ABSTRACT

This study reviews the literature to see how school education as a form of human capital investment has been treated in the empirical studies of its contribution to economic growth, and to highlight the importance of technological context in estimating the return to schooling using cross-country aggregate data. Results and arguments in the literature that seem to be inconsistent are presented in order to illustrate that a missing perspective leads to weak implications. That is, this review shows that introducing technological context is a key to improve the accuracy of the estimation and the implication to policy making.

Keywords: education, economic growth, human capital, technology
1. Introduction

Labor economics have long been estimating the return to educational investment by individuals. Psacharopoulos and Patrinos (2004) summarizes the large body of estimates of the Mincer’s rate of return to education around the world, finding that there is a pattern of classic “diminishing return” to human capital investment. That is, the return is higher in the developing countries with relatively low level of education and low per-capita GDP than in the advanced countries. This finding has a very important policy implication; educational investment is effective for the economic growth and poverty reduction in many developing countries.

Table 1. Estimates of the rate of return to schooling by income group

<table>
<thead>
<tr>
<th>Per capita income group</th>
<th>Mean per capita income (US$)</th>
<th>Years of schooling</th>
<th>Return to schooling (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High income ($9,266 and more)</td>
<td>23,463</td>
<td>9.4</td>
<td>7.4</td>
</tr>
<tr>
<td>Middle income</td>
<td>3,025</td>
<td>8.2</td>
<td>10.7</td>
</tr>
<tr>
<td>Low income ($755 or less)</td>
<td>375</td>
<td>7.6</td>
<td>10.9</td>
</tr>
<tr>
<td>World</td>
<td>9,160</td>
<td>8.3</td>
<td>9.7</td>
</tr>
</tbody>
</table>

*Source: Psacharopoulos and Patrinos (2004)*

This motivates studies on testing the effect of educational investment on economic growth, and a large body of empirical studies using cross-country aggregate data exist in order to test the notion above. However, there seems no single consensus about the macroeconomic effect of education in the literature; it is not yet clear whether the increase in average education in a country leads to the country’s economic growth.

The objective of this study is to review the literature on this topic to see how school education as a form of human capital investment has been treated in the empirical studies of its contribution to economic growth, and to present a possible reason why the results vary among those studies and make it difficult to induce conclusion. This study then highlights the importance of considering technological context in the estimation of the return to schooling. Results and arguments in the literature that seem to be inconsistent are presented in order to illustrate that a missing perspective leads to weak implications.
The structure of this study is as follows. In Chapter 2, three frequently-cited growth models with special attention to the role of human capital stock are reviewed as a foundation of empirical analyses. Empirical studies are then reviewed in Chapter 3 to indicate that a single conclusion with consistent results has not been obtained yet. Some estimation issues are also raised such as model specification, choice of variables representing human capital stock or its accumulation speed, and quality of data. Chapter 4 reviews empirical studies using household data to examine if educational attainment improves individual worker’s productivity, and how technological context plays a role in this linkage. Based on the review, suggestion is made for improving the accuracy of estimation of macroeconomic effect of education. Chapter 5 summarizes.

2. Theoretical foundation of the role of human capital on economic growth

The empirical studies estimating the aggregate impact of education are founded on the growth models with special attention to the role of human capital stock. The following three models are frequently-cited growth models with human capital as a source of aggregate technological advancement. In these models, relationship between human capital, education, and technology are clearly considered.

Nelson and Phelps (1966) consider that education improves the country’s ability to adopt new technology from more advanced countries. In their model, the speed of advancement in “technology in practice” in an economy is increasing with the level of education, and the speed is also increasing with the gap between the technology in practice and “theoretical technology”, the exogenously available best-practice level of technology;

\[ \frac{\dot{A}}{A} = \Phi(h) \left[ \frac{T_0 e^{\lambda t} - A}{A} \right] \]

where \( A \) is the aggregate technology level, \( h \) is the level of human capital measured by average level of education, and \( \Phi(0) = 0, \Phi'(h) > 0. \lambda \) is the rate of progress of theoretical technology. If the educational level is sufficiently high so that \( \dot{A}/A > \lambda \), then the technological gap, \( (T_0 e^{\lambda t} - A)/A \), becomes narrower, until the progress slows down to \( \dot{A}/A = \lambda \). The equilibrium level of technology in practice, \( A^* \), is
The implied elasticity of $A^*$ with respect to $h$ is an increasing function of $\lambda$; aggregate return to educational investment is higher where the theoretical technology advances faster, and the return is positive only if there is some advancement, $\lambda > 0$. Their argument explicitly relates education and human capital, and its association with technological progress through imitation. The rate of progress of theoretical technology is exogenously determined, but the progress is not automatically reflected to macroeconomic productivity. A country with higher human capital stock benefits more from the technological progress. The implication is that the rate of return to education is higher where the available technology is advancing more quickly.

Lucas (1988) constructed endogenous growth model incorporating human capital as a driver of sustainable growth. The model specifies aggregate production function as

$$Y = AK^\alpha[h \cdot u \cdot N]^{1-\alpha}h_a^\beta,$$

where $K$ and $N$ are physical capital stock and the number of workers. $h$ denotes individual human capital of an average worker that augments his own productivity for current production, and $h_a$ denotes average skill level, human capital that accumulates in a society and generates externality if $\beta > 0$. It is assumed that all workers are identical, i.e., $h = h_a$, but no workers take the effect of his decision on $h_a$ into consideration. The workers spend a fraction $u$ of their time on their work, and the remaining $1 - u$ is devoted to “human capital” accumulation. The rate of accumulation of human capital is assumed to be directly proportional to $1 - u$ without depreciation, so the human capital continues to grow as far as $1 - u$ is positive. The representative household faces the choice of $1 - u$ and consumption to maximize its utility in the model. The implication is that the increase in human capital, rather than its stock level, is associated with increase in per-capita income growth, and the economic growth is sustainable because there is no diminishing returns to the accumulation of human capital. If $1 - u$ is interpreted as a share of working age population enrolled in school, a higher enrollment rate means higher growth of human capital. The relationship between human capital and technology is not explicitly discussed in the model; rather human capital is directly interpreted as technology. However, the knowledge and skills improving productivity accumulate in the economy, without depreciation, outside the finitely-lived individual workers, and they are shared in the economy due to spillover effect represented by $h_a^\beta$. 

$$A^* = \frac{\Phi(h)}{\Phi(h) - \lambda} T_0 e^{\lambda t}$$
In the model of Romer (1990), human capital is explicitly connected to creation of technology. The model consists of R&D sector, capital goods producing sector, and final goods manufacturing sector. Aggregate production function in the final goods manufacturing sector is specified as

\[ Y = H_Y^\alpha L^\beta \int_0^\infty x(i)^{1-\alpha-\beta} \, di \]

where \( L \) is labor input, \( H_Y \) denotes human capital devoted to final goods production, and \( x(i) \) is physical capital input. Index \( i \) denotes the distinct technology required for producing specific physical capital goods. The physical capital is produced using a part of produced final goods together with “technology” produced in R&D sector. The production function of technology is linear in human capital in this sector and existing stock of technology;

\[ \dot{A} = \delta \cdot H_A \cdot A \]

where \( H_A \) is human capital in R&D sector, \( A \) is the current stock of technology which is accessible to any researchers. This technology can be considered as a count of blueprints or patents that live infinitely without depreciation, so it can grow unlimitedly. Similar to Lucas (1988), there is no diminishing return to the production of technology, so sustainable growth is possible. It is assumed that the total amount of human capital does not change, and is split by workers between \( H_A \) and \( H_Y \) taking into account the level of \( A \) and the wage rate in manufacturing sector. \( H_A \) is directly linked to a creation of technological knowledge which accumulates in the economy, as opposed to \( H_Y \) which accumulates within individual workers who live finite time. The former apparently has a spillover effect due to its association with non-rival feature of technology. The human capital in this model is given more active role as it contributes to “creation” of new technology, compared to that of Nelson and Phelps (1966) which contributes to “adoption” of exogenously created advanced technology. An empirical implication of this model is that higher stock level of human capital generates faster growth in technology, and thus faster per-capita income growth. A sustainable growth is possible without growth in the total stock of human capital, because it is assumed that the innovation occurs as far as a positive share of human capital is allocated to R&D sector, and the created innovation accumulates unlimitedly in the economy.

These three models have a very important perspective in their underlying mechanism; that is, the accumulation of human capital and its effect on aggregate productivity is directly associated with some forms of technology. However, they all reduce to the models implying that an increase in human capital stock causes an increase in aggregate productivity and per-capita income growth,
with a causal relationship running from education to growth. Many of the empirical works might be missing the critical role of technology in the effectiveness of education, in spite of the sophistication in the construction of these three models.

Furthermore, the empirical implications among these models differ; the growth of human capital contributes to the growth of per-capita income in Lucas’s (1988) model, while the level of the human capital stock at the initial year contributes to the per-capita income growth in the subsequent periods in Nelson and Phelps’s (1966) and Romer’s (1990) models. Since positive Mincer’s returns to schooling indicates the effect of a worker's schooling on his current productivity, the level of average schooling should be translated to the level of current aggregate productivity, rather than to the subsequent growth of productivity. In this sense, microeconomic findings of positive return to schooling are consistent with macroeconomic implication of Lucas's models. There are many literatures examining which of the level of human capital or the growth of human capital contributes to per-capita income growth, some of which are reviewed in the next chapter.

3. Empirical literature with conventional approach

In this chapter, empirical studies are reviewed which have attempted to investigate the effect of education on economic growth. Macroeconomic empirical studies have extensively examined the effect of human capital on GDP growth using cross-country dataset. In this conventional approach, human capital variable is regressed on per capita GDP, and the variables representing educational level of the average population are used as proxies of the aggregate human capital. Influential studies are reviewed and compared in the following sections with a special attention to the mechanisms implied in the model specification. Some issues observed in the conventional approach of estimation are also discussed.

3.1. Model specification - dynamic and static effect

As discussed in the previous chapter, the empirical analyses can be divided into two groups: studies examining dynamic effect and static effect of education on economic growth. The dynamic
effect refers to the effect of the education at a certain year to the productivity growth during subsequent years, whereas the static effect refers to the effect of the current education to the current productivity. This is closely linked to an argument whether the level of education or the growth of education causes economic growth, both of which are implied by the growth models reviewed above.

The convergence model implied by Solow growth model is often employed in the empirical analyses examining dynamic effect of human capital on growth. Expected causality is from education to income growth.

Barro (1991) conducts a conditional convergence growth regression using cross-country data of 98 countries from 1960 to 1985. The model specifies

$$\frac{1}{T} [\ln y_{i,t} - \ln y_{i,t-T}] = \alpha + \beta_1 \ln y_{i,t-T} + \beta_2 h_{i,t-T} + \varepsilon_i$$

where $\beta_1$ is the rate of convergence. $h_{i,t}$ is the human capital stock in a country $i$ at year $t$, and it is proxied by the secondary school enrollment ratio, the percentage of students enrolled in secondary school over the total number of children in the corresponding age group. A positive coefficient of the initial level of human capital, $\beta_2 > 0$, implies higher steady state income, meaning quicker per-capita income growth. The results show a positive association between the initial level of human capital and subsequent 25-year’s average annual growth rate. Levine and Renelt (1992) conducts cross-country regressions using large number of explanatory variables analyzed in the past literature, to examine if the conclusions derived in these studies are robust to infer the causes of long-run growth. This confirms the robustness of the contribution of secondary school enrollment ratio at the initial year to subsequent growth, which supports Barro’s (1991) result.

Mankiw, Romer, and Weil (1992) (henceforth MRW) estimate the Solow growth model augmented by human capital. The model employs a Cobb-Douglas aggregate production function with labor-augmenting technology $A$;

$$Y_{i,t} = K_{i,t}^\alpha H_{i,t}^{\beta}(A_{i,t}L_{i,t})^{1-\alpha-\beta}$$

(*)

in a country $i$ at year $t$. Human capital, $H$, is introduced as a factor of production into the Solow growth model; it accumulates with the saving rate $s_h$ and depreciates with the rate $\delta$, in a process similar to physical capital;

$$\dot{K}_{i,t} = s_k Y_{i,t} - \delta K_{i,t}$$
\[ \dot{H}_{i,t} = s_h Y_{i,t} - \delta H_{i,t} \]

It is assumed that the saving rate can vary by country, but does not vary overtime. \( L \) and \( A \) grow by the exogenously given constant speed; the growth rate of labor, \( n \), can vary by country, but \( g \), the growth rate of \( A \), is universally identical. In this model, a country’s per-capita income level at the steady state is positively dependent on the saving rate of capital stock similar to Solow model, but the capital now includes both physical capital and human capital. Therefore, increase in saving rate of human capital increases the level of steady state income. The study tests the implied model

\[ \ln y_i = \alpha + \beta_1 \ln s_{k,i} + \beta_2 \ln(n_i + g + \delta) + \beta_3 \ln s_{h,i} \]

where \( y_i \) is real GDP per working-age population, and \( s_{h,i} \) is proxied by the share of working-age population who are enrolled in secondary education. The cross-country data covers 98 countries from 1960 to 1985, and the annualized average values are used for OLS estimation of the model. The results indicate that the coefficient of the human capital saving rate is positive and significant, without violating the model restriction on the parameters (\( \beta_1, \beta_3 > 0, \beta_2 < 0, \beta_1 + \beta_2 + \beta_3 = 0 \)).

While these studies evaluate dynamic effect of education, many other studies evaluate static effect of education, by estimating aggregate production functions which include human capital as a factor input. Since this type of studies seek a positive association between the level of educational attainment and the level of per-capita GDP, they are supposed to confirm the effect of education implied by the estimates of wage function. However, the results of many of these analyses seem to be contradictory to what we expect.

Benhabib and Spiegel (1994) estimates the aggregate production function without imposing any specific model restrictions other than the functional form. They estimate the log-differenced production function that includes human capital stock, \( H_{i,t} \):

\[ Y_{i,t} = K_{i,t}^{\alpha} H_{i,t}^\beta L_{i,t}^\gamma \]

The estimation is based on the data of 78 countries from 1965 to 1985, and it uses average school attainment data constructed by Kyriacou (1991) and Barro and Lee (1993) as human capital stock. The results indicate that the effect of growth of educational attainment is not significant for both series with robustness under the inclusion of several control variables and the selection of subsample countries. The human capital growth gained significance slightly after including the initial level of GDP per capita as an explanatory variable, but its contribution is still weak.
Bils and Klenow (2000) do not use mere educational attainment data. Instead, they estimate and use annual growth rate of human capital from 1960 to 1990, which is defined based on micro-Mincer wage function and several assumptions on associated parameters, as well as schooling attainment data.\(^1\) The results suggest that the growth of human capital explains relatively a small portion of economic growth. Pritchett (2001) also construct a series of growth rates of human capital stock defined as a discounted wage premium due to educational attainment.\(^2\) The study then estimates a growth accounting regression using cross-country data of 91 countries. The results indicate that the coefficient of human capital stock is actually negative with statistical significance, and the result persists if sample consists of only developing countries. As one of a few SSA studies, Lau et al (1991) use the average years of schooling as human capital variable, to estimate the log-differenced Cobb-Douglas production function with panel data of 26 SSA countries from 1960 to 1986. The results indicate that the increase in average years of education does not significantly affect the real GDP growth, or at best, the years of secondary schooling is slightly positively related to economic growth, while primary education is not.

In the empirical researches like above, the effect of human capital measured as current level of educational attainment on current productivity is identified weak or even negative. This is arguably contradicting the microeconomic observations; i.e., a micro-macro puzzle, as named in the literatures.

Macroeconomic empirical literature which conduct cross-country growth regressions using school enrollment rate as a proxy of human capital tend to show positive and significant effect of the level of education on subsequent income growth rate. The literature using average years of educational attainment show similar results. However, correlation between growth of education and per-capita GDP growth are empirically detected weak or negative. These results favor initial level of human capital rather than its change as a driver of economic growth. Therefore, the evidence from the empirical works are consistent with dynamic effect of education promoting technological adoption and diffusion in Nelson and Phelps’ models, and/or the effect promoting innovation activities in Romer’s model. On the other hand, positive private return to education

---
\(^1\) The definition of human capital growth includes that it allows for diminishing rate of return to education, and that the level of human capital in the earlier generation (25-year lag) can speed the accumulation of the present human capital because younger generation benefits from highly-educated teachers.

\(^2\) The discounted wage premium is computed based on the average years of schooling and the assumed Mincer’s rate of return to education (10% based on micro literature)
found in labor economics literature should conform to static effect; human capital stock of the current workers should be associated with the workers’ current productivities, and therefore the growth of education implies the growth of income during the same period.

3.2. Variable choice

The studies using enrollment rate as a human capital variable, following Barro (1991) and MRW (1992), tend to find a positive and significant effect of schooling. However, the enrollment rate is not well justified as an educational variable. Bils and Klenow (2000) shows that the enrollment rate is actually not correlated with the subsequent growth of human capital series they constructed based on the educational attainment data. Pritchett (2001) argues that the use of enrollment rate is justified only when the countries are in the steady state at which enrollment rate is constant over time, which means the enrollment rate cannot be applied to the studies using data of developing countries where educational growth is accelerating. It is then shown that the enrollment rate is negatively correlated with the growth rate of educational capital stock he constructed. The argument is that the educational capital stock should increase depending on the difference in the enrollment rate between the groups of those leaving labor force and those entering it, and not depending on the current enrollment rate.

In addition, what enrollment rate represents are actually different in Barro (1991) and MRW (1992) studies; Barro uses it as a direct proxy of human capital stock level at the initial year, while MRW use it as speed of human capital accumulation that generates cross-country variation in the steady states. Therefore, Barro’s results indicate a positive effect of the initial level of human capital on the subsequent per-capita income growth. MRW’s results, on the other hand, should actually imply that the growth of education is associated with the growth of per-capita income during the same period.

A more reasonable variable for educational attainment of the current workforce is the average years of schooling of the domestic population. There have been many empirical studies using this variable since the studies such as Kyriacou (1991), Barro and Lee (1993), and de la Fuente and Domenech (2001) constructed the series of average years of schooling covering sufficient number of countries. For example, Easterly and Levine (1997), in their analysis examining the impact of
ethnic diversity on economic performance, also conducts a cross-country convergence growth regression with (logarithm of) average years of schooling at the initial year using Barro and Lee’s dataset, as opposed to enrollment ratio in Barro’s (1991) convergence regressions. The results indicate that the initial level of this human capital variable is positively linked to per-capita GDP growth rate during the subsequent decade. The estimates of convergence growth regressions in several literatures tend to indicate that the association between per-capita GDP growth and human capital level at the initial year is positive and significant, detecting dynamic effect of education, as observed in those studies using enrollment ratio.

On the other hand, studies tend to find weak or negative static contribution of education even when the average schooling years data is employed. As shown above, Bils and Klenow (2000) and Pritchett (2001) constructed more reasonable human capital variable based on the average years of schooling for their estimation and failed to detect positive static effect of education.

3.3. Data quality

Some studies consider that the reason of this insignificance of education is due to data quality of the employed educational variables. Temple (1999) examined the analysis by Benhabib and Spiegel (1994) and showed, by using the same cross-country dataset, that the positive and significant coefficient on human capital can be obtained by reasonably trimming outliers in terms of OLS residuals away from the sample. Krueger and Lindahl (2001) argue that the measurement errors in the educational dataset used by Benhabib and Spiegel (1994) cause the downward bias of the estimate of the schooling coefficient, showing that such bias can be eliminated by considering a longer time span as a change.³

There are also attempts to construct more accurate data series. Cohen and Soto (2007) constructed a new dataset of the average years of schooling from 1960 to 2000 based on several data source such as an OECD database on education, UNESCO’s statistical yearbook, and census

³ They show that the change in the educational variable is positively related to the change in GDP when the time span of such change is relatively long, such as 10 to 20 years. When the span is longer, variability of the true change in educational variable becomes relatively larger than the component of measurement error, so an analysis of longer period is preferable.
The dataset covers 95 countries. The several cross-country growth regressions of 59 countries from 1960 to 1990 they conducted using this dataset obtain results indicating a significant and positive effect of education. Barro and Lee (2010) also have continued to update and modify their database correcting for measurement errors pointed out by several previous studies. The dataset is then used to conduct panel estimation of aggregate production function, and Fixed Effects instrumental variable estimation detects a positive effect of educational attainment on economic growth. Konishi (2003) estimates the log-differenced Cobb-Douglas aggregate production function similar to Benhabib and Spiegel (1994), using Japanese prefectural data. The data covers 36 regions from 1980 to 1995, based on census data. Least absolute deviations (LAD) method is employed to minimize the effect of outliers of educational data. The results indicate a positive and significant influence of the growth of average years of schooling on output growth in LAD (and OLS) estimates. These studies thus show a possibility that an accurately compiled educational attainment data is actually a good proxy of human capital.

Although several studies report that the correction of measurement error in aggregate educational data improves the significance of the educational attainment variable, empirical analyses have often failed to support the positive aggregate return to education. This missing static effect of education in macro empirical literature corresponds to the puzzle raised by Pritchett (2001).

This chapter reviewed conventional approach of testing the effect of education on economic growth, based on a simple causal relationship from educational attainment to productivity increase. But this approach seems to lack a perspective regarding more concrete mechanisms in which skills and knowledge obtained through education are utilized. In the next chapter, this perspective is brought in the discussion of the effect of schooling, by focusing on the technological context.

---

4 The improvement in accuracy comes from using the educational attainment data by age-group and maintaining consistency in classification system of education in each country.
5 They use perpetual inventory method to estimate the average years of education based on the census and survey data. The latest version in 2010 improves in accuracy by using recent census and survey data disaggregated by age and sex.
6 The coefficient is insignificant for the Fixed Effects estimation without instruments.
4. Technological context in the effect of schooling - an alternative approach

The previous chapter shows the conventional approach detecting the positive effect of education on macroeconomic productivity, as well as the weakness of this approach and contradictory findings. In this chapter, an alternative view is introduced: the role of technology in determining the effect of education on productivity improvement. The basic argument here is that the skills and knowledge that workers obtain through education enhances their productivity, only when these skills are connected with technologies complementary to them. By taking into consideration the role of technological context, we will find that the provision of better access to school education service is not a sufficient development aid for poor countries. This chapter starts with introducing Easterly’s (2002) argument about the importance of technological context in determining the effect of education in developing countries focusing on a few of its implications, followed by reviewing literature related with them.

4.1. Technological improvement in developing countries - Easterly's argument

In the endogenous growth model by Romer (1990), technological capacity is assumed to advance through innovation activities such as R&D, leading to aggregate productivity improvement. Educated people are considered to play a role in this process. While this is intuitively a reasonable assumption for countries with advanced economies, it may be rare to observe this situation in developing countries. This is because in these countries, the extent of industries requiring such technological innovation activity is limited, and the average educational attainment is still at the primary level.

More plausible process of technological improvement in developing countries may involve adoption of existing technology from relatively developed countries. Easterly (2002) provides a clear illustration of this process with a specific example. He characterizes the effect of new technology and skills in developing countries using the terms “leak”, “match”, and “trap”. When an advanced technology is transferred from outside the country through foreign direct investment, technological knowledge can “leak” to the domestic economy through local employees’ entrepreneurship, because the knowledge is non-rival. Easterly’s (2002) account of Daewoo, a
South Korean company that was contracted to train more than 100 workers from Desh, a Bangladesh textile company, is a dramatic example of the leaks; many of the 100 workers left Desh with their skill base to set up new textile and apparel companies, eventually enabling Bangladesh to become an international exporter in these industries. The leak of technology induced the establishment of new production capacity and expansion of these industries, and more opportunity for investing in new knowledge which in turn created more skilled workers. If that industry requires corporative tasks by workers with certain levels of skill and knowledge, there will be an incentive for skilled workers to “match up” with other skilled workers, leaving unskilled workers “trapped” in poverty.

This illustration provides some implications regarding the function of education. First, educational attainment promotes adoption of technology complementary to education. The key assumption of the leak story is that a new technological knowledge is complementary to existing skills and technology. If skilled workers tend to be able to handle new technology, higher average human capital in a community could spur adoption of available technology there. On the other hand, an expansion of education alone does not provide higher productivity, unless there are available technologies that can be linked to the skills and knowledge obtained by workers. This illustration thus suggests a critical role of technological context in the effect of education in developing countries, where the current technological level is relatively low.

Secondly, the leak story also implies that the technology is not necessarily the product of educated workers, but rather a cause of educational demand. Once a productivity-enhancing technology becomes available within the economy, return to acquiring the skills and knowledge that are complementary to such technology goes up. This in turn creates incentive to go to school. If the size of industries requiring such skills and knowledge further develops in the region, the value of being educated for workers increases furthermore, spurring prevalence of educational attainment by the population. However, there will be no incentive for students to go to school if there is no opportunity to use their skills and knowledge.

Thirdly, education may have an external effect. The matching story implies that an educated worker can take advantage of similarly educated other workers surrounding him to be more productive, meaning that the benefit from education is higher at the workplace where the average educational level is higher. Since the presence of positive externality of education makes aggregate
benefit bigger than just the sum of individual benefits from educational attainment, it justifies subsidization to schooling by government from efficiency perspective.

The following sections review the literature along the implications of Easterly's (2002) argument raised above.

4.2. Individual educational attainment and technological adoption

In the standard wage function, the rate of return to education, or equivalently the return to individual human capital accumulation due to schooling, is mostly treated constant across individuals as far as the quality of education is homogeneous. Here this assumption is slightly relaxed; the rate of return is allowed to vary depending on the worker’s tasks which are determined by the industry the worker engages in, whereby it is argued that the role of education is sensitive to technological environment.

Consider that the rate of return to education varies across industries. To take into account this variation, simplest extension of Mincer’s equation is to replace $\rho$ with $\rho_I$, where $\rho_I$ is the industry-specific rate of return to schooling for workers in industry $I$. The human capital stock of an individual $j$ working at the industry $I$ in the region $i$ at year $t$ is thus

$$H_{ijkt} = (1 + \rho_I)^s H_{ij,t-s},$$

and this leads to the individual Mincer’s equation;

$$\varphi(S_{ijt}) = \theta_{ijt} + \rho_I \cdot S_{ijt}.$$

In the estimation of private return to education using the data of wage earners, this model can be estimated by interacting educational variable and dummy variables indicating type of industry or category of business into wage regressions, to see the variation of the effects of education among industrial sectors. Formal employment in the sectors such as manufacturing and service sectors tends to be the target of such studies.

To see how educated workers tend to improve their productivity in the concrete, there are studies that investigate the role of education on workers’ specific technology use and adoption. For example, Krueger (1993) uses a survey data in the US to examine how an expansion of computer use in the 1980’s affected the workers’ wage and the return to education. The study finds that those workers who use computer on the job earn 10-15 percent higher than those who do not. Also, more
educated workers are more likely to use computers in their work, and the estimates imply that almost a half of the increase in the return to education during the observation period is attributed to the spread of computer usage in the workplace. A study by Riddell and Song (2011) assesses the effect of education on workers’ probability of using computer-based technology, based on the survey data in Canada from 1999 to 2005. The estimation employs a change in the educational legislation as an instrument for educational attainment, and shows that there is the causal effect of worker’s education on his technology adoption on the job. It is also found that more educated workers have longer experience of using computers in the workplace. Both of these studies thus illustrate education’s positive effect on technological adoption, especially in the environment where productivity-enhancing advanced technology is prevailing.

These studies are conducted using the data of wage earners in developed countries, and the advanced technology is considered. The following studies are those microeconomic studies focusing on agricultural sector in developing countries. Foster and Rosenzweig (1996) examine the effect of educational attainment by farmers on their adoption of new technology for agricultural production called Green Revolution. The study uses the data of rural households in India during the green revolution period in 1960’s and 1970’s, and examines the impact of an exogenous technological change, which is the introduction of high-yielding variety (HYV) seeds to agriculture from outside of India, on local economy. It is found that a farming household with one or more primary-school graduates is more likely to adopt the newly available HYV seeds than a household with no schooled member. In addition, the households with primary education are able to reap more profit from using the HYV seeds than those with no education, which means a positive return to education due to adoption of new technology. Also, the return grows faster in the districts where the technological progress is quicker, indicating that educated workers are more able to utilize a new technology.

Jolliffe (1998) examines the relationship between cognitive skills and farmers’ income in Ghana. The estimations are conducted for income from farming and non-farming separately. The cognitive skills are measured by test scores of mathematics and reading, so this variable represents quality-adjusted educational attainment. The results indicate no significant impact of education on farming income. This result and the result of Foster and Rosenzweig (1996) clearly show that the educational attainment alone does not necessarily enhance farmer’s productivity. Technological
innovation due to school attainment is not explicitly observed in these studies; exogenously introduced technological knowledge provides productivity gain by education.

It is found in the literature for both developed and developing countries that the educated farmers are more likely to adopt a new technology and to earn more, according to Foster and Rosentzweig (2010) who examine the literature about the process of technological adoption. This positive influence of education on technological adoption is, not to mention, conditional on the availability of the adoptable technology. The evidences suggest that the availability of new technology is necessary for the positive effect of schooling, so the absence of the positive return may simply imply the absence of new technology, and does not necessarily deny the motive of promoting education.

Using survey data in Kenya, Duflo et al (2008) find that there was no effect of education on farmers’ return to adopting fertilizer for maize production recommended by the government. The adoption of the technology takes learning process regarding the profitability and the most efficient usage, and education is expected to play a role in this process. Foster and Rosentzweig (2010) explain that the technology considered in Duflo et al’s (2008) study is relatively old, so the learning process does not involve the skills due to schooling. These findings are thus supporting a policy that local government and global community actively provide access to schooling in rural regions where agriculture is a major industry, given that productivity-enhancing new technology is accessible for farmers in the regions.

The effect of education on technological adoption seems highly complex. Dunne and Troske (2005) test the hypothesis that a manufacturing plant with more skilled workers are more likely to adopt and use several types of computer-based technology, using the plant-level data in the US. The results show that such likelihood varies depending on the type of technology, indicating a complex relationship between technology and education even within the same manufacturing industry and the same category of technology. Most of the microeconomic evidences do not imply a simple causal effect of education on higher productivity; there is a variety of mechanisms connecting technologies with skills obtained through education, behind a detected return to education.
4.3. Average educational attainment and the aggregate technological advancement

How has the technological advancement been taken into account in the study of the effect of education on regional aggregate income growth? Three growth models incorporating human capital are reviewed in Chapter 2. Each of them has distinctive feature in it regarding the way of treating technology. The model by Lucas (1988) implicitly treats human capital and technology interchangeably, so an increase in human capital is immediately translated to macroeconomic productivity enhancement. On the other hand, those of Nelson and Phelps (1966) and Romer (1990) relate human capital with certain types of mechanisms advancing technological status; the former emphasizes adoption of existing advanced technology, and the latter emphasizes innovation and invention of advanced technology.

Nelson and Phelps (1966) discuss the process of technological adoption in their macroeconomic modeling as follows. For individual workers, their jobs and functions require certain level of skills and knowledge. These skills enable workers to learn new tasks and/or to conduct tasks more efficiently, so new technology diffuses quicker where the workers have more skills and knowledge. The effect of education in industrial corporations also appears as abilities of scientists and top management to introduce the latest technology to their production process. In their model, therefore, the benefit of education is realized when some advanced and accessible technology exists, even if such technology is not invented by their own human capital.

Some studies empirically examine the relationship between average education and aggregate technological advancement. Benhabib and Spiegel (1994) test the hypothesis that human capital contributes to the diffusion of technology between countries, as discussed by Nelson and Phelps. It is tested if a country’s educational level is positively related to the speed by which the country fills the technological gap with the most advanced country, where the gap is measured by difference in total factor productivity (TFP). The estimated coefficient of human capital (average years of education, averaged over the period of analysis) is positive and significant once convergence effect is controlled. This evidence supports the argument of technological catch-up effect of education. Also, the results indicate that the growth of total factor productivity, and thus the growth of GDP per capita, is positively dependent on the level of human capital stock.

Benhabib and Spiegel (1994) also examines the notion by Lucas (1990) that the low human capital stock in the low income countries is one of the reasons that physical capital does not flow
into these countries, because the human capital is the factor complementary to physical capital. Their test supports this notion. While physical capital investment does not necessarily mean technological advancement, a technology embodied in the physical capital newly invested might require skills for its operation, and such skills could be acquired through education. The results of these studies are consistent with a notion that the human capital contributes to the following technological advancement through adoption of a new technology and capital investment, although not an immediate benefit. Increment in human capital may be a priority in development strategy, as it induces future improvement in productivity.

The innovation process assumed in the endogenous growth models like Romer's (1990) may not be likely the role of workers’ skills obtained through basic education, so the low educational attainment level in developing countries implies an absence of regular innovative activities. Some studies argue that the highly skilled workers in rich countries contribute to enhancement of technological innovation, rather than imitation. Vandenbussche et al. (2006) distinguish the difference in role of human capital between primary/secondary education and tertiary education. As a country moves closer to the frontier, productivity gain from adopting advanced technology becomes less and less, and therefore the country allocates more high-skilled workers to innovation activities, which corresponds to the attainment of higher education. The rich countries that are relatively close to the frontier tend to benefit from tertiary education due to its innovative skills. This therefore implies the complementarity between tertiary education and proximity to technological frontier. This goes beyond the notion that the farther the country is from the frontier, the more the average education enhances country’s ability to catch up with the frontier. The empirical analysis using the data of OECD countries indicates that the TFP growth is positively dependent on the interaction term between technological proximity in terms of TFP and the share of tertiary-educated workers.

These results suggest that higher education is important for innovation, while initial phase of education like primary and secondary education is more important for the process of adopting technology. So the role of education can be different depending not only on the technological level, but also on the stage of average education. Rich countries, like Japan where the average years of education corresponds to relatively higher level of education, are expected to benefit from their high human capital stock by its innovative function, and poor countries, like SSA countries where the average education corresponds to basic education, benefit from education by fostering ability
of technological adoption. Both of these countries can generate positive return to average education although their functions of education are different.

Nelson and Phelps’s (1966) argument is in line with some studies directly linking average education and indicators of aggregate productivity in poor countries. A possible scenario in developing countries where technology is not advanced yet is that the adoption of the technology available outside the countries is promoted by the educational attainment of the domestic average workers. As a result, macroeconomic productivity grows. While the technological innovation due to human capital is a key assumption for the endogenous growth models, education is not likely to spontaneously cause such innovation often in African countries, as long as we observe the fact that the average level of educational attainment in this region corresponds to the primary education stage.

4.4. Variation in return to schooling across industries

Pritchett (2001) raises the following three potential reasons for insignificance of the effect of regional average educational attainment on their income variation; (i) Many educated workers might work for unproductive and rent-seeking activities in the sectors such as public sector, (ii) Demand for educated workers is stagnant due to absence of sectoral shift and technological progress, and (iii) Education creates few skills due to its low quality.

The quality issue raised at (iii) is discussed as one plausible argument in many studies. The other two are partly related to the discussion so far in this chapter, in a sense that the adoptable technology or invention associated with worker's skills varies according to the industrial sector he or she engages in. If an individual return to schooling can be affected by his or her tasks and functions, there must be some variation in return to education across industrial sectors, and such variation may be reflected by the diversity in industrial structure from macroeconomic viewpoint.

As Easterly (2002) observes, an existing pattern is that the poor nations with low-skill workers produce more raw materials, while rich nations with high-skill workers produce more of secondary or tertiary industries’ products. This may mean that the industrialized nations, where the required level of skills and knowledge for their production is high, exhibit higher returns to education, while developing countries exhibit low or no return to education because the skills are simply not
demanded in less industrialized economy. In this case, the educational attainment of general population in SSA countries may be facing a problem in its utilization, rather than its quality. It may be the case for SSA countries that from a macroeconomic perspective the educational investment is rather too large, leaving rapidly accumulating human capital unutilized. The implied policy recommendation is the “investment in new technology” which makes the private rate of return to education higher, further generating private incentive to education.

4.5. Endogeneity

In the situations considered in the previous sections, productivity-enhancing technologies are introduced exogenously, and a worker's educational attainment is expected to help him adopt that technology. Easterly (2002) notes that an increase in accessibility to a new production technology positively affects the return to schooling, and the increased return to education is then expected to create incentive to go to school and acquire the skills and knowledge complementary to the technology. Pritchett (2001) argues that the absence of the expansion of skill-intensive sectors, or a rapid technological progress, or both of these, makes the demand for educated workers stagnant. The causality is considered going not only from education to technology, but from technology to education in their view.

Foster and Rosentzweig (1996), in their study of farmers in India reviewed above, found that the introduction of HYV increased demand for schooling for farmers. Munshi and Rosenzweig (2006) is one such study of the formal service sector in the context of globalization. They examine how higher return to acquiring English skill due to globalization changed the school choice, by caste and gender. The study uses a sample collected in Bombay, whose economy shifted from manufacturing sector to corporate and financial sectors in 1990’s. This structural change lead to higher returns to English skill, and affected choice of school based on the language of instruction between English- and non-English medium schools. The results reveal that the girls in the lower caste, who traditionally do not often participate in labor market, tend to choose English-medium schools, and this tendency increased along with the increase in opportunity of white-collar occupation, leading to higher return to English skill. This finding is consistent with the idea that a
sectoral transition, associated with new technological requirement, increases return to a specific skill obtained through education, and increase the demand for education as a result.

Shastry (2010) studies the impact of technological progress associated with globalization on the supply of educated workers in India. The study tests the hypothesis that the districts in India where the cost of learning English is lower should have more population who learn English, the skill required for service-exporting industry. Globalization leads export-oriented IT firms to be established more in the districts where the “linguistic distance” of local language from Hindi is further (meaning lower relative cost of learning English). This generates more opportunity for English learners, and thus school enrollment grows faster in these regions. The result shows that an exogenous positive shock on demand for skilled labors fosters the school enrollment in the regions where the workers have advantage in acquiring skills in terms of cost of learning. These studies illustrate a link between educational attainment and technological adoption in service sectors, with the causality running from a new technology to growth of education, not the opposite.

The causality from technology to educational demand is examined not only in analyses of individual workers but also aggregate data analyses. Bils and Klenow (2000) test this causality by hypothesizing that higher anticipated technological advancement (expected growth in TFP) induces more schooling demand. According to the results, this channel from technological growth to growth in schooling is quite strong to explain the positive relationship between human capital and income growth in cross-country observation. In this argument, therefore, technological advancement causes education, but not the other way, similar to the implications of microeconomic literature discussed above.

This argument of causal relationship between technology and schooling leads to a concern that the estimate of aggregate return to education may be biased due to endogeneity. Higher level of technology, as well as higher income level, could motivate a higher demand for education, as discussed above. In this case, a region or a country which has relatively higher average income or technological level should experience lower marginal return to educational investment than the other regions, because of a diminishing return to human capital investment. That results in equalized marginal return to education across countries, and an estimation of aggregate production function may lead to downward-biased estimate of return to education. Therefore, it is necessary to address this endogeneity bias when an empirical analysis is conducted, taking into account the causal relationship between educational attainment and technological context.
A common approach to overcome the endogeneity bias is to use instrumental variables. While microeconomic studies using household data employ a variety of variables as instruments for schooling such as parents’ education and their level of asset, macro studies using aggregate data suffer from limitation in the choice of such variables. Most of the macro literatures use the lag of the schooling variables. Barro and Lee (2010), for example, employ 10-year lagged average years of schooling as an instrument for the contemporaneous average years of schooling. The idea behind this choice of instrument is that the decision of schooling by workers is positively affected by the workers’ parents’ schooling, supported by a typical finding in microeconomic literature. In this sense, the instrumental variables should explain the demand for educational investment, and the productivity improvement due to this investment materializes in the current workforce with time lag of several years. Variables representing available new technologies are the candidates for such instruments.

5. Summary

This study reviews empirical literature on the effect of school education on economic growth, with special focus on technological context. The growth models by Lucas (1988), Romer (1990), and Nelson and Phelps (1966) provide different empirical implications. The former model implies that the growth of human capital is associated with the growth of per-capita GDP during that period (static effect). In contrast, the latter two models imply that the initial level of human capital is associated with the subsequent growth of per-capital GDP (dynamic effect). This difference comes from their perspectives about underlying mechanism of how education works in productivity improvement. While empirical studies using macroeconomic cross-country data is consistent with the model of dynamic effect, this is inconsistent with the typical findings in the estimations of wage function. Moreover, the estimates and the conclusions vary among studies.

Microeconomic empirical studies suggest that the education is complementary to technology. While large body of literature indicates significantly positive returns to education, more extensive analyses indicate that a positive return to investment in human capital is realized only within economy that connects skills and technologies. A positive return to education estimated by wage function can be understood in this context. The benefit of education is observed even in agricultural
sector, if the introduction of a new technology from outside the economy increases returns to education. Thus, any type of sector/industry can enjoy productivity improvement due to higher average educational attainment, conditional on availability of a new technology within the industry. As Nelson and Phelps (1966) discuss in their model, and Pritchett (2001) argues, there is little or no return to education where the economy is technologically stagnant, but an exogenous technological advancement increases the return to education.

The estimation of macroeconomic return to education requires some treatment. For example, dividing the sample between advanced countries and developing countries is necessary, because the role of education is different between them due to existing technological gap. Level of education, such as primary education and higher education, should be in consideration due to the same reason. It is also necessary to consider the industrial structure of the sample countries. Selection of instrumental variables is important to avoid estimation bias due to reverse causality between schooling and income growth. Educational demand due to technological environment is expected a key to set the estimation model specification.
References


