than my estimate, 0.12% per year. Higher labor quality growth requires higher productivity of school spending in human capital production, inducing individuals to spend more while in school on average than we observe in the data, expecting a higher return on spending. In addition, more rapid labor quality growth also implies that human capital increases very steeply with experience after completion of schooling, to be consistent with the fact that earnings increase with work experience in the cross-sectional data. Since a very steep return to post-schooling experience makes staying in school too costly for individuals, this would have individuals spend more per year on schooling while leaving school early, compared to what we see in the data.

In the following exercise, I examine what would have been the level of school spending per pupil, relative to what we observe in the data, if the labor quality growth due to rising school spending had actually been higher or lower than my estimate, holding the growth rate of expenditures per pupil and the distribution of schooling as they are in the data. Figure 5 plots the results. If labor quality indeed grew by 0.25% per year – about twice my estimate – over the sample period, the level of school spending per pupil would have to have been about 3 times that of what is actually observed in the data. If the increased school spending per pupil instead induced a labor quality growth of only 0.05% per year, we should have observed only one third of the school spending per pupil we observe in the data. This confirms that the estimated labor quality growth due to rising school spending is fairly robust.

The key to estimating the impact of increased school expenditures on labor quality growth is obtaining a precise estimate for the elasticity γ_2 of school quality with respect to school expenditures. In order to provide intuition about how the productivity of school spending in human capital production is identified, I present the responses of each moment exploited for the estimation – the estimated Mincer return to schooling, the cross-sectional return to experience, and the expenditure share in the marginal cost of schooling – to changes in γ_2, holding other parameters fixed at their estimates from the skill premium model. Figure 6 plots the percentage deviation of the three model moments from their data counterparts for various values of γ_2. As school spending becomes more productive in improving school quality than I estimate γ_2 to be, any given number of years of schooling generates higher earnings, with this effect more prominent for younger cohorts due to increased school expenditures. This raises the level of the Mincer return to schooling from the model above what we actually see in the data. A value of γ_2 double my estimate generates about 10% of the Mincer return to schooling, where its estimate from the data is 8%. This higher elasticity of school quality with respect to school spending also flattens the cross-sectional experience-earnings profile compared to what we observe in the data. If spending is more productive, earnings differentials between younger and older cohorts, attributable to schooling, become larger. Holding the evolution of individual earnings with experience fixed, this offsets the experience premium older cohorts have compared to younger cohorts in the cross-sectional data, thereby decreasing the cross-sectional return to experience below what the data suggests. In this exercise, I define the cross-sectional return to experience as the log wage differential between cohorts with no experience and with 20 years of experience based on Mincer regression coefficients. Doubling my estimate for γ_2 reduces the cross-sectional return to experience by 20% below the estimate using the data.

Figure 6 shows that the expenditure share in the marginal cost of schooling is even more sensitive to γ_2 than the other two moments. If school spending becomes more productive in increasing human capital as γ_2 increases, the marginal cost of schooling increases because of higher foregone earnings, and hence the expenditure share in the marginal cost of schooling declines. Unless individuals had spent more while in school than we actually observe, the higher the value of γ_2 is, the farther it moves away from the expenditure share of the marginal cost of schooling. As Figure 6 implies, this channel is quantitatively very powerful in estimating γ_2.

5.3 Literature Discussion

In this subsection, I relate my results to those in Manuelli and Seshadri (2005) and Erosa, Koreshkova, and Restuccia (2006), which explore the role of human capital in explaining income differences across countries. Both studies consider not only time but also market goods as inputs for human capital production, as I do in this paper, and analyze how much cross-country income differences can be attributed to differences in human capital stocks, using a structural model.

The key difference between their studies and this paper is that they consider no quality differences in schooling across cohorts. If younger cohorts face better quality of schooling, the cross-sectional experience-earnings profiles fall apart from how individual human capital evolves with work experience. Relatively higher human capital stocks held by younger cohorts crowd out earnings differentials across cohorts due to their differences in work experience in cross-sectional data. They, however, do not consider this possibility and use the cross-sectional relationship between experience and earnings as the evolution of individual human capital stock after completion of schooling.

I analyze how the estimated growth in the pure quality component of the U.S. workforce between 1967 and 2000 would change if I consider the cross-sectional relationship between experience and earnings as the individual return to experience. I re-estimate the human capital production technology while in school with individual return to experience fixed at the coefficient estimates for experience and its square from the cross-sectional Mincer regression. This experiment implies that rising school spending increased the human capital of the U.S. workforce by 0.16%, which is 30% higher than my estimate. The counterfactual exercise in the previous subsection implies that a labor quality growth of 0.16% per year requires 50% more school expenditures per pupil than we observe in the data.

6 Conclusion

Building upon Denison (1962), the Bureau of Labor Statistics incorporates labor quality growth as a source of U.S. labor productivity growth and attributes a little more than 10 percent of U.S. labor productivity growth to labor quality growth between 1967 and 2000. Although the BLS measure of labor quality growth adjusts for the increases in mean years of schooling of the workforce during that period, it fails to capture the impact of changes in school quality on the human capital of the workforce. The mean school spending per pupil in the U.S. more than tripled for that period, which suggests that the BLS measure of labor quality growth may miss a significant part of labor quality growth.

This paper attempts to measure how much U.S. labor quality has risen in response to the increase in public school spending per pupil, and how much U.S. labor productivity growth is due to labor quality growth. To approach the question, it is critical to identify the productivity of school spending in human capital production. In this paper, I propose a new way of estimating this productivity by comparing earnings of different cohorts that appear in the same market, beyond the estimated Mincer return to schooling.

If the human capital of the workforce increased due to rising school spending, we should observe higher earnings for younger cohorts than older cohorts for given years of schooling, after controlling for years of schooling and work experience. Accordingly, the profile of experience and log earnings in the cross-sectional data should be flatter than the actual post-schooling human capital profile. The more labor quality growth generated by increased school spending, the steeper the post-schooling human capital profile relative to the cross-sectional experience-log earnings profile. Since a steeper post-schooling human capital profile induces individuals to spend more money on schooling, it cannot be too steep in accordance with school expenditures we observe in the data. Conversely, it cannot be too flat, either, or else individuals would not spend as much as we see in the data. In this way, I simultaneously identify a post-schooling human capital profile that is consistent with the data on school spending, and the impact of rising school spending on labor quality growth.

I find that rising school spending is about half as important as the increases in mean years of schooling for U.S. labor quality growth and that about a quarter of U.S. labor productivity growth can be attributed to labor quality growth between 1967 and 2000. Despite a remarkable increase in school spending, U.S. labor quality growth has been surprisingly modest. Controlling for a skill premium is important – ignoring the rise in skill premium would double the estimated importance of increased expenditure to growth in human capital. The growth of human capital of the workforce due to rising school spending explains only a quarter of the increases in the estimated Mincer return to schooling over that period, and the rest is ascribable to a rise in the skill premium.

In this study, I abstract from the causes of the increase in school spending and focus on its consequences in terms of labor quality growth. The finding that the drastic rise in school spending contributed only modestly to growth in labor quality raises a question of what has driven such a rise in school expenditures. Exploring this may help us better understand the role of education in economic growth.

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Table 1. BLS Growth Accounting for private business sector between 1967 and 2000

	Y/L	TFP	$s_K \times K/L$	$s_L \times H$
Annual growth rate	1.66	0.66	0.77	0.22
Contribution (%)	100.0	39.8	46.4	13.3

Table 2. Pooled Sample Mincer Regression Results for 1968-2001 Surveys

S	Exp	Exp^2	R-squared	obs.
0.080038	0.031478	-0.0000525	0.31	$1,343,830$
(0.0002)	(0.0001)	(0.0000)		

Note: Numbers in parentheses stand for standard errors.

Table 3. Mean Years of Schooling ($\overline{S}$) and Estimated Returns to Schooling (β_1)

year	$\overline{S}$	β_1	year	$\overline{S}$	β_1
1968	11.22	0.056	1985	12.63	0.082
1969	11.28	0.054	1986	12.68	0.085
1970	11.39	0.056	1987	12.71	0.088
1971	11.49	0.054	1988	12.73	0.088
1972	11.57	0.058	1989	12.76	0.089
1973	11.68	0.057	1990	12.79	0.091
1974	11.79	0.057	1991	12.85	0.093
1975	11.97	0.054	1992	13.01	0.091
1976	11.97	0.066	1993	13.08	0.096
1977	12.02	0.063	1994	13.13	0.099
1978	12.07	0.065	1995	13.13	0.096
1979	12.20	0.065	1996	13.17	0.097
1980	12.26	0.065	1997	13.15	0.101
1981	12.32	0.067	1998	13.18	0.100
1982	12.43	0.069	1999	13.22	0.104
1983	12.56	0.076	2000	13.24	0.101
1984	12.58	0.079	2001	13.27	0.103

Table 4. Pre-Set Values

Variable	R	r	g_p	P_{1982}	$h(6)$	γ_1
Value	65	0.05	0.0115	1	1	$0.3 \sim 0.7$

Table 5. Parameter Estimates

γ_0	γ_1	γ_2	ϕ_0	ϕ_1	σ_{γ_0}
		Baseline model			
0.0811	0.30	0.1263	0.0345	−0.0005	
(0.0334)	(..)	(0.0510)	(0.0012)	(0.0000)	
0.0559	0.50	0.1299	0.0347	−0.0005	
(0.0235)	(..)	(0.0510)	(0.0013)	(0.0000)	
0.0417	0.70	0.1332	0.0349	−0.0005	
(0.0179)	(..)	(0.0511)	(0.0013)	(0.0000)	
		Skill premium model			
0.0312	0.30	0.1235	0.0332	−0.0005	
(0.0135)	(..)	(0.0569)	(0.0008)	(0.0000)	
0.0272	0.50	0.1236	0.0333	−0.0005	
(0.0118)	(..)	(0.0568)	(0.0009)	(0.0000)	
0.0241	0.70	0.1237	0.0334	−0.0005	
(0.0105)	(..)	(0.0567)	(0.0009)	(0.0000)	
μ_{γ_0}	γ_1	γ_2	ϕ_0	ϕ_1	σ_{γ_0}
		Heterogeneous agent model			
−3.5382	0.7457	0.1307	0.0343	−0.0006	0.0600
(0.0615)	(0.0679)	(0.0123)	(0.0006)	(0.0000)	(0.0047)

Note: Numbers in parentheses stand for standard errors.

Table 6. Growth Accounting

Year	Y/L	TFP	$s_K \times K/L$	$s_L \times H$	
				$s_L \times H_q$	$s_L \times H_c$
BLS					
1967 – 2000	1.66	0.67	0.77	..	0.22
1967 – 1984	1.43	0.50	0.81	..	0.12
1984 – 2000	1.90	0.85	0.72	..	0.32
Baseline Model					
1967 – 2000	1.66	0.39	0.77	0.19	0.31
				(0.08)	(0.00)
1967 – 1984	1.43	0.14	0.81	0.19	0.29
1984 – 2000	1.90	0.54	0.72	0.20	0.34
Skill Premium Model					
1967 – 2000	1.66	0.46	0.77	0.12	0.31
				(0.05)	(0.00)
1967 – 1984	1.43	0.28	0.81	0.11	0.23
1984 – 2000	1.90	0.66	0.72	0.12	0.40
Heterogeneous Agent Model					
1967 – 2000	1.66	0.43	0.77	0.14	0.32
				(0.02)	(0.04)
1967 – 1984	1.43	0.23	0.81	0.10	0.29
1984 – 2000	1.90	0.65	0.72	0.18	0.35

Note: Numbers in parentheses stand for standard errors.

Table 7. Sensitivity Analysis

	$s_L \times H_q$			$s_L \times H_c$		
			Baseline Model			
Year	$\gamma_1 = 0.3$	0.5	0.7	0.3	0.5	0.7
$1967-2000$	0.18	0.19	0.20	0.31	0.31	0.31
	(0.08)	(0.08)	(0.09)	(0.00)	(0.00)	(0.00)
$1967-1984$	0.18	0.19	0.20	0.28	0.29	0.29
$1984-2000$	0.18	0.20	0.21	0.33	0.34	0.34
			Skill Premium Model			
Year	$\gamma_1 = 0.3$	0.5	0.7	0.3	0.5	0.7
$1967-2000$	0.11	0.12	0.12	0.31	0.31	0.31
	(0.05)	(0.05)	(0.05)	(0.00)	(0.00)	(0.00)
$1967-1984$	0.11	0.11	0.11	0.23	0.23	0.23
$1984-2000$	0.12	0.12	0.13	0.40	0.40	0.40

Note: Numbers in parentheses stand for standard errors.

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

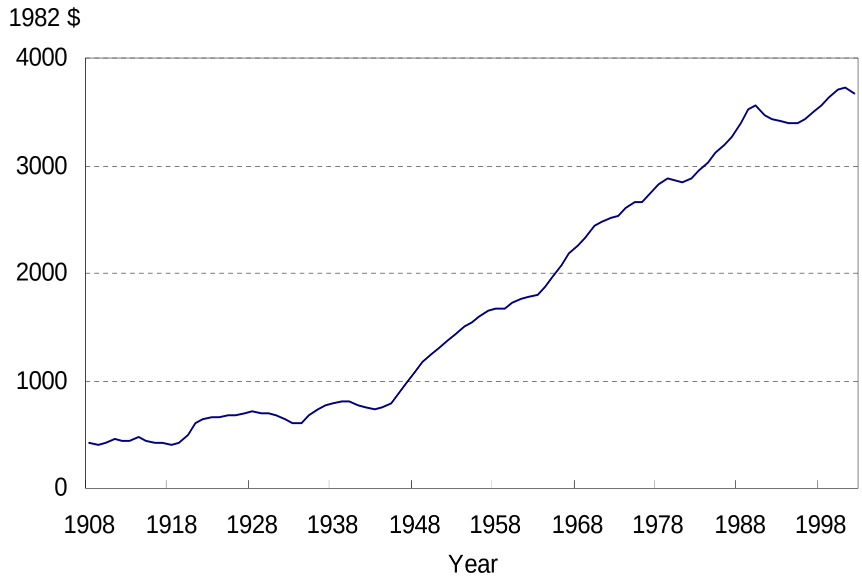

Figure 2: Diminishing Returns to Schooling and Rising School Quality

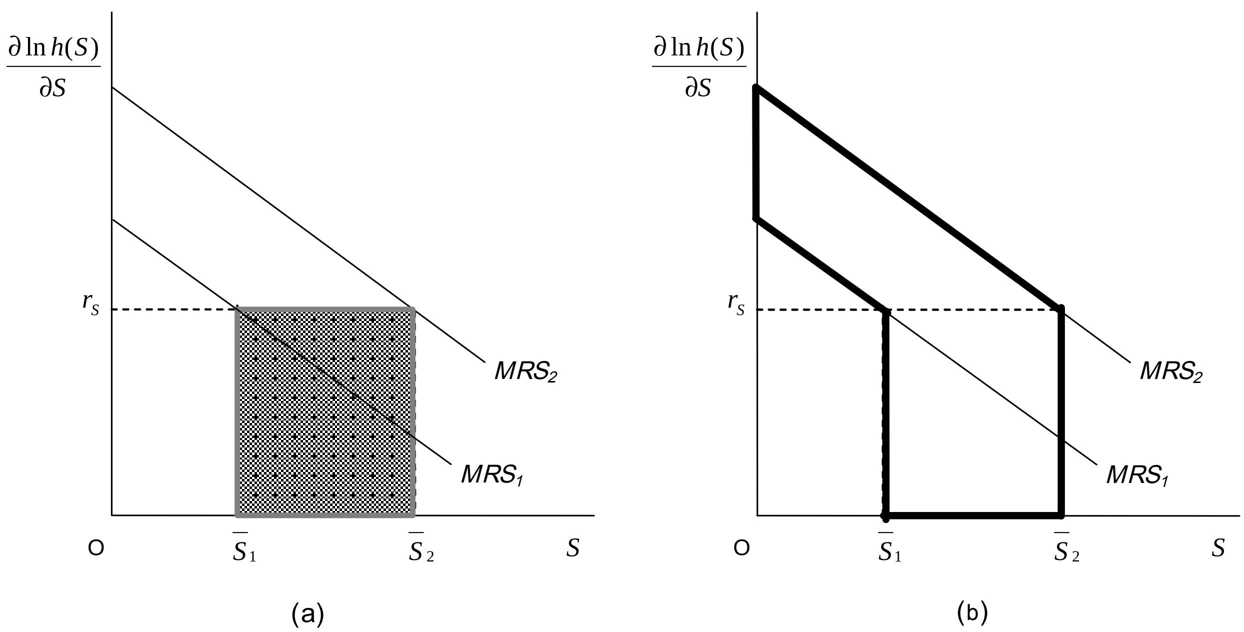

Figure 3: Rising School Quality and Experience-Earnings Profile

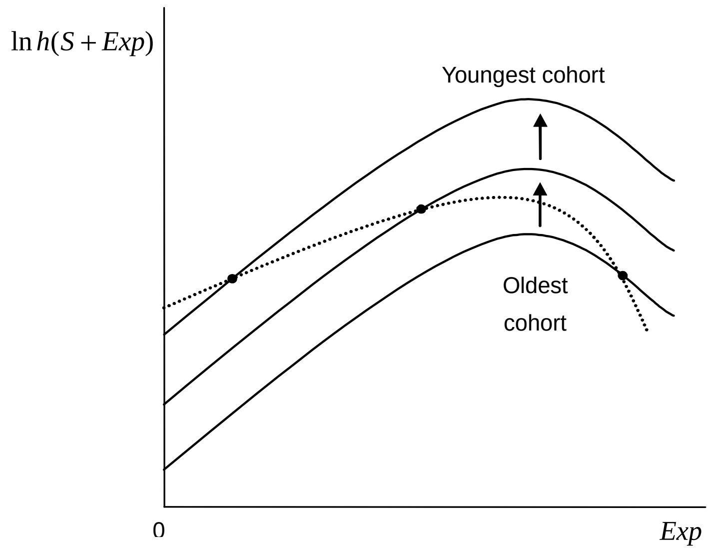

Figure 4: Trends in Mincer Return to Schooling

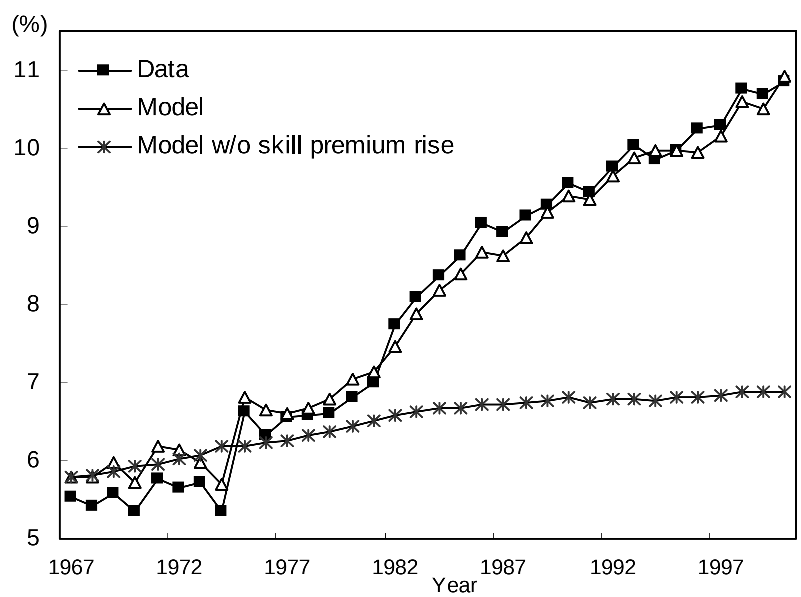

Figure 5: Level of Spending per Pupil Relative to Data Required for Pure Quality Growth

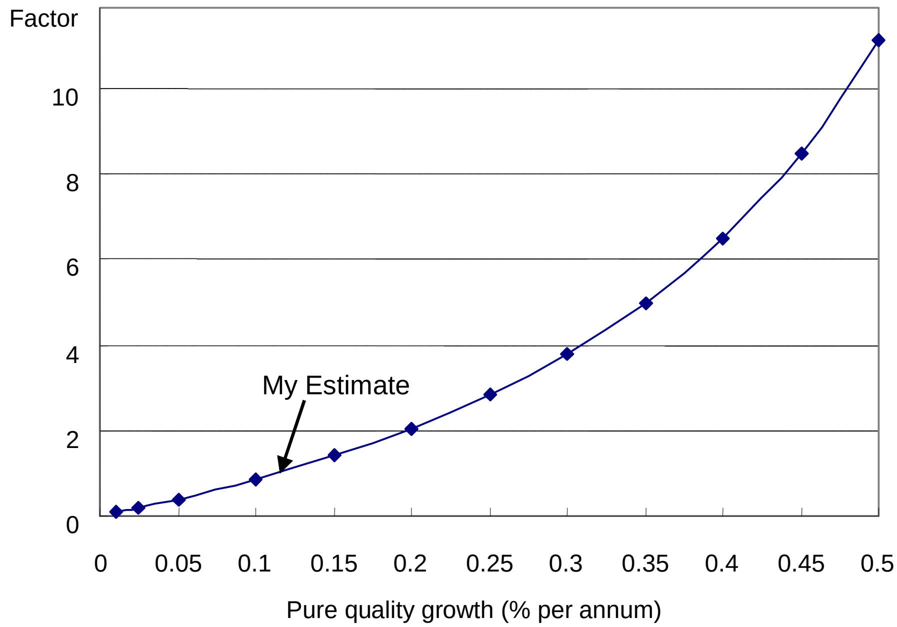

Figure 6: Responses of Model Moments to Various Values of γ_2