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Human Capital, Education, and Economic Growth

인적자본, 교육, 그리고 경제성장

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Abstract

Human Capital, Education, and Economic Growth

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There has been an ever-heightened interest in the role of human capital. This thesis surveys the existing theoretical and empirical literature on human capital and economic growth in an attempt to discuss the importance of adequate education. The role of human capital in economic growth is largely categorized by improving productivity, enhancing innovation, and facilitating technology adoption. Empirical literature has been inconclusive on the role of human capital in improving productivity but supports the significance of human capital in driving the technological progress either by innovation or adoption. Also, this paper discusses the limitation of approaching education only in a quantitative perspective. Hence, different aspects of education, such as quality, distribution, and utilization, and their relationship with economic growth are discussed.

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1 Introduction

The modern economy is often characterized as a 'knowledge-based' economy where knowledge and information are key factors creating economic values. In correspondence, recent economic literature has been active in analyzing the impact and dynamics of human capital investment, defined as any activity to improve "the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being" (Brian, 2007). In this regard, the role of education in fostering human capital has also gained attention from numerous economists. This thesis provides a survey of theoretical and empirical literature on the role of human capital in economic growth, and the effectiveness of education in human capital development and economic growth.

While the concept of human capital existed since William Petty and Adam Smith, it was only taken seriously taken in economic analysis since the 1950s. Economists like Schultz (1961), Mincer (1958), and Becker (1962) were few of first to present theoretical mechanisms behind human capital investment at an individual level. Their underlying theoretical approaches have been foundational for later literature focusing on estimating the return to human capital investment and the factors affecting the rate of return, and the consequences of differing human capital investment, such as wage differentials.

Later in the 1980s, Romer (1986) and Lucas Jr (1988) introduced growth models incorporating the direct and indirect effect of human capital. Such attempts were made in order to address issues unex-

plained by existing growth models, such as a significant gap between the growth rate of total output and that of major inputs, and the persistent divergence of growth rates among different countries, against the prediction of the Solow growth model.

The role of human capital in growth models has evolved differently and it is still controversial which one captures the full dynamics of economic growth. Yet, in essence, the literature focuses on two aspects of human capital in affecting aggregate growth. One, human capital directly affects the growth factors as it improves the labor productivity or increases the return of other capital (Mankiw et al., 1992; Lucas Jr, 1988). On the other, human capital plays a key role in adopting, imitating (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994), and creating new technologies (Romer, 1990; Aghion et al., 1998), and thus indirectly driving economic growth.

Building on these theoretical approaches, the literature assessing the role of human capital in economic growth has expanded massively. Undoubtedly the role of human capital in enhancing technological progress has become critically important in these days where developed countries are struggling to find a growth momentum on the verge of the Fourth Industrial Revolution. However, despite this importance, little is known about what kinds of human capital under what circumstances leads human capital investment to technological progress. Therefore, this thesis attempts to survey literature that has assessed the impact of human capital on economic growth and discussed what may affect the effectiveness of education in fostering human capital in order to draw implications for public policies.

The following chapters are organized as: Chapter 2 explains theoretical development of human capital in growth models and Chapter 3 reviews literature estimating the impact of human capital on economic growth. Chapter 4 discusses how education is related with human capital by looking at quality, distribution, and utilization of education and each of their impacts on growth. Chapter 5 includes some concluding remarks with policy implications.

2 Human Capital in Growth Theory

2.1 Productivity Improvement

By investing in human capital, the productivity of labor improves and such improvement also enhances productivity of capital to a degree where labor and capital are complementary. Papers emphasizing this role of human capital stress the importance of accumulation of human capital.

Mankiw et al. (1992) (henceforth, MRW) present an augmented version of the Solow model where human capital enters growth equation as a third factor of production,

$$Y = AK^{\alpha}H^{\beta}L^{1-\alpha-\beta} \tag{1}$$

where A is technology level, K is physical capital, H is human capital and L is labor. Then, the accumulation of human capital follows

$$\frac{dH_t}{dt} = s_h Y_t - \delta H_t \tag{2}$$

where s_h is the saving rate for human capital, and δ is the depreciation rate. MRW model, like Solow model, predicts that all economies eventually converge to a steady state but at slower pace than the conventional Solow model predicts because adding human capital counteracts the decreasing returns to physical capital K. One of the possible ways to obtain a positive growth rate at steady state is by having an outer force like government policy to maintain a positive rate of human capital accumulation, e.g $H_t = e^{mt},\ m > 0$. Then, the

long-term rate of growth is possible at the rate of $m\beta$ (Aghion, 2009).

On the other hand, Lucas Jr (1988) presents a growth model, usually known as the endogenous growth theory, where a positive long-term growth rate can be obtained without the outer force. Lucas model assumes infinitely-lived individuals who choose either to work or invest in human capital at each period, and the output is

$$y = k^{\alpha}(uh)^{1-\alpha} \tag{3}$$

where h is current human capital stock of the representative agent and u is fraction of time allocated to production, and k denotes physical capital stock. Human capital accumulates at a speed proportional to existing stock of human capital,

$$\dot{h}_t = \delta(1 - u_t)h_t,\ \delta > 0 \tag{4}$$

where $(1 - u)$ is the amount of time devoted for schooling and δ is the productivity of schooling. After solving for consumer's utility maximization problem to choose an optimal amount of u^*, the steady state growth rate of output is equal to $g = \delta(1-u^*)$. Hence, total output growth at steady state is determined by the growth of human capital accumulation which is dependent on the amount of time devoted to education.

2.2 Innovation Enhancement

In the conventional Solow model, technological progress is treated as an exogenous factor while some modern growth theories attempt to endogenize the technological progress as a function of human capital. One of them is Romer (1986), presenting a R &D-base model in which the improvement in technology is driven by the knowledge spillover effect, which can happen because knowledge is nonrival and partially excludable.

Romer (1986) assumes three sectors of economy. A research sector uses only human capital to create new knowledge. Human capital is a distinct measure from physical labor, taking into account the effect of education and experience. Then, an intermediate sector uses the outcome from the research sector to make producer durables, or physical capital. Once an intermediate firm claims a knowledge to produce a differentiated intermediate good, the firm has a sole right to produce that intermediate good. Finally a final good sector uses intermediate inputs and employs human capital and labor to produce consumer goods. Under these assumptions, Romer (1990) presents the model where output is determined by

$$Y = H_y^{\alpha} L^{\beta} \int_0^A x_i^{1-\alpha-\beta} di \tag{5}$$

where H_y is human capital employed in the non-R&D sector, L is labor, x_i is input of the intermediate good i and A is number of intermediate inputs. Here, knowledge, represented by the varieties of intermediate

inputs, evolves as

$$\frac{dA_t}{dt} = \eta H_A \tag{6}$$

where H_A is human capital employed in R&D and η reflects the productivity of research. When the human capital devoted to the research sector and the stock of existing knowledge increase, more new knowledge is created, leading to an improvement in the intermediate sector, resulting in a greater variety of inputs for the final-goods sector. Hence, the overall growth rate of output is affected by the total human capital, and the degree of growth rate may increase when human capital devoted in R&D increases.

While Romer (1990) considers the measure of knowledge as the varieties of intermediate inputs, Aghion and Howitt (1992), often referred to as the Schumpeterian approach, focus more on the enhanced quality of the intermediate-good sector as a source of technological advancement. The critical difference between Aghion and Howitt's model and Romer's model is that the former assumes that newly developed intermediate input makes the older one obsolete (see equation (7)). In the model presented by Aghion et al. (1998), output of final good is

$$Y = \int_0^1 A_i x_i^{1-\alpha} di \tag{7}$$

where each intermediate sector is monopolized, variety of intermediate input is fixed and normalized to one, each sector is assumed to have no complementarities, and each intermediate input i has (quality-improving) productivity parameter A_i. Total labor supply in sector i is divided into either producing intermediate input (one-

to-one) or doing research, i.e. $L_i = n_i + x_i$. Innovation in each sector evolves as

$$A_{it} = \gamma A_{it-1},\ \gamma > 1 \tag{8}$$

at probability of $\mu_{it} = \lambda n_{it}$ where n_{it} is the amount of labor in R&D in that sector. Hence, more labor in R&D raises the probability of successful innovation, increasing the growth rate of productivity and, hence, raising the total output growth rate as well. [1]

2.3 Technology Adoption

Instead of technology creation, some economists shed the light on the role of human capital in technology adoption and diffusion of knowledge, and stress the importance of the stock of human capital (Schultz, 1963; Nelson and Phelps, 1966; Welch, 1970).

Technology adoption or diffusion was first formalized by Nelson and Phelps (1966) presenting a model within which technological improvement ($\dot{A}_t$) occurs by adopting the advanced technology (T_t) with utilization of human capital, i.e.

$$\dot{A}_t = \Phi(h)[T_t - A_t],\ \Phi(0) = 0,\ \Phi'(h) > 0 \tag{9}$$

where $T_t - A_t$ is the technology gap between the best-practice level of technology, which evolves exogenously, and the level of technology in practice, and $\Phi(h)$ is absorptive capacity of human capital h. With the output function $Y_t = F(K_t, A_t L_t)$ at given K_t and L_t, the growth rate of aggregate output is dependent on two factors: how far the technology

[1] Equilibrium analysis is not laid out here. For details, see Aghion et al. (1998)

level in practice now is from the frontier technology, and the level of human capital. [2]

Such idea of 'distance to technology frontier' has evolved and become incorporated into the endogenous growth theory where frontier technology is also endogenously determined by human capital. For instance, Benhabib and Spiegel (1994) extends the Nelson and Phelps' model by assuming a country i's growth rate of total factor productivity to be

$$\frac{\dot{A_{it}}}{A_{it}} = g(H_i) + \Phi(H_i)[\frac{A_{mt} - A_{it}}{A_{it}}] \tag{10}$$

where H_i is level of human capital, and $g(H_i)$ reflects the contribution from technology creation and the latter part represents the impact of technology diffusion from a leading country m. Hence, the overall growth rate is affected by the creation of new technology and adoption of advanced technology, both of which are dependent on the human capital. Further variation of this model has been made such as having an extra term working as a technology barrier, making it more difficult to improve the technology level as it gets closer to the technology frontier (Benhabib and Spiegel, 2005).

2.4 Unified Growth Theory

Unified Growth Theory suggested by Galor (2005) attempts to fill in the ambiguous parts of endogenous growth theory by presenting a more comprehensive picture of the formation of human capital, its

[2] This is second model presented by Nelson and Phelps. First model assumes that technology level at t is technology invented $w(h)$ time ago, i.e. $A_t = T_{t-w(h)}$.

interaction with technological progress, and its impact on growth in the process of development. Basic model presented by Galor (2005) assumes an overlapping-generation economy where output is

$$Y_t = H_t^{\alpha}(A_t X)^{1-\alpha} \tag{11}$$

where H_t is aggregate labor with human capital taken into account and is determined at $t-1$ by household, X is land employed in production whose supply is given exogenously. A_t is the endogenously determined technology level whose progress rate is $g(e_t, N_t)$, depending on education per capita, e_t, and population size, N_t. Galor (2005) distinguishes human capital from education, and development of individual human capital is dependent on education and technological progress, i.e. $h_{t+1} = h(e_{t+1}, g(e_t, N_t))$.

The amount of education for generation t is decided by parents who maximize their utility, which is assumed to be $u^t = c_t^{1-\gamma}(n_t h_{t+1})^{\gamma}$ where c_t is consumption and h_{t+1} is human capital of their offspring. From this utility function, it can be seen that parents make a trade-off decision between number of children, n_t, and the level of human capital of each child.

Solving these dynamics, Galor (2005) lays out the dynamic process of economic development. Initially, a small population with a slow technology progress rate characterizes the steady state of zero education and slow technological progress. Then, as the population grows bigger, the technology progress rate improves. Once technology progress proceeds, the demand for human capital increases and

more investment in human capital at an individual level follows. Because technology progress rate is determined by education level and population size, the economy reaches a steady state characterized by high education level and high technological progress. Hence, the aggregate growth rate is dependent on technology progress rate, level of education, growth rate of resources per capita, and population growth. In summary, the unified growth theory attempts to embrace all aspects of human capital, such as improving productivity and enhancing technology diffusion and innovation, to show the dynamics of technological progress and human capital investment.

3 Empirical Evidence on the Role of Human Capital

In theory, there is no controversy over the role of human capital in economic development. How human capital functions to drive economic growth can be categorized largely by increasing productivity, enhancing technology innovation, and facilitating adoption of advanced technology as previously noted.

Regarding the impact of human capital investment, general consensus admits the positive and statistically significant association between education and productivity or wage at individual level (Krueger and Lindahl, 2001). On the other hand, the assessment on the impact of human capital on the aggregate productivity has been inconclusive.

The inconsistency between micro and macro evidence is, in part, due to the difficulty in measuring human capital and estimating the positive social externalities from aggregate human capital, and the limited understanding on what kinds or types of education under what circumstances through what channel influences the technological progress. Hence, this chapter looks through the literature focusing on the role of human capital in improving productivity, enhancing technological progress through innovation and adoption of advanced technology.

3.1 Productivity Improvement

Along with the theoretical framework, Mankiw et al. (1992) (MRW) present the empirical result from testing their augmented

version of the Solow model, i.e. $Y_t = K_t^{\alpha} H_t^{\beta} (A_t L_t)^{1-\alpha-\beta}$. They assume $\alpha + \beta < 1$ where α is share of income for physical capital and β is that for human capital to ensure the existence of steady state by having decreasing return to all capitals. Solving for the steady state production function and taking log transformation of it gives a regression equation for income per capita as

$$\ln(\frac{Y_t}{L_t}) = \ln A(0) + gt - c_1 \ln(n + g + \delta) + c_2 \ln(s_k) + c_3 \ln(s_h)$$

where $A(0)$ is initial level of technology, g is exogenous technology growth rate, n is exogenous population growth rate, δ is depreciation rate, and s_h, s_k are saving rates for human capital and physical capital respectively. They use the data from the Real National Accounts for 98 countries over the period 1960-1985. The percentage of the working-age population in secondary school, obtained from the UNESCO yearbook, is used as a proxy for the rate of human capital accumulation s_h. The result supports the role of human capital in improving productivity with a positive significant coefficient of human capital, c_3. This result is consistent in all three samples (all 98 countries excluding countries with oil production as a dominant industry, 75 countries excluding countries with population less than one million in 1960, and 22 OECD countries with population greater than one million).

On the other hand, a number of papers find empirical results refuting that there is a direct impact of accumulation of human capital on economic growth. Benhabib and Spiegel (1994) perform a

regression based on the theoretical framework of MRW, within which human capital enters the model as a separate production factor. They use years of schooling as a proxy for human capital. Benhabib and Spiegel (1994) use the cross-country data in 1965-1985 and the log differences regression to capture the relationship between long-term growth and input factors,

$$\begin{aligned}\log Y_T - \log Y_0 =& (\log A_T - \log A_0) + \alpha(\log K_T - \log K_0) \\ &+ \beta(\log L_T - \log L_0) + \gamma(\log H_T - \log H_0) \\ &+ (\log \epsilon_T - \log \epsilon_0)\end{aligned}$$

and find a negative and insignificant γ, suggesting a weak relationship between the increase in human capital from the improvement of education attainment and output growth. The result does not change even after controlling for regional differences, income distribution, and political instability.

However, Krueger and Lindahl (2001) argue that the result from Benhabib and Spiegel (1994) is due to the measurement error of schooling, which attenuates the impact of schooling so much that their model fails to measure the impact of change in schooling.[3] Correcting the data measurement error by choosing number of schooling years instead of the logarithm of that number, Krueger and Lindahl (2001)

[3] Benhabib and Spiegel (1994) use education data constructed by Kyriacou (1991) and use log specification of education. If schooling does not enter the Cobb-Douglas production function linearly, taking log of schooling may mislead the result.

perform a regression

$$\Delta Y_j = \beta_0 + \beta_1 Y_{j,t-1} + \beta_2 S_{j,t-1} + \beta_3 \Delta S_j + \beta_4 Z_{j,t-1} + \epsilon_j \tag{12}$$

where ΔY_j is change in log GDP per capita from $t-1$ to t, ΔS_j is change in average years of schooling, and $Z_{j,t-1}$ is other macroeconomic variables such as inflation. Their results show that β_2, β_3 are statistically significant and positive, implying that the relationship between output growth and both level and accumulation of education attainment are positive.

In summary, empirical studies estimating the impact of accumulation of human capital are still inconclusive. The reason could be due to the limitation of using a quantity measure of education as a proxy for human capital. Also, this analysis is limited in a sense that it does not explain the exogenous technological progress.

3.2 Innovation Enhancement

Recent studies focus more on the composition of human capital in driving innovation (Grossman, 1991). In fact, the composition of human capital may have a different impact on economic growth, depending on the development stage as Krueger and Lindahl (2001) find a significantly positive relationship between level of education and growth to disappear when the regression is restricted to OECD countries.

In this regard, the literature has evolved into distinguishing education by types after the idea brought by Acemoglu et al. (2006)

(henceforth, AAZ). Based on their finding that the closer developing countries are to the technology frontier, the lower their growth rates are, AAZ suggest a theoretical model in which different types of human capital may play varying roles in promoting technological progress. AAZ emphasize the importance of the appropriate strategy in selecting human capital or the size of investment depending on the distance to technology frontier. Building on AAZ, Aghion and Howitt (2006) focus on dividing education by types (primary/secondary vs. tertiary) under the assumption that a year of primary school should have a different impact on growth from that of graduate school. Aghion and Howitt (2006) suggest that when a country moves closer to the technology frontier, spending on higher education should increase in order to encourage innovation, a more important driver of growth.

Recognizing that, at the given level of total stock of human capital, the composition of human capital and the economy's distance to the technology frontier matter in enhancing economic growth, Vandenbussche et al. (2006) (VAM) test the impact of each types of education on growth, using the panel data of 19 OECD countries in 1960-2000 (subdivision in five-years). VAM assume that productivity growth is dependent on the composition of human capital (u, s),

$$A_{i,t} - A_{i,t-1} = u_{m,i,t}^{\sigma} s_{m,i,t}^{1-\sigma} \bar{A}_{t-1} + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{1-\phi} A_{t-1},\ \sigma > \phi \qquad (13)$$

where $\bar{A}_{t-1}$ is frontier productivity at $t-1$, A_{t-1} is average productivity in the country, u_m (resp. u_n is number of workers with primary/sec-

ondary education used in imitation (resp. innovation), s is number of workers with higher education. Their specification for total factor productivity of country j is

$$g_{j,t} = \alpha_0 + \alpha_1 a_{j,t-1} + \alpha_2 f_{j,t-1} + \alpha_3 a_{j,t-1} * f_{j,t-1} + v_j + \epsilon_{j,t} \tag{14}$$

where $a_{j,t-1}$ is the log of proximity to total productivity frontier at $t-1$, $f_{j,t-1}$ is the fraction of population with higher education, and v_j is country's fixed effect. The result shows that, without country dummies, α_1 is negative and α_3 is positive, indicating that countries closer to the frontier face a slower growth, and higher education is more important for growth. The significance disappears once country dummies are introduced, but is restored again when subregion dummies are used rather than country dummies. Empirical evidences from VAM show that there is a strong and positive interaction between tertiary education and proximity to the technology frontier and that tertiary education has a growth-enhancing impact in countries close to the technology frontier. Though meaningful, VAM model is limited in a sense that it does not imply causality of higher education attainment and productivity growth as its estimations are based on the reduced form regression without considering for other potential variables that might have increased productivity growth and education attainment at the same time.

Aghion et al. (2009) (henceforth, ABHV) utilize a similar theoretical framework of VAM, but use the cross-states data from the US. The data ABHV are using is richer than VAM, but requires considering

an additional condition, the migration decision. They introduce the possibility for a person with higher education to migrate to more productive states while lower educated people are not allowed to migrate. Their results yield a similar implication from VAM, such that there is a positive relationship between research-type education and economic growth only in states fairly close to technological frontier.

Islam et al. (2010) adopts the theoretical framework from VAM as well, but divide the sample into high, medium, and low income countries in order to test whether the importance of higher education in driving productivity growth when a country is close to the technology frontier differs depending on the economic development stage. Islam et al. (2010) use the panel data set of 87 countries in 1970-2004, and the model is slightly different as

$$\begin{aligned} g_{jt} =& \alpha_0 + \alpha_1 PRI_{j,t-1} \alpha_2 SEC_{j,t-1} + \alpha_3 TER_{j,t-1} + \alpha_4 a_{j,t-1} \\ & + \alpha_5 PRI_{j,t-1} * a_{j,t-1} + \alpha_6 SEC_{j,t-1} * a_{j,t-1} + \alpha_7 TER_{j,t-1} * a_{j,t-1} \\ & + v_j + \theta' X_{jt} + \epsilon_{jt} \end{aligned}$$

where the elements represent the same as VAM except PRI, SEC, TER are a fraction of working age population with primary, secondary and tertiary education, and X_{jt} includes the control variables such as inflation, openness, foreign direct investment, etc. Performing the regression for high, medium, low income countries, Islam et al. (2010) present the result showing that α_4 is negative and significant for all countries and α_7 is positive and significant only in high and medium income countries. Combining primary and secondary together yields

a similar result, indicating tertiary education is more important in high and medium countries that are getting closer to the technology frontier.

So far, the role of human capital affecting technological progress via innovation has been examined. As technological progress is dual (imitating and innovating), the literature has evolved to consider the composition of human capital and the effect of each type in affecting technological progress. Higher education is more related with innovation and lower education with technology adoption.

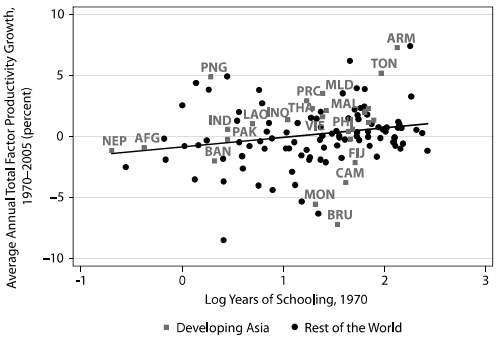
3.3 Technology Adoption

Education may enhance growth as "education can lower the cost related to information gathering and processing, labor mobility, technology adoption, and others (Kim and Lee, 2011)." Kim and Terada-Hagiwara (2013) show a clearly positive raw correlation between the initial human capital level, measured by log years of schooling, and the subsequent total factor productivity growth over 1970-2009.

Nelson and Phelps (1966) initiated the idea to incorporate the technology adoption role of education in a growth model. Extending their model, Benhabib and Spiegel (1994) perform a different set of regression from the one in Chapter 3.1, using an alternative model in which growth of technology or the Solow residual is

$$\frac{\dot{A}_{it}}{A_{it}} = g(H_i) + \Phi(H_i)[\frac{A_{mt} - A_{it}}{A_{it}}] \tag{15}$$

Figure 1: Initial Human Capital Levels and Subsequent Total Factor Productivity Growth



Source: Kim and Terada-Hagiwara (2013)

depending on human capital, H_i. This implies that the total factor productivity in country i is composed of its own innovation effect and the catch-up effect by adopting the advanced technology from country m. If the difference between A_i and A_m is substantially bigger than education gap, the catch-up effect can dominate and output growth rate of i may exceed that of m. Therefore, to see whether education enhances technology adoption, it is necessary to assess the catch-up effect, controlling for initial technology level. Benhabib and Spiegel (1994) do that by adding an initial income level term in the regression. They run a regression similar to one noted in Chapter 2.2, but instead of log difference of years of schooling, they use the average level of the log of years of schooling, ($\frac{1}{T}\sum_{t=0}^{T} logH_t$) because the stock of human capital is of interest here. Their result shows a positive and significant γ, coefficient of average human capital level, only when

initial technology level is controlled, implying that the higher the average education level, the bigger the catch-up effect. However, there is a possibility that higher level of education is associated with unobserved social externalities which might have helped total productivity growth. Benhabib and Spiegel (1994) control for income distribution and political instability to address this issue. Size of γ decreases but still remains significant and positive.

Borensztein et al. (1998) also find the supporting evidence of the role of human capital in helping technology adoption. Based on the theoretical framework from Romer (1990), Borensztein et al. (1998) consider an economy where aggregate output depends on human capital H, physical capital K, and exogenous environment A, affecting the overall productivity of economy, i.e. $Y_t = AH_t^{\alpha}K_t^{1-\alpha}$. Technological progress means the increase in the number of varieties of capital goods and can be obtained by adopting advanced technology, which requires a fixed setup cost of F, depending on the foreign direct investment, n^*/N, and the difference between number of domestic capital varieties, N, and number of advanced countries capital varieties, N^*, i.e.

$$F = F(n^*/N, N/N^*), \ \frac{\partial F}{\partial(n^*/N)} < 0, \ \frac{\partial F}{\partial(N/N^*)} > 0 \tag{16}$$

where n^* is number of capital produced by the foreign firms. They perform the cross-country regression, using the panel date of 69 countries over the period 1970-1989,

$$g = c_0 + c_1 FDI + c_2 FDI * H + c_3 H + c_4 Y_0 + c_5 A \tag{17}$$

where Y_0 is initial GDP per capita, FDI is foreign direct investment, H is stock of human capital, measured by average years of male secondary schooling [4], and A is policy environment including government consumption, black market premium on foreign exchange, political instability, political rights, financial development, inflation, and quality of institutions. From the regression, the variable Y_0, initial GDP per capita, represents the catch-up effect stemming from the technological difference ($\partial(N/N^*)$). Their result shows a positive and significant c_2, even after controlling for the policy environment. Interestingly, c_1 is negative. This implies that stock of human capital needs to be above a certain threshold in order for FDI to have an overall positive impact. They conclude that foreign direct investment can serve as an effective measure to transfer the advanced technology from abroad only when the host country is embodied with sufficient level of education.

There have been some attempts to estimate the relationship between technology adoption and human capital more directly. For instance, under the assumption that computer usage represents technological progress and contributes positively to economic growth, Caselli and Coleman (2001) estimate the effect of human capital in adopting computers. They use the panel data of different countries in 1970-1990, and estimate

$$log(I_{it}^c) = \alpha + \delta_t\beta + X_{it}\gamma + \eta_i + u_{it} \tag{18}$$

[4] Data from Barro and Lee (1993)

where I_{it}^{c} is value of computer imports per worker measured in USD in country i at year t, δ_t is a set of year dummies, X_{it} is explanatory variables, η_i is country effect, and u_{it} is iid residual term. Human capital is one of the explanatory variables[5] and is measured by the fraction of the labor force with at least primary school completion. The result shows a positive and significant coefficient on human capital even after controlling for other macroeconomic factors, implying that higher education level of population helps computer adoption. One advantage of their model is that there is little concern on the reverse causality. Because computer adoption was limited between 1970 and 1990, it is unlikely that computer adoption might have caused improvement in explanatory variables. However, their work is limited in a sense that computer adoption is only one kind of technology adoption, and there could be a non-independent relationship between region and educational attainment.

In summary, the role of human capital in technology adoption is assessed here. Overall results show that stock of human capital and the distance to technology frontier are important factors determining the aggregate growth rate.

[5]Other explanatory variables include the log of real per capita in- come; the log of real investment per worker; the share of agriculture in GDP; the share of manufacturing in GDP; the share of government spending in GDP; the extent of property-rights protection, as measured by an index (taking values from 1 to 10) based on international surveys; the share of the population who speak English; and (log) imports per worker, broken down by nature (manufacturing vs. nonmanufacturing goods) and source (OECD vs. non-OECD).

4 Education and Human Capital

Voluminous empirical researches have been conducted to estimate the relationship between human capital and economic growth, and Chapter 3 reviewed the relevant literature with evidences supporting the positive role of human capital in enhancing technology adoption and innovation. However, despite the importance of their findings, papers reviewed in Chapter 3 bear limitations stemming from their usage of quantity measure of education as a proxy for human capital.

Although education is one of many obvious ways to attain knowledge, quantity measure of education can only capture a limited aspect of human capital, defined as "the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity (OECD, 1998)." Education is a process of transmitting knowledge and does not guarantee producing or improving human capital. Therefore, this chapter is devoted to accommodating different aspects, such as quality, distribution, and utilization of education and to discuss what can be done to facilitate the translation of education to human capital.

4.1 Quality of Education

As the importance of human capital in driving economic growth has gained interest, many countries have set their goals and increased the budget allocation to widen the access to primary school or to encourage people to acquire higher-level education. Although education

may bring social benefits, such as improving public health, parenting, environment, reducing crime, or increasing civil and political participation (Wolfe and Haveman, 2001), most of economics literature focuses on the contribution of education on productivity. A strand of literature in labor economics has examined the relationship between education and productivity at an individual level. It was questioned whether education improves people's productivity or only reflects innate ability as higher ability people tend to stay longer in school (Spence, 1978). It has become a consensus that, even though return to education might differ across countries, education serves more than a signalling role and improves productivity at some degree (Chevalier et al., 2004; Glewwe, 1991; Alderman et al., 1996; Knight et al., 1990).

Among many approaches to explain the divergence in return to education, the differences in education quality is considered to explain the heterogeneity in the impact of schooling on economic growth. Hanushek et al. (2008) emphasize that cognitive skill of the labor force is important in encouraging economic growth and schools are meaningful only when they improve cognitive skills of students. They stress that estimating the impact of the quantitative change in education attainment on growth is not appropriate because a year of schooling in Kenya is different from that in Finland.

Hanushek and Kimko (2000) use the international test scores,[6]

[6]Test scores of mathematics and science were used to reflect the idea of Romer (1990) emphasizing the role of R&D as a source of growth. They use total of six international tests, four administered by International Association for the Evaluation of Educational Achievement (IEA) and two by International Assessment of Educational Progress(IAEP) in order to derive two measures of labor force quality, QL1 and QL2. QL1 combines all six test scores while QL2 is benchmarked to the US performance, provided by National Assessment of Education Progress (NAEP) tests.

Table 1: Estimates of 1960-1990 Cross-country Growth Models with Labor-Force Quality

(Dependent variable: Avg. annual growth rate in real per capita GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Initial per capita income (*Y*60) [$1,000]	−0.609	−0.472	−0.460	−0.745	−0.481	−0.517
	(0.186)	(0.096)	(0.103)	(0.181)	(0.093)	(0.112)
Quantity of schooling (*S*)	0.548	0.103	0.100	0.519	0.106	0.116
	(0.209)	(0.126)	(0.146)	(0.195)	(0.119)	(0.139)
Annual population growth (*GPOP*)				−0.713	−0.038	−0.250
				(0.224)	(0.215)	(0.211)
Labor-force quality (*QL*1)		0.134			0.133	
		(0.023)			(0.024)	
Labor-force quality (*QL*2)			0.104			0.098
			(0.015)			(0.015)
Constant	2.265	−1.900	−0.989	4.092	−1.756	−0.151
	(0.863)	(1.004)	(0.910)	(0.974)	(1.346)	(1.142)
R^2	0.33	0.73	0.68	0.41	0.73	0.69

Source: Hanushek and Kimko (2000)

reflecting cognitive skills learned, as a proxy for labor force quality. They assume that the growth rate is directly related with stock of human capital and put the labor force quality variable in the regression of average annual growth rate on the initial per capital income, the quantity of schooling, and the average rate of population growth. With a sample of 31 countries over the period 1960-1990, the result shows a statistically positive coefficient of the labor force quality and the magnitude of coefficient is bigger than that of the quantity of schooling (see Table 1, column (5)).

There is a potential problem of this regression whose result may overstate the impact of quality of labor force on growth due to the reverse causality. Growth rate is dependent on labor force quality which is not exogenous but is determined by the resources devoted to education. If high growth countries put more resources to education, improving the quality of the labor force, the impact of the labor force

quality on economic growth may be overstated. In order to address this problem Hanushek and Kimko (2000) test a direct education production function where quality of labor force is the dependent variable and the resource devoted to education is the independent variable. They find little evidence to support the significantly positive relationship between resources devoted to education and math and science test performances, implying that overestimation of the effect of labor force quality on growth is unlikely.

There is another concern for omitted variables which might affect labor force quality, growth rate, and test performance all at the same time. Hanushek and Kimko (2000) address the concern by performing the regression using the data of immigrants working in US. Because immigrants share different family and cultural backgrounds, and are subject to different country-specific conditions, their productivity, proxied by earnings, should not significantly differ regardless of where they went for school, holding other things, such as years of schooling, constant. Their findings suggest that the quality measure is related to individual productivity, implying the limited bias from the omitted variable concern.

Taking into account causality tests, Hanushek and Kimko (2000) conclude that there is a statistically positive causal effect of the quality of the labor force on economic growth. Such conclusion is supported by other papers. Barro (2001) conducts a similar regression but with the panel data of around 100 countries from 1965-1995 and a different indicator for education quality, using international test scores of

mathematics, science, and reading.[7] Barro (2001) uses the method of three-stage least squares where the dependent variable is the growth rate of real GDP per capita in each periods of 1965-75, 1975-85, and 1985-1995 with lags of independent variables, which are used as instruments to control the endogeneity problem.[8] His result shows that the estimated coefficient of school quality is positive and significant while that of average years of school attainment of adult males at the secondary and higher levels is positive but much smaller. Using the extended data and different achievement tests, other studies draw similar conclusion that quality measure of education outperforms quantity measure of education to explain growth rate (Lee and Lee, 1995; Wößmann, 2003; Bosworth and Collins, 2003; Ciccone and Papaioannou, 2009; Coulombe et al., 2004).

4.2 Distribution of Education

Galor and Zeira (1993) recognize that income distribution may affect the human capital investment decision and translate into the distribution of education. In this regard, attempts to incorporate the distribution of education in the analysis estimating the impact of education on growth have also been made.

For each economic agent, the level of income affects human capi-

[7] Number of countries with available test scores are limited to 43 countries.

[8] Independent variables include per capita GDP, quality of schooling measured by test scores, quantity of schooling measured by male population with secondary and higher schooling attainment ratio, government consumption (excluding education and defense)/GDP, rule-of-law index, openness ratio measured by ratio of exports and imports to GDP, inflation rate, fertility rate, investment/GDP, and growth rate of terms of trade.

tal or education investment decisions which, in turn, affect the later income level (Galor and Zeira, 1993). Depending on the initial condition such as initial wealth or parental background, different evolutionary patterns of income and education distributions can emerge (Galor and Tsiddon, 1997). Among them, polarized distribution are subject to a persistent and low long-term growth rate. Unequal distribution of income is inherited from unequal distribution of education, which again causes unequal distribution of income. In other words, inequality translates through the human capital investment channel, and hinders economic growth.

Lopez et al. (1999) point out the non-tradabilitiy of education and little correlation between education and ability as the reasons to consider the distribution of education when estimating the relationship between the overall education level and the aggregate output growth. Because education is embodied in individuals and cannot be traded or divided, the marginal productivity of education is not equalized across individuals. Therefore, the market has a limited role in allocating education. If the education level is highly correlated with ability, the divergence in the marginal productivity of education may represent that ability and the allocation of education may not be largely inefficient. However, the correlation between education level and innate ability is not significant. Moreover, education attainment is largely affected by factors other than natural abilities, such as parental backgrounds or government policies. Hence, the misallocation of education may have negative consequences on aggregate output, and Lopez et al. (1999) believe that such effect should be

considered.

They construct a structural estimation model under the assumption that the production function of an individual i is $y_i = AK_i^{\beta} a_i h_i^{\alpha}$, where A is total factor productivity, k_i is share of physical capital, a_i is ability level, and h_i is education level of i. The effect of distribution of education is reflected in the following average or per capita production function,

$$y_0 \equiv \frac{1}{N}\int_0^{y^M} y dy = AK_0^{\beta}[\frac{1}{N}\int_0^{a^M}\int_0^{h^M} ah^{\alpha} da\, dh] \tag{19}$$

where N is population, and a^M, h^M are the maximum levels of ability and education of the population. The term inside the brackets represents the aggregate per capita level of education. After approximating the aggregate level of education by using Taylor expansion up to the second degree and taking the log transformation of the production function, the estimation model becomes

$$\ln y_0 = \ln A + \ln a_0 + \beta \ln k_0 + \alpha \ln h_0 + \ln[1 + \frac{1}{2}\alpha(\alpha-1)(\sigma_h/h_0)^2 + \alpha(\rho\sigma_a)\sigma_h/h_0] \tag{20}$$

where σ_a and σ_h are standard deviation of ability and education, respectively, and ρ is correlation coefficient, $\sigma_{ah} = \rho\sigma_a\sigma_h$. Hence, the impact of distribution of education on output depends on $\frac{\rho\sigma_a}{1-\alpha}$.

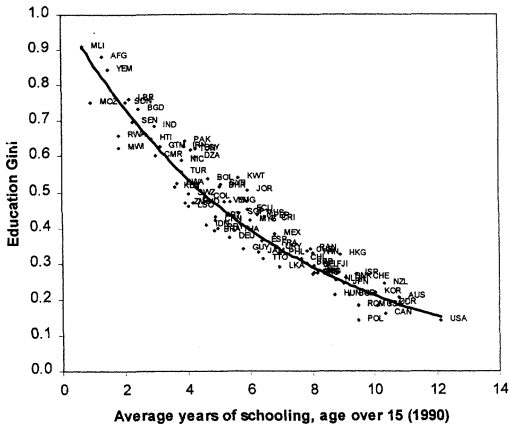
Based on this theoretical framework, Lopez et al. (1999) perform the regressions using the panel data of 12 middle income countries over the period 1970-1994. Their production function estimation tests the impact of human capital and capital, controlling for financial

crisis in 82-85 dummy and the distribution of education. Their results show that the effect of average education on economic growth is positive and significant only if the education distribution variables are taken into account. Such results confirms that the distribution of education needs to be considered altogether in order to estimate the impact of education on output more appropriately.

As the impact of the distribution of education is found to be a significant factor, other studies have attempted to reveal the linkage between the distribution of education and economic growth. When the average education level of a population is positively related with economic growth, unequal distribution of education may be negatively associated with economic growth if unequal distribution of education induces a lower average education level. Thomas et al. (2001) find the supporting evidence of this argument. They calculate the education Gini indexes for 85 countries over the period 1960-1990, using the school attainment data of the population aged over 15, and find a negative and significant relationship between education Gini index and the average years of schooling (see Figure 2). However, their results do not imply causality.

Another strand of literature focuses on the reinforcing effects between the distribution of income and that of education because the education investment decision is affected by parental background or initial wealth/income level. Castelló-Climent and Doménech (2008) suggest that, because the parental human capital affects the life expectancy of the offspring and lower life expectancy implies a higher opportunity cost for investing in education, the distribution of edu-

Figure 2: Education Gini and Average Years of Schooling



Source: Thomas et al. (2001)

cation is inherited and becomes persistent. Therefore, initial distribution of education is critical in determining the steady state human capital accumulation rate and long-term growth of the economy.

Another approach is taken by Galor and Zeira (1993), assuming the imperfect credit market, which hampers the human capital investment decision of the poor who may not have an access to the financial market. Because of the imperfect credit market, people can invest in education only if they inherit large enough wealth. Because the education level affects the wage level, the distribution of education translates into the distribution of income which changes the distribution of wealth. As a result, a rich dynasty and a poor dynasty emerge. Within a rich dynasty, all generations invest in education while all generations do not invest in education in a poor dynasty. Therefore, the initial wealth distribution determines the relative size of these

two dynasties, affecting the longer-term growth rate.

4.3 Utilization of Education

In Chapter 3, the importance of having an appropriate composition of human capital was noted especially when technology advancement is considered. While higher education is considered relatively more important in countries close to the technology frontier, simply having more people with higher education is probably not a sufficient condition for leading to higher economic growth. Whether people are getting the right kind of education or educated people are placed at workplaces requiring and fully utilizing their knowledge in productive activities are also important to facilitate the translation from education to growth. Therefore, this section attempts to address the issue of education mismatch and its (potential) impact on productivity.

Education mismatch is usually defined as a mismatch between the education level of a worker and the education level required by the firm. Over-education holds when the education level of the worker is higher than the level required by the firm, while under-education is the other way around. Skill mismatch is defined in a similar manner but with respect to skill. Both mismatches may reflect inefficient utilization of human capital, lowering productivity.

Though seemingly similar, educational mismatch does not necessarily mean skill mismatch and vice versa because skills can be obtained or lost outside of formal education, and education systems differ in quality and orientation (McGowan and Andrews, 2015a).

Such distinction was not taken seriously until Allen and Van der Velden (2001) differentiated education mismatch from skill mismatch. Usage of education mismatch as skill mismatch has also been criticized by Green and McIntosh (2007) and Mavromaras et al. (2009).

McGowan and Andrews (2015a) attempts to find a direct impact of labor market mismatch, including skill mismatch and education mismatch, on productivity. Using the survey data from the Programme for the International Assessment of Adult Competencies (PIAAC), McGowan and Andrews (2015a) find evidence of a negative relationship between education mismatch and productivity. Most of the negative impact comes from under-education in 19 OECD countries.

Mismatch is measured by using the data from OECD *Survey of Adults Skills*.[9] Three measures of productivity used are the weighted average productivity, allocative efficiency, and within-firm productivity, using data from ORBIS and Structural Demographic Business Statistics (SDBS).[10] McGowan and Andrews (2015a) perform an industry level regression of labor productivity on mismatch, controlling country- and industry-specific fixed effects:

$$prod^{j}_{s,c} = \alpha + \beta_1 Mismatch^{k}_{s,c} + \delta_s + \delta_c + \epsilon_{s,c} \tag{21}$$

[9]Over/under education is classified by comparing the respondents answer on the appropriate education level to get the type of job respondent have and their actual education level. Over/under skill is also classified by combining the self-reported skill mismatch and the respondents' actual proficiency.

[10]The weighted average productivity equals the within-firm productivity (unweighted average productivity capturing the fraction of more productive firms to less productive firms) plus allocative efficiency (reflecting that more productive firms are relatively larger): $P_j = \sum_{i \in j} \theta_i P_i = \bar{P}_j + \sum_{i \in j} (\theta_i - \bar{\theta}_j)(P_i - \bar{P}_j)$

where *prod* is labor productivity in country c and industry s and δ are fixed effects. The results of their regression are shown in Table 2. The result reveals that over-education is uncorrelated with produc-

Table 2: Baseline results of the link between mismatch and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted Productivity		Allocative Efficiency		*Within-firm* Productivity	
Over-qualified workers		0.0039		0.0005		0.0033
		(0.009)		(0.005)		(0.005)
Under-qualified workers		-0.0216***		-0.0087*		-0.0129**
		(0.007)		(0.005)		(0.005)
Over-skilled workers		-0.0094**		-0.0124***		0.0030
		(0.003)		(0.004)		(0.003)
Under-skilled workers		-0.0047		0.0016		-0.0063
		(0.004)		(0.003)		(0.004)
Workers with qualification mismatch	-0.0077*		-0.0070*		-0.0007	
	(0.004)		(0.003)		(0.003)	
Workers with skill mismatch	-0.0036		-0.0045*		0.0010	
	(0.002)		(0.002)		(0.001)	
AdjR2	0.887	0.901	0.601	0.636	0.924	0.930
Observations	205	205	205	205	205	205

Source: McGowan and Andrews (2015a)

tivity while under-education is negative and significantly associated with productivity, inducing a negative and significant relationship between education mismatch and productivity except for within-firm productivity.

What is then causing education mismatch? One possible reason could be the structure of the economy compensating occupations differently. When the professions offer different wages and working environments beyond the productivity differences, people may not choose an occupation that they can utilize the obtained education at most if such an occupation offers a sufficiently high wage. Similar analysis is constructed by Murphy et al. (1991) but in regard to talent

rather than education. They present a theoretical framework which formalizes the mechanism of occupational choice. People choose occupations to maximize their return to ability and the choices are dependent on the market size, the characteristic of the occupation in regard to the degree of returns to scale, and the compensation contract. They show that the resulting allocation of talents has a critical impact on economic growth. For instance, reallocation of talents can improve the aggregate output growth if high-ability people are attracted to rent-seeking sectors rather than productive sectors. Analysis from Murphy et al. (1991) can be used to analyze the efficient utilization of education. If people make optimal occupation choices which are against the full utilization of their obtained education, such incidence may be reflected in the education mismatch data and can be improved through reallocation.

5 Concluding Remarks

This thesis reviews modern growth theories incorporating human capital, and empirical findings testing these theories. In theoretical models, the roles of human capital in driving growth can largely be categorized into three channels, directly improving productivity, enhancing technological innovation, and facilitating technology adoption. Empirical findings support the positive association between human capital and technological progress while there exists an inconclusiveness in supporting the productivity improvement role of human capital. Part of such inconclusiveness comes from the measurement issue of human capital. A large portion of empirical investigations use some quantity measures of education as a proxy for human capital. Their findings bear a limitation stemming from the possible gap between education and human capital. In order to supplement the quantity measure of education, there have been attempts to incorporate the quality and distribution of education in the analysis of estimating the impact of education on growth. Also, estimating whether the acquired education is fully utilized is important because the incidence of misallocation of educated people is quite prevailing.

In order to fully capture the growth enhancing effect of education, government policies are important. In practice, educational policies include improving school quality, widening the access to education, encouraging more schooling, etc. Though such policies are all important, it is critical for governments to adopt policies more strategically in accordance to the level of economic and technological

development.

If the technology advancement is almost at the global technology frontier, policy makers should focus more on higher education to encourage the innovation. If skills demanded at the market change rapidly, policy makers should find ways to make schools more responsive to provide the knowledge more needed. At the same time, improvement in the utilization of education should be concerned. McGowan and Andrews (2015b) suggest that a relatively immediate way to see the effect of policy is to facilitate the reallocation of mismatched workers. As education and skill mismatch reflects the inefficient utilization of human capital, improvement in such inefficiency will have a positive impact on aggregate output growth.

In order to relieve the misallocation of workers, well-designed framework policies are critical. McGowan and Andrews (2015b) find that less stringent labor market regulations, lower product market regulations, lower costs of closing business, lower housing market regulations (to make the geographical mobility easier), more flexibility in wage bargaining, higher participation in lifelong learning programs, and higher managerial quality are all associated with the decrease in the probability of skill mismatch. A lot more research is still required to find ways to improve the inefficient utilization of education.

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국문초록

인적자본, 교육, 그리고 경제성장

경제성장에 있어서 인적자본의 역할이 더욱더 중요해졌다. 본 논문은 인적자본과 경제성장에 대한 기존의 이론 및 실증 분석들을 살펴봄으로써 향후 경제성장을 위해 교육이 가지는 시사점을 논의하고자 한다. 기존 연구들은 인적자본이 경제성장에 있어서 어떠한 역할을 하는지를 기준으로 분류된다. 인적자본의 역할은 크게 요소 생산성을 증가시키거나, 기술혁신을 견인하거나, 기술도입을 진작시키는 것으로 나뉘어진다. 생산성을 증가시키는 역할에 대한 실증분석 결과들은 아직 결론이 불분명하지만, 기술발전에 있어서 인적자본의 역할이 중요하다는 것은 실증분석 결과들이 뒷받힘 한다. 또한, 본 논문은 교육이 과연 인적자본형성에 영향을 미치는지, 교육을 경량적으로만 측정하는 것이 가지는 한계에 대해 논의하고 있다. 따라서, 교육의 질, 분포, 그리고 활용이 경제성장과 어떻게 연관이 있는지 살펴보고 있다.

주요어: 인적자본 (Human Capital), 교육 (Education), 성장 (Growth)
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