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Quantitative Analysis of Human Capital Accumulation:

R&D Investment on Manufacturing Sector and Human Resource Development Program on Renewable Energy Sector

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Abstract

This thesis conducted quantification analysis on the endogenous characteristics of human capital accumulation. In particular, based on the theory that human capital is accumulated as a return on investment just like tangible assets, this thesis suggested a framework for the quantification analysis of the stock of human capital in consideration of the return on investment and investment rates of each industry. Moreover, using this analysis method, I proposed the

utilization potential for an index for national human resource development.

I conducted two empirical analyses and an in-depth examination of existing studies on domestic/overseas methods to estimate human capital and proposed a framework for quantification analysis. In the methodology, I analyzed how human capital was adapted in various fields of research such as growth models, wage disparities, human capital policies, and R&D investment. I proposed a framework that enables quantifying the outcome of investment activities throughout the life of an individual as accumulation of human capital.

First empirical analysis examined the effects of accumulation of human capital in accordance with R&D investment. R&D and human capital have been recognized as key factors in the growth of a nation in the knowledge-based industry and have been considered in the growth models. After 1990s, the extent of the research has become narrower as it focuses on mutual interactions between the two factors. In this thesis, the focus was on the effects of human capital in accordance with R&D investment. To this end, the manufacturing sectors were classified into three different groups depending on the R&D intensity: high and medium high, medium low, and low.

The findings from the analysis of effect of R&D investment on human capital are follows. The accumulated return on investment of human capital differed in accordance with R&D investment; it was the highest in the high-tech group, in which R&D investment is also the greatest. Such an outcome implies that greater returns can be expected as investment of equal human capital leads to innovation of technology for R&D investment. Moreover, the rate of investment in human capital where an individual participates in manufacturing activities for thirty years for return on investment turned out to be highest in the industry for which R&D investment is low. This outcome can be interpreted as follows: in the case of the medium- and low-tech industries, as accumulated knowledge through direct experiences is more important than technological innovation or productivity, a significant percentage of an individual's total human capital stock is invested.

Second empirical analysis quantified the accumulation of human capital of renewable energy and the possibility of utilizing the quantification as an index for human resource development programs. The government's project for human resource development support started from its recognition that individuals were not reaching optimal levels of investment because they tend to underestimate the benefits of investment in education. Accordingly, I analyze the accumulation of inherent human capital development in accordance with human resource development project for renewable energy that has been being implemented in Korea. I classified the energy sources into photovoltaic, wind power, bio, fuel cell, and geothermal and then analyzed them.

The findings from analysis of renewable human resource development program are as follows. I discovered that the amounts of investment in accumulation of human capital varied depending on the sources of renewable energy. Workers in the wind power, geothermal, and bio energy industries invested less in human capital than those in photovoltaic and fuel cell industries. It is considered that the first group of industries has more industries focusing on labor power itself, such as agriculture, civil engineering industry, than other energy sources, and so, the amount of investment in accumulation of human capital is not great. Moreover, in the photovoltaic, wind power, bio, fuel cell industries, there was greater support for Ph.D. courses than for undergraduate programs, which is in line with the perceived greater returns of human capital accumulation in these industries. On

the other hand, in the case of the geothermal industry, in which the rate of return for education is the lowest, the amount of human capital accumulated in individuals at the undergraduate level was higher. These findings imply that as the level of education becomes higher and thereby the period for accumulating human capital becomes shorter, the impact of accumulating human capital in accordance with the policies of the rate of return on education can be different for each energy source.

The significance of this study lies in its establishment of a method for quantifying human capital accumulation. Quantitative decisions regarding the supply and demand of manpower relate closely to industry needs and are thus useful for determining the amount of human capital that may be produced through government mandated HRD initiatives.

Key words: Human capital accumulation, Panel estimation, R&D investment, Korean manufacturing, Renewable energy, Government human resource development policy

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Chapter 1 Introduction

1.1 Issues

Human capital refers to knowledge and technological skill embodied to produce economic value. Human capital accumulation is the means by which skills are improved for carrying out any type of productivity activity (Blackburn *et al.*, 2000). Education is a means to accumulate human capital, since knowledge is embodied in a person through education. The knowledge possessed by an individual can be accumulated to serve as a foundation for the growth of related industries and the country (Scicchitano, 2010, Blundell et al., 2005).

In perspective of classical economics, capital is one of the production factors. It can be accumulated by reducing present consumption along with expectation of increasing future consumption. In this way, the decision as to whether an increase in future wages is worth additional investment in human capital. According to Mincer's (Mincer, 1974) human capital theory, a laborer's wage is a compensation that an individual expects in return for the application of his/her education and industry experience in the workplace.

Efficacy of human capital accumulation as a predictor of economic growth and technological innovation has been studied from 1960 by Schultz (1961) and Becker (1964). The definitions and conceptual arguments associated with Mincer’s accumulation model have been used in an array of recent studies((Polachek and Siebert, 1993, Sjögren, 1998). Contemporary discussions related to the human capital accumulation model itself are rare.

In previous researches, the effect of human capital on economic growth was analyzed with proxy variables as schooling, companies' investment in training, and so forth. Schooling, however, is a form of human capital in the initial stage of a person’s life that does not include accumulation of human capital during the occupational career. Thus, human capital accumulation which accumulated after entering employment is not included.

The ultimate aim of this thesis is to conduct quantitative analysis of human capital accumulation. To achieve the goal, the quantification method is settled. Also two empirical analysis are carried out using the method.

First empirical study examined the effects of accumulation of human capital in accordance with R&D investment. R&D and human capital have been recognized as key factors in the growth of a nation in the knowledge-based industry and have been considered in the growth models of Lucas (1992) and Scicchitano (2010). Lately, the extent of the research has become narrower as it focuses on mutual interactions between the two factors. In this thesis, the focus was on the effects of human capital in accordance with R&D investment.

Second empirical study analyze the NRD HRD. I quantified the accumulation of human capital of renewable energy and the possibility of utilizing the quantification as an index for human resource development programs. Human resource development (HRD) programs are educational, policy-based initiatives that are being implemented by the government to promote the efficient use of human resources and enhance national competitiveness in the global market. Government-supported HRD projects have particularly useful outcomes since assimilated knowledge is embodied in an individual. However, the use of indices to measure knowledge accumulation is based on the premise that all forms of manpower produced by HRD initiatives are homogenous (Canton et al., 2005). As a result, these projects have limitations in that their unique characteristics are not properly reflected in the laborers productivity. Therefore, human capital that is accumulated through educational programs like HRD initiatives generates a number of tangible social effects (Lucas, 1988, Lucas, 1993).

1.2 Research framework and thesis structure

The purpose of this thesis is to set up the qualification method of human capital accumulation and apply the method on empirical analyses. First, to examine the theoretical context, I analyzed how human capital was adapted in various fields of research such as growth models, wage disparities, human capital policies, and R&D investment.

I proposed a framework that enables quantifying the outcome of investment activities throughout the life of an individual as accumulation of human capital. Features are based on a comprehensive examination from Mincer's (1974) early model. This model is then leveraged to quantitatively determine human capital accumulation of the industry. When the model is used, the amount of an industry's accumulated human capital can be determined. To increase the reliability of the wage function estimation, a panel analysis was utilized.

In the first of two empirical analyses, the effect of R&D on human capital accumulation were analyzed. The industries are categorized as low, medium-low, or high and medium-high technology based on R&D intensity. The total accumulation of human capital, as well as the rate of return on human capital investment, is compared by industry.

In the second empirical analysis, compare and analyze the tangible effects of established HRD programs by applying a human capital accumulation model. To empirical investigate these issues, the amount of human capital that can be obtained through different strategies can be estimated with a wage function associated with five renewable energy sources. In addition, to show the outcomes associated with utilizing human capital obtained through policy, the amount of basic, advanced, and industrial human resources accumulated through various HRD strategies was calculated. With regard to theory, the operational mechanism of each renewable energy HRD project in Korea was evaluated. Principles related to individual participation in policy-mandated HRD programs were reviewed, and limitations associated with HRD in the new and renewable energy industry were considered. On the basis of these discussions, the role of each policy was re-examined. This thesis represents a novel attempt to explore the effects of HRD policy.

The remainder of thesis is organized as follows: Chapter 2 describes a particular emphasis on the methodologies. The human capital accumulation model and earnings function are derived for quantitative analysis. For estimation method pooled ordinary least squared (Pool-

OLS), fixed effect, random effect, and hausman taylor method are described.

In chapter 3, effect of R&D investment on human capital accumulation is analyzed. Manufacturing industries in Korea are divided three: high-, medium-, and low- technology industry by R&D intensity. Individual characteristic data are corrected form Korean labor panel data (KLIPS).

In Chapter 4, the human capital accumulation structure through NRE HRD programs are analyzed. The overall new and renewable energy industry was divided into the photovoltaic, wind energy, fuel cell energy, geothermal energy, and bio energy industries. NRE HRD program are consisted with basic, industry, and high level human resource development. In addition, operational mechanisms of three Korean renewable energy HRD policies are considered in individual perspective of human capital accumulation.

Finally, In chapter 5, summarizes and presents implications derived from these results.

Chapter 2 Theory of human capital accumulation

2.1 Literature reviews

Human capital refers to the knowledge and technological ability that an individual possesses (Ehrenberg and Smith, 2006, Engelbrecht, 1997). More generally, however, human capital comprises all the factors that are accumulated through experience, and affect production. Based on these definitions, it follows that education can be a means to accumulate human capital, since knowledge is embodied in a person through education. The knowledge possessed by an individual can be accumulated to serve as a foundation for the growth of related industries and the country (Scicchitano, 2010, Blundell et al., 2005).

Human capital is being recognized as an important factor for leading the growth. The concept of human capital includes the knowledge and technology levels of labour within small rage. It also includes all factors of production accumulated thorough labour, such as education, training level, and health status.

From the two decades ago, systematic researches on how to incorporate human capital in theories of growth stated rapidly. There is an understanding that the contribution of labour to economic growth can be underestimated when not considering the human capital (Bell, Burriel and Jones 2005; Schwerdt and Turunen 2007) (Fig. 2-1).

Lucas(1990) show that the physical capital(as implied by neo classical model) tends to move towards countries with more human capital. In the 1990s the standards neoclassical growth model has been revised by introducing human capital in many studies (Mankiw *et al.* caselli, Bosworth and collins).

Lucas(1988) proposes to introduce endogenous growth model through human capital accumulation. Before the study long-run economic growth is assumed that is exogenous. An increase in human capital leads to higher production levels, but does not affect the balance rate. However, the endogenous growth model assume that there are constatn returns to scale with regard to reproducible factor inputs caphysical capital and and human capital(Barrow and sala-i martin1995).

Early research on human capital was focused on establishing the concept and quantifying any relevant discoveries. A representative study in this area was conducted by Mincer(1974) and Becker(1964). Becker(1964) define human capital is acquired as education like physical capital can earn from investment. Mincer introduce wage function called Mincerian wage. It was derived from his accumulation model has been used to conduct to a wide range of analyses, including an examination of factors that affect wage and wage inequality (Killingsworth, 1982, Lemieux, 1998, Pissarides, 1997). Other studies, such as Polacheck and Siebert (1993) and Barro and Lee (1993), attempted to explicate mechanisms of human capital accumulation, develop applicable theories, and likewise quantify any discoveries they may have made.

Since then, the focus of human capital researches has dived in three groups (Fig 2-1). Firstly, Application of mincerian wage function on examination of factors that affect wage and wage inequality. This area deal with the gender wage differences, industrial differences and so on. In second area, studies have examined the effect of human capital on national economic growth theoretical studies. Lastly, human capital accumulation theory are applied to national human resource programs. and study has assumed researches ceria transitioned to the role of human capital in affecting a variety of outcome variables. Several studies (Pissarides, 1997; Dakhli and De Clercq, 2004; del Barrio-Castro et al., 2002).

From the literature review, I found that the concept of human capital is applied in many field. However, there are lack of studies which are deal with the quantification or empirical analysis on human capital. Table 2-1 represents the method for evaluation of human capital accumulation used in literatures.

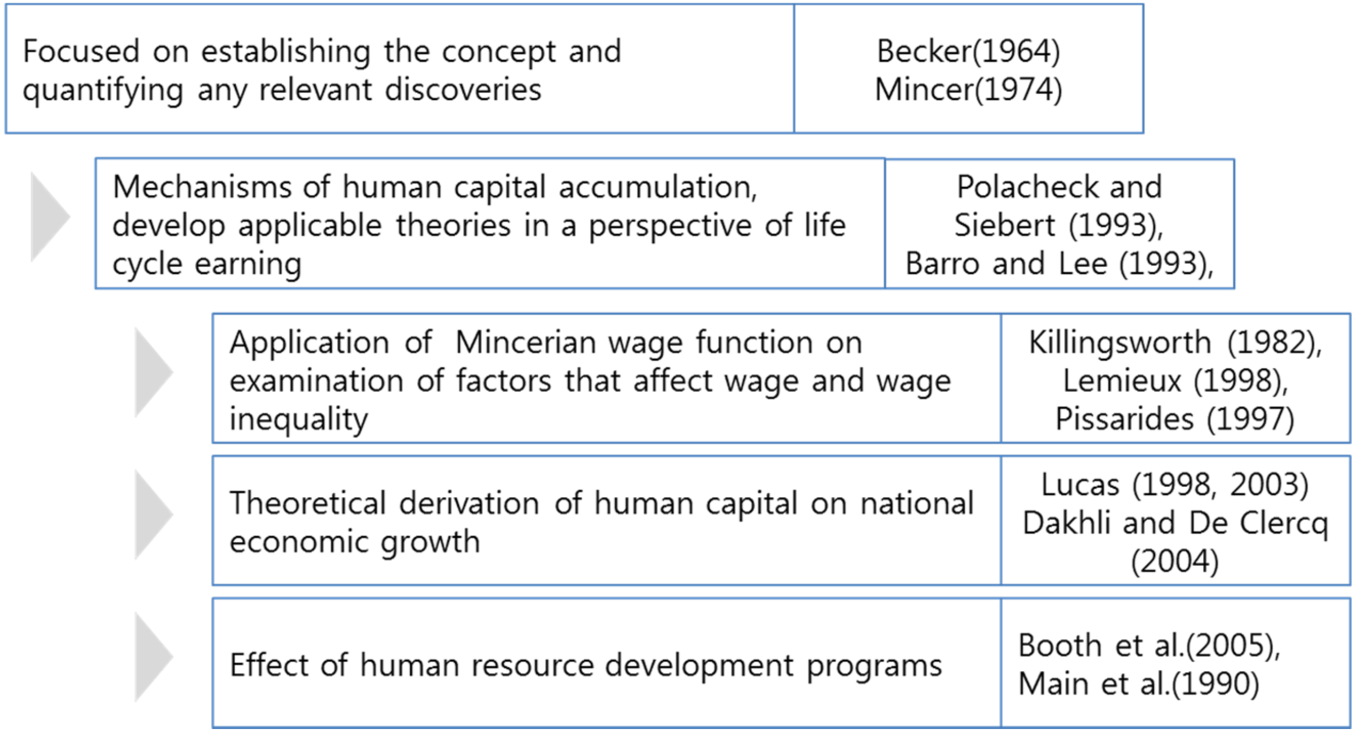


Figure 2-1 Development of human capital accumulation studies

Table 2-1 Methods for evaluation of human capital accumulation

Index		Element
Knowledge input index	Stocks	Number of researchers
		Proportion of college graduates
	Flow	Investment in R&D compared to GNP
		Education spending compared to GNP
		Investment in vocational training in the enterprise
Knowledge Performance Index	Output	Number of paper publish
		Patent
	Effect	Proportion of knowledge-intensive industries
		Foreign royalty receipts compared to GNP
		Contribution to growth
Knowledge Process Index	Infrastructure	The number of computers
		Internet hosts
		Proportion of research support services practitioners
		Number Professors
	Utilization	Commercialization of research results index
		Proportion of R & D investment, the University of
		Employment rate of college graduates

2.1.1 The relationship between R&D and human capital

Human capital and R&D is being recognized as an important factor for leading the growth of a knowledge-based society. The relationship between human capital and R&D has been studied. Some prior studies have considered the effect of R&D and human capital using one framework by looking at the interaction of these two production factors (Eicher, 1996; Redding, 1996; Engelbrecht, 1997; Chuang and Lin, 1999; del Barrio-Castro et al., 2002).

The relationship between R&D and human capital is shown in Figure 2-2. R&D affects the human capital accumulation not only of individuals participating in the process but also of the entire industry. Lucas (1993) mentioned that R&D as well as schooling is a means of human capital accumulation. Individuals or those who directly participate in R&D would accumulate know-how and improve proficiency (Scicchitano, 2010). Such an accumulation of human capital through direct experience, which is defined as 'learning by doing', takes into consideration the proficiency of individuals participating in the R&D project and may result in higher innovation efficiency for R&D in the short term.

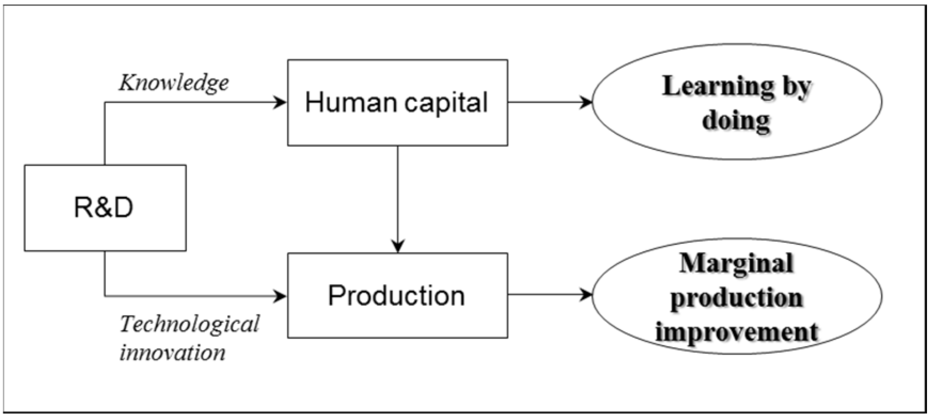


Figure 2-2 Effect of R&D investment on human capital accumulation

Recent studies have examined the scale and direction of interaction between the two elements more specifically. Initially, the influence of human capital on R&D was considered (Bils and Klenow, 2000; Blackburn et al., 2000; Canton et al., 2005; Beugelsdijk, 2008). The implications of these studies are that highly skilled labour can improve R&D results because such labourers understand the processes and absorb previous knowledge better than others in addition to having more creative ideas. Bils and Klenow (2000) analyzed the positive effect of human capital accumulation on the technology growth rate over a cross section of countries from 1960 to 1990. Blackburn, Hung and Pozzolo (2000) demonstrated that the accumulation of human capital is effective in terms of expanding the possibilities for innovation activity and the efficiency of manufacturing.

The effect of R&D on human capital has recently attracted interest (van Bergeijk et al., 1997; Sjögren, 1998; Mathur, 1999; Scicchitano, 2010). van Bergeijk et al. (1997) proved that a 0.1% increase of investment in the public sector R&D could increase human capital as much as 1.3%. Sjögren (1998) also analyzed that a lack of R&D capital results in slowed economic growth, despite rich human capital. In contrast, it was proven that rich R&D capital results in high rates of return from human capital, which may be an incentive for human capital accumulation. However, most of the studies on the effect of R&D on human capital are based only on theoretical demonstrations (Sjögren, 1998; Mathur, 1999; Scicchitano, 2010).

The effect of long-term investment in R&D leads to a high level of industry technological innovation. Technological innovation leads to a down sloping of the production function of a product, which enables more production with the same input. This development also means the increase of the marginal production of an individual. Thus, different levels of R&D in each industry may result in different levels of technological innovation, which, in turn, lead to differences in the marginal production of the workers. Additionally, since technological innovation through R&D affects the labourers across the industry, the absolute effect is more comprehensive than the learning-by-doing effect.

2.1.2 HRD and human capital accumulation

Human resource development (HRD) programs are educational, policy-based initiatives that are being implemented by the government to promote the efficient use of human resources and enhance national competitiveness in the global market (Blaug, 1976).

(1) Program evaluation[1]

Program evaluation refer to a "judgment of interventions according to their results, impacts and needs they aim to satisfy"(European commission, 2004). The key notion in this definition is that it is a process that culminates in a judgment (or assessment) of an intervention. Moreover, the focus of evaluation is first and foremost

[1] This chapter refer to Blaug (1976) pp23-45.

on the needs, results and impacts of an intervention. The main purposes for carrying out evaluations are as follows:

- To contribute to the design of interventions, including providing input for setting political priorities,
- To assist in an efficient allocation of resources
- To improve the quality of the intervention
- To report on the achievements of the intervention

Evaluation seeks to determine as systematically and objectively as possible the relevance, efficiency and effect of an activity in terms of its objectives, including the analysis of the implementation and administrative management of such activities. The scope and methods of evaluation differ according to the questions to be addressed and the character of the policy measure. Thus, they can be retrospective (ex-post), current or prospective (ex-ante) evaluations, producing information that can be used in the assessment of past policies, the monitoring of ongoing initiatives or the forward planning of innovation and technology policies (Georghiou, 2000).

Evaluations can also have different purposes. In effect, part of the difference in opinions expressed in some of the contributions to this conference and in the various discussions can be traced to different perspectives on what evaluations aim to achieve. Policy makers and economic analysts stress the role of evaluation in examining the justification of a program. They analyze its economic effects through its impact on the incentives of firms and individuals, and thus providing information to guide resource allocation as well as more strategic decision processes which involve selection of instruments (e.g. using tax-based measures vs. grants in order to support industrial R&D), or the thrust and direction of technology policies in general.

Alternatively, many professional evaluators as well as policy makers involved in hands-on running of programs stressed the role of evaluation in improving the conduct, quality, responsiveness and effectiveness of a program, thus raising its leverage effect. Clearly, these objectives are complementary; achieving them, however, often calls for different evaluation tools and institutions carrying out the evaluations (Table 2-2).

Table 2-2 Bennett's hierarchy of evidence for extension program evaluation

Indicator	**Including**
Impact	Social, economic, environmental conditions intended as end results, impact or benefits of programs; Public and private benefits
Actions	Patterns of behavior and procedures, such as decisions taken, recommendations adapted, practices implemented, actions taken, technologies used, policies enacted
Learning	Knowledge(awareness, understanding, mental abilities); opinions(outlooks, perspectives, viewpoints)
Reactions	Degree of interest; feelings toward the program; positive or negative interest in topics
Participation	Number of people reached; Characteristics/ diversity of people; frequency and intensity of contact
Activities	Events, educational methods used, subject matter taught; media work, promotional activities
Resources	Staff and volunteer time; Salaries; Resource used; Equipment: travel

A crucial issue in evaluation is the criteria to be used for judging programs and policies. The basic rationale for government initiatives to stimulate technological development in the first place is the recognition. There is a difference between the expected private rate of return and the social rate of return. With the private rate being too low to induce firms to engage in innovative activities that would be beneficial from a societal standpoint. This “market failure” situation suggests that while “additionally” and the existence of positive private returns to firms as a result of government programs are preconditions for success. For policy to be fully justified the net social benefits of a government program must be positive; the program needs not only to be effective in changing behavior, but also efficient from a social point of view.

(2) Human capital accumulation for evaluation HRD programs

Until recently, HRD programs have been evaluated focusing on the number of educated employees produced through the project. The government has analyzed the effectiveness of HRD initiatives with specific indices that focus on specific outcomes associated with specialized training (Clean Energy Council, 2009; Lee et al., 2011; Bessent et al., 1982; Choi., 2009). For example, indices used by the government to evaluate HRD programs focus on the amount of manpower produced by particular academic backgrounds or the manpower produced as a function of financial investment.

Government-supported HRD projects have particularly useful outcomes since assimilated knowledge is embodied in an individual. Unlike other forms of technological innovation, knowledge production and accumulation cannot be lost or depreciate, and it functions as a foundation for the growth of a nation’s industry (Blackburn et al., 2000). However, the use of indices to measure knowledge accumulation is based on the premise that all forms of manpower produced by HRD initiatives are homogenous (Canton et al., 2005). As a result, these projects have limitations in that their unique characteristics are not properly reflected in the laborers they produce.

Other studies have demonstrated that education positively influences productivity at the corporate level (Hatch and Dyer, 2004; Booth and Bryan, 2005; Baltagi and Khanti-Akom, 1990; Beugelsdijk, 2008). These studies showed that the implementation of governmental HRD was appropriate for inciting positive economic outcomes.

More recently, the study of human capital accumulation has focused on the positive effects of HRD on other sectors of the economy. For example, many studies have shown that skilled laborers, who understand research and development processes and transfer knowledge more easily, enhance the positive effects of sound R&D strategies (Beugelsdijk, 2008; Bils and Klenow, 2000; Cameron, 1998). In addition, Blackburn, Hung, and Pozzolo (2000) and Bils and Klenow(2000) demonstrated that the accumulation of human capital was an effective method for enhancing the efficiency of the manufacturing industry and promoting corporate innovation.

Because efficient implementation of the government's HRD projects is critical, the mechanisms of operation for each policy have also been studied. Studies in this area have focused on not only individual satisfaction but also positive influences on social utility(Main and Shelly, 1990; Booth and Bryan, 2005; Mathur, 1999; Taleghani et al., 2010; Tortop, 2012). Specifically, work conducted by Stevens (1999) that explored language education policy in the UK introduced education market failure as part of an overall evaluation of governmental policy.

2.2 Quantification human capital from earning function

2.2.1 Characteristics of human capital

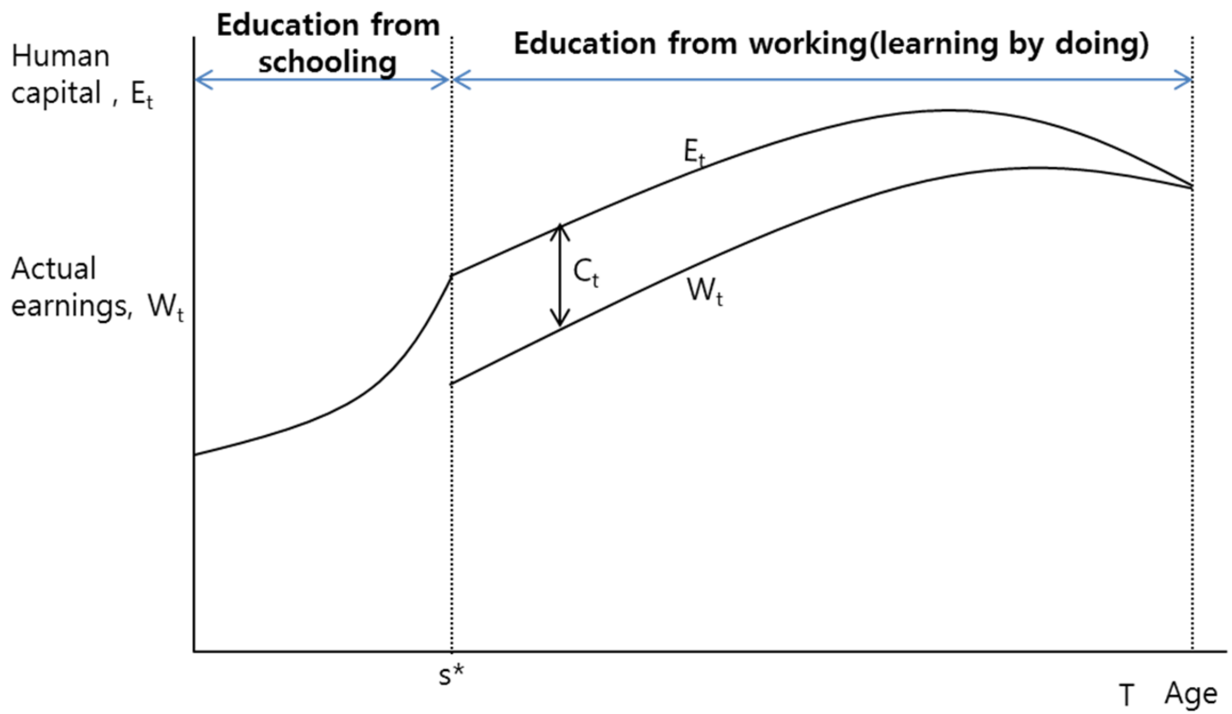
Human capital refers to the knowledge and technological skills that are embodied in people and that are capable of generating income (Engelbrecht, 1997). Similar to financial capital, these resources can be increased through investment (Becker, 1964).

However, studies that quantify human capital are not sufficient because human capital has characteristics unlike those of tangible assets; it is not tangible, but is inherent in an individual and, therefore, not tradable. Further, as a factor of input in production, returns on investment on human capital vary depending on production technologies. Thus, the indices of level of education, wages, and total cost of education have been used as indirect means for estimating human capital until now (Table 2-3).

Table 2-3 Method for evaluation of human capital accumulation

	Methods	Researcher
OUTPUT-based approach	educational attainment adult literacy average years of schooling	Choi(2005), Lee(1995), Stevens(1999) Barro and Lee (1993)
COST-based approach	Direct expenses	Kendrick(1976)
INCOME-based approach	labor income increasing	Killeen et al.(1999) Booth et al.(2005), Main et al.(1990) Mulligan and Sala-i-Martin, 1995

According to Mincer's (1974) human capital theory, a laborer's wage is a compensation that an individual expects in return for the application of his/her education and industry experience in the workplace. This definition is based on the premise that productivity is a function of education and experience and an increase in productivity should result in a higher wage (Fig 2-3).



< Polachek and Siebert (1993) >

Figure 2-3 Fame of human capital stock and investment through life cycle

An individual is thought to have the freedom to invest in human capital throughout his or her life (in the form of schooling or extensive work experience), human capital is essentially a profit that is earned from making these investments. In this way, the decision as to whether an increase in future wages is worth additional investment in human capital (i.e., traditional education or on-the-job training) falls to the individual. Changes in the labourer's marginal profit after investment in R&D affect the return of profit from the investment of human capital, which may result in differences in the amount of accumulated human capital in the industry.

2.2.2 Derivation of wage function

Human capital stock (E_t) can be defined as the total amount of human capital that can be possessed by a given individual at time t. If C_t represents the amount of investment in human capital in t time and r represents the return on human capital investment, the amount of human capital that is accumulated in E_t time can be represented as an aggregation of E_{t-1} and a profit from the investment (rC_{t-1}).

Given the investment rate of the total human capital stock is defined as $S_{t-1} = C_{t-1} / E_{t-1}$, the following formula (1) is obtained:

$$E_t = E_{t-1} + r\,C_{t-1} \tag{1}$$
$$= E_{t-1}(1 + r\,S_{t-1})$$

Taking the logarithms of both sides yields:

$$E_t = E_0 \prod_{\tau=0}^{t-1} (1 + r\,S_\tau) \tag{2}$$
$$\ln E_t = \ln E_0 + \sum_{\tau=0}^{t-1} \ln(1 + r\,S_\tau)$$

$\ln(1 + r\,S_\tau) \cong r\,S_\tau$ when S_τ is small. S_τ divided into two segments, during schooling and after schooling. During schooling, S_τ equals one since schooling is a full-time task, but after formal schooling S_τ declines (Ehrenberg and Smith, 2006).

$$\ln E_t = \ln E_0 + r_s\,S + r_p \sum_{\tau=1}^{t-1} S_\tau \tag{3}$$

After school rate of return S_τ are assumed that it declines linearly and must become zero when capacity earnings peak (Polachek and Siebert, 1993).

$$S_\tau = \alpha - \alpha\tau/30 \tag{4}$$

Thus:

$$\ln E_t = \ln E_0 + r_s S + r_p \sum_{\tau=1}^{t-1} \left(\alpha - \alpha\tau/30\right) \tag{5}$$

Where τ ranges over the years between school and retirement. The sum is an arithmetic progression with value:

$$\alpha t - \alpha t\left(t-1\right)/(2\times 30) \cong \alpha t - \alpha t^2/60 \tag{6}$$

Thus

$$\ln E_t = \ln E_0 + r_s S + r_p \alpha t - r_p \alpha t^2/60 \tag{7}$$

Since earning capacity (E_t) is unobservable, it must be substituted by earnings, which are observable. Besides, the total human capital of individuals`, as well as general capital, generates depreciation (δ)—that is, depreciation of previously acquired human capital that occurs because of deteriorating health or out-of-date knowledge (Polachek and Siebert, 1993; Mincer,1974; Ehrenberg and Smith, 2006).

$$E_t = Y_t + C_t + \frac{\delta}{r_p} E_t \tag{8}$$

$$Y_t = E_t \left(1 - S_t - \frac{\delta}{r} \right)$$

$$\ln Y_t = \ln E_t - S_t - \frac{\delta}{r}$$

Substituting equation (8) for equation (7) yields:

$$\ln Y_t = \ln E_0 - \delta / r_p - \alpha + r_s S + \left(r_p \alpha + \alpha / 30 \right) t - r_p \alpha t^2 / 60 \tag{9}$$

$$= \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2$$

Equation (9) is a basic wage function and add individual or firm characteristic variables; gender, firm size, marriage and union.

2.2.3 Calculation of human capital accumulation

From the earning function estimation, coefficients β_2 and β_3, r_p and α can calculated. The following steps

$$\beta_2 = r_p a + a/30 \qquad (10)$$

$$\beta_3 = -r_p a/60$$

There is two unknown variables (r_p, a) and two equation. So r_p and a can be calculated. S_t is given as the linear function of a in equation (4).

Using the relationship of human capital investment (C_t), rate of investment human capital (S_t)

$$C_{nt} = S_t E_t = S_t Y_t / (1 - s_t - \delta / r) \qquad (11)$$

When know that wage in specific year t, C_t is calculated.

Also human capital accumulation (E_t) is a result from previous investment of human capital(equation (1)), previous human capital E_{t-1} can be calculated.

Therefore, rate of investment human capital (S_t), human capital investment (C_t) and acquired earning form investment of human capital (Y_t) can be calculated. Finally, mechanism of human capital accumulation (E_t) can be analyzed until retirement based on average carrier and the wage by bootstrap methods.

2.3 Estimation method of wage function

The earnings function approach suggested by Mincer (1974) can be modified to account for panel data. An important advantage of using panel data is that such data have the ability to control individual-specific effects that are probably unobservable and may be correlated with other variables included in the specifications of an economic relationship (Hausman and Taylor 1981). Let

$$\ln W_{it} = \alpha_i + X'_{it}\beta + Z'_i\gamma + \upsilon_{it}, \tag{12}$$

where $i = 1, \cdots, N$ and $t = 1, \cdots, T$. Z_i is an individual time-invariant regressor; X_{it} is time-variant and α_i is assumed to be $iid\,(0, \alpha_{\alpha}^2)$; and υ_{it} is $iid\,(0, \alpha_{\upsilon}^2)$, both independent of each other and among themselves.

However, there are certain limitations in the above estimation of the earnings function using the OLS estimator. The presence of measurement errors and unobserved variables, such as ability and motivation that may be correlated with schooling, causes a bias in the OLS estimates (García-Mainar and Montuenga-Gómez 2005).

Specifically, it has been shown that the measurement error bias pulls the OLS estimates downward (Card 2001). By contrast, since schooling and the unobserved ability may be positively correlated omitting measures of ability results in the schooling coefficient being biased upwards. The latest studies seem to coincide in finding that this source of bias prevails over the measurement-error bias, resulting in an overall upwards bias of the OLS estimates (see, for example, Brunello, 2002; Trostel,Walker, & Woolley, 2002)

Moreover, the strength of these results has been questioned in various studies because statistical difficulties may obstruct the validity of OLS specifications. There are at least three biases: heterogeneity, endogeneity, and selectivity (Kim and Solomon 1994).

Heterogeneity biases arise because unobserved worker characteristics such as motivation can be correlated with work continuity. For example, if a less motivated worker has both more intermittent labor force participation and lower wages, then estimates of the effects of intermittency might be picking up motivation and not earnings power losses caused by intermittency. Heterogeneity biases thus can occur when unobserved worker characteristics are correlated both with wages and such exogenous regressors as intermittency.

Examples of work analyzing female wages that use FE approaches to estimate earnings function models include Mincer and Polachek (1978), Corcoran et al. (1983), Sundt (1987), and Licht and Steiner (1991).

Endogeneity biases arise when intermittency and/or other labor market variables are viewed as labor supply decisions, so that labor supply is really best depicted as a function of the dependent variable, wages. Thus if low waged workers find it inexpensive to drop out of the labor force then low wages might not be caused by intermittency, but instead intermittency might be caused by low wages. In this case it is possible that low wages lead to high intermittency levels rather than the reverse, thus leading to biased inferences.

When conducting panel analysis, it is possible to control the endogeneity and heterogeneity caused by the individual effect. The within-group fixed-effect and Hausman-Taylor estimation methods are suggested.

2.3.1 Fixed effect model

The within-group fixed-effect estimation method excludes the latent unobservable variable (α_i) from the earnings function by transforming each observation with a first-difference or mean-deviation operator (Kim and Solomon 1994). This implies that the fixed-effect estimator is obtained by subtracting the mean variable value for each individual and each time period observation, as indicated by the following equation:

$$\ln(W_{it} - W_i) = (X'_{it} - X_t)\beta + \upsilon_{it} - \upsilon_i. \qquad (13)$$

As a result, the fixed-effect estimation method considers the individual effect with regard to the endogeneity of variables. However, the time-invariant variables (gender and other socioeconomic background variables that do not vary over time) may also be correlated with α_i, which is correlated with the time-variant variables X_{it}. In this case, Z_i and α_i are omitted from the equation by using the fixed-effect estimation method.

2.3.2 Random effect model

Random effect model assume u_{it} that $u_{it} \sim N(0, \sigma_u^2)$, $e_{it} \sim N(0, \sigma_e^2)$.

$$y_{iy} = (\alpha + u_{it}) + \beta X_{it} + e_{it} \tag{14}$$

Fixed model treats $(\alpha + u_{it})$ is a constant representing individual panel characteristic. Random effect model treats $(\alpha + u_{it})$ is a random variable. The expectation value of random variable $(\alpha + u_{it})$ is represented

$$E(\alpha + u_{it}) = \alpha + E(u_{it}) = \alpha \,. \tag{15}$$

One can compute variance-covariance matrix

$$\begin{aligned} \Omega &= E(uu') = Z_\mu E(\mu\mu')Z'_\mu + E(vv') \\ &= \sigma_\mu^2 (I_N \otimes J_T) + \sigma_v^2 (I_N \otimes I_T) \end{aligned} \tag{16}$$

This implies a homoscedastic variable $\text{var}(u_{it}) = \sigma_\mu^2 + \sigma_v^2$ for all i and t, and an equicorrelated block-diagnoal covariance matrix which exhibits serial correlation over time only between the disturbances of the same individual. In fact

$$\begin{aligned} \text{cov}(u_{it}, u_{js}) &= \sigma_\mu^2 + \sigma_v^2 \quad \mathit{for} \quad i = j, t = s \\ &= \sigma_\mu^2 \qquad\quad \mathit{for} \quad i = j, t \neq s \end{aligned} \tag{17}$$

and zero otherwise. In order to obtain the GLS estimator of the regression coefficients, we need Ω^{-1}. One replace J_T by TJ_T and I_T by ($E_T + \overline{J_T}$) where E_T is by definition ($I_T - \overline{J_T}$). In this case

$$\Omega = T\sigma_\mu^2 (I_N \otimes \overline{J_T}) + \sigma_v^2 (I_N \otimes E_T) + \sigma_v^2 (I_N \otimes \overline{J_T}) \tag{18}$$

2.3.3 Hausman and Taylor estimation

Hausman and Taylor (1981) suggest an alternative procedure. This procedure permits simultaneous control of the correlation between the regressors and unobserved individual effects; to identify the estimates of the time-invariant variables and to avoid the insecurity associated with the choice of suitable instruments, since the individual means over time of all the included regressors can serve as valid instruments (García-Mainar and Montuenga-Gómez 2005).

The following is the statistical outline of the Hausman-Taylor estimation[2]: The matrices may be divided into two sets of variables: $X = [X_1, X_2]$ and $Z = [Z_1, Z_2]$. X_1 and Z_1 are assumed to be exogenous and not correlated with α_i and υ_{it}, while X_2 and Z_2 are assumed to be endogenous due to their correlation with α_i but not with υ_{it}. Consequently, the education variable is included in Z_2, since it is time-invariant and endogenous. Work experience is a time-varying, endogenous variable that is included in X_2.

The procedure suggested an instrumental variable estimator that premultiplies the equation(13) by $\Omega^{-\frac{1}{2}}$, where Ω is the variance-covariance term of the error component $\alpha_i + \upsilon_{it}$, and performs 2SLS using the $[\Omega, X_1, Z_1]$ as instruments. Q is the within-transformation matrix with $X^*_{it} = X_{it} - \overline{X}_i$, and $\overline{X}_i$ is the individual mean This is equivalent to running 2SLS with as the set of instruments. The

2. This chapter refer to Baltagi(2003) pp.118-121.

Hausman-Taylor estimation method is more efficient than the fixed-effects when the model is identified-there are at least as many time-varying exogenous regressors.

Education is the only time-invariant endogenous variable, although there are several time-varying exogenous regressors. As a result, the Hausman-Taylor estimation method is more efficient than the fixed-effect estimation method for measuring human capital accumulation. As Baltagi et al. (2003) argue, this is equivalent to running 2SLS with $[X^*, \overline{X_1}, Z_1]$ as the set of instruments.

If the model is identified, in the sense that there are at least as many time-varying exogenous regressors X_1 as there are individual time-invariant endogenous regressors Z_2, i.e. $K_1 \geq Z_2$, then this Hausman–Taylor estimator is more efficient than fixed effects. In the model, the only time invariant endogenous variable is education, whereas there are several time-varying exogenous regressors. [for more details, see Hausman and Taylor (1981); García-Mainar and Montuenga-Gómez (2005); Wooldridge (2002); Hansen and Wahlberg (1997); Kalwij (2000); Baltagi, Bresson and Pirotte (2003)]. Stata 11 program is used in estimation.

Chapter 3 The effect of R&D investment on human capital accumulation

3.1 Introduction

In the business world, research and development (R&D) and human capital have been regarded as engines of endogenous growth that rely on economic development factors inside of an economy. R&D enables development of new technologies and products as well as innovation of existing technologies. In addition, a positive spill over generated by investment into R&D is regarded as a vital production element for national development (Griliches, 1992; Coe and Helpman, 1995; Cameron, 1998; Griffith et al., 2004; Kim, 2012).

Human capital refers to individuals' repository of knowledge and technological skill, and human capital accumulation is the means by which skills are improved for carrying out any type of productivity activity (Blackburn et al., 2000). High human capital not only improves production capacity but also enables the assimilation of new technology (Schultz, 1961; Becker, 1964; Lucas, 1990; Mankiw et al., 1992; Barro and Lee, 1993; Barro and Sala-i-Martin, 1995).

The roles of human capital accumulation or R&D in economy growth have been studied separately from each other, but few studies have tried to integrate the two factors within a unified framework (Eicher, 1996; Redding, 1996; Engelbrecht, 1997). Those studies have emphasized the potential interaction between investments in education and investments in R&D focusing on the theoretical aspect of growth models (Sjögren, 1998; Mathur, 1999; Scicchitano, 2010).

The reason theoretical approaches have been used in most of these studies is that it is difficult to quantify human capital accumulation. In previous research, the effect of human capital on economic growth and R&D was analyzed with such proxy variables as schooling, companies' investment in training, and so forth. Schooling, however, is a form of human capital in the initial stage of a person’s life that does not include accumulation of human capital during the occupational career. Thus, the effect of R&D on human capital accumulation is limited to that after entering employment, concerning which few empirical analyses exist.

This chapter analyzes the effect of R&D on human capital accumulation in korea manufacturing sector. The industries are categorized as low, medium-low, or high and medium-high technology based on R&D intensity. Quantative method are based on previous studies.

3.2 Data

3.2.1 Classification of manufacturing groups

Manufacturing sectors are classified based on R&D intensity. Technological effort, an important factor of productivity growth and international competitiveness (OECD), is not spread evenly across the economy. Thus, decisions concerning technological criteria are very important. The OECDs 'classification of industries on the basis of R&D intensity' has been used in order to group the manufacturing industries by technology level into low, medium-low, high, and medium-high. R&D intensity is defined as R&D expenditure divided by value added. Industry classification in terms of R&D intensity enables comparing the extent and nature of technology innovation in various manufacturing sectors (Cox, Frenz and Prevezer, 2002).

The differences of innovation in industry circles in terms of R&D intensity may affect the productivity of capital and labour and of human capital stock. Regardless of some disadvantages, R&D intensity is adopted as the most useful factor for studying technological development and innovation in industries. Certain studies (Apergis, Economidou and Filippidis, 2008; Cox, Frenz and Prevezer, 2002; Heidenreich, 2009;) classify industries based on R&D intensity for purposes of a comparative study on technological developments among various industries. OECD classifies industries in the member countries into four different levels (high, medium-high, medium-low, and low) in consideration of the average R&D intensity from 1991 to 1999(OECD 2005a). Likewise, classifies domestic industries into four different groups according to R&D intensity from 2002 to 2008 (Table 3-1).

Table 3-1 Classification of manufacturing industry by R&D intensity in Korea (2002-2008)

	Industry	R&D intensity
High	C353 Aircraft and spacecraft C32 Radio, television and communication equipment C30 Office, accounting and computing machinery C34 Motor vehicles, trailers and semi-trailers	(36.22) (24.45) (19.09) (14.48)
Medium high	C33 Medical, precision and optical instruments C24X Chemicals excluding pharmaceuticals C2423 Pharmaceuticals C352A9 Railroad equipment and transport equipment n.e.c.	(9.98) (8.16) (8.02) (7.30)
Medium low	C29 Machinery and equipment, n.e.c. C31 Electrical machinery and apparatus, n.e.c. C25 Rubber and plastics products C351 Building and repairing of ships and boats C15T16 Food products, beverages and tobacco C23 Coke, refined petroleum products and nuclear fuel	(5.44) (4.35) (2.84) (2.56) (2.47) (2.13)
Low	C26 Other non-metallic mineral products C36T37 Manufacturing n.e.c. and recycling C27T28 Basic metals and fabricated metal products C17T19 Textiles, textile products, leather and footwear C21T22 Pulp, paper, paper products, printing and publishing C20 Wood and products of wood and cork	(1.69) (1.61) (1.40) (1.01) (0.35) (0.34)

Table 3-2 R&D intensity for aggregate of 12 OECD countries, 1991-1999

	Industry	R&D intensity
High	C353 Aircraft and spacecraft	(13.3)
	C2423 Pharmaceuticals	(10.5)
	C30 Office, accounting and computing machinery	(9.2)
	C32 Radio, television and communication equipment	(8.0)
	C33 Medical, precision and optical instruments	(7.7)
Medium high	C31 Electrical machinery and apparatus, n.e.c.	(3.9)
	C34 Motor vehicles, trailers and semi-trailers	(3.5)
	C24X Chemicals excluding pharmaceuticals	(3.1)
	C352A9 Railroad equipment and transport equipment n.e.c.	(2.9)
	C29 Machinery and equipment, n.e.c.	(2.1)
Medium low	C351 Building and repairing of ships and boats	(1.0)
	C23 Coke, refined petroleum products and nuclear fuel	(0.9)
	C26 Other non-metallic mineral products	(0.9)
	C27T28 Basic metals and fabricated metal products	(0.6)
Low	C36T37 Manufacturing n.e.c. and recycling	(0.5)
	C17T19 Textiles, textile products, leather and footwear	(0.3)
	C21T22 Pulp, paper, paper products, printing and publishing	(0.3)
	C20 Wood and products of wood and cork	(0.3)
	C15T16 Food products, beverages and tobacco	(0.3)

In general, the R&D intensity categories in Korea are higher than those of OECD. In Korea, the range for high intensity is 14.48–36.22, medium-high is 7.30–9.98, medium-low is 2.13–5.44, and low is 0.34–1.69. The OECD classification puts the high intensity range at 7.7–13.3, medium-high at 2.1–3.9, medium low at 0.6–1.0, and low at 0.3–0.5.

If the existing OECD standard is adopted, the classification based on R&D intensity cannot be accurate because of the differences in the industrial classifications of Korea and OECD. The average standard derivate of the intensity of industries using the Korean standard is 8.77. When reclassified on the basis of the OECD standard, however, the standard deviation of the group decreases to 7.32. This disparity may make it difficult to observe the differences in human capital accumulation in relation to R&D investment, which is the major goal of the thesis. Thus, analysis for each group is based on the Korean classification standard of intensity.

3.2.2 Data sources

The data used to analyze patterns of human capital among R&D intensity groups in the Korean manufacturing industry was derived from the Korean Labour & Income Panel Study (KLIPS[3]). This annual survey was conducted to record the characteristics of households—as well as the economic activities, income, education, job training, and social activities of individuals—from 1998 to 2008. It is the only data that can track individual job characteristics over a long period. The dataset has the strength of retaining approximately 76% of its respondents.

The analysis are based on the labourers who are working in the manufacturing sector and who are wage earners. This thesis examined 2,516 out of 11,756 individual samples for this paper. Table 3-3 shows the breakdown of the 2,516 manufacturing workers' responses by industry class as a derivate from the R&D intensity of high and medium-high, medium-low, and low technology industries. Out of the

[3] Data is downloaded from online (http://www.kli.re.kr)

2,516 individual samples, 818 are categorized as high and medium-high, 707 are categorized as medium low, and 991 are categorized as low.

Table 3-3 provides the means, as well as the respective overall and between-group standard deviations, for the variables. There are differences in the average wage per month in the three manufacturing groups. Average wage is the highest in medium-technology industry, lower in high- and medium-high technology industries, and lowest in low-technology industry. The difference in the average wage per month between high/medium-high technology industry and medium-low was only $13, whereas the difference between medium-low and low-technology industry was $414. It is expected that such a difference in the average wage per month among industries may also result in a difference pattern in terms of human capital accumulation.

Table 3-3 Basic statistics

Variables	High and medium-high technology industry	Medium-low technology industry	Low technology industry
Wage	1,794 (1,223/903)	1,807 (1,715/1,410)	1,393 (1,128/752)
Education	12.99 (2.65/2.68)	12.10 (2.99/3.00)	11.17 (3.21/3.20)
Career	16.13 (10.95/11.26)	19.60 (12.00/12.65)	22.34 (12.05/12.85)
Gender	0.67 (0.47/0.48)	0.74 (0.44/0.46)	0.60 (0.49/0.49)
Marriage	0.67 (0.47/0.48)	0.71 (0.46/0.47)	0.72 (0.45/0.46)
Union	0.21 (0.40/0.31)	0.17 (0.38/0.29)	0.08 (0.27/0.21)
1≤Work size≤20	0.11 (0.31/0.32)	0.26 (0.44/0.41)	0.41 (0.49/0.45)
21≤Work size≤100	0.21 (0.41/0.35)	0.24 (0.43/0.38)	0.29 (0.45/0.38)
201≤Work size≤500	0.31 (0.46/0.41)	0.19 (0.40/0.34)	0.18 (0.38/0.33)
500≤Work size	0.35 (0.48/0.42)	0.29 (0.45/0.40)	0.11 (0.32/0.27)
Number of observation	2679	2268	3265
Number of groups	818	707	991

Regarding academic background, a higher level of R&D investment reflects a higher level of schooling. The average level of schooling in high and medium-high technology industry was 12.99 years, which was the highest, with medium-low technology industry at 12.10 years, and low technology industry at 11.17 years. In Korea, if a person gets a high-school diploma, that means 12 years of schooling, a university degree means 16 years.

The difference between high and medium-high technology industry and medium-low technology industry in terms of level of schooling was 0.89, which is rather notable, considering that the average wages of the two categories were almost the same.

The difference between medium-low technology industry and low technology industry regarding level of schooling was 0.93. Higher R&D intensity industries require abundant human resources not only to implement R&D within the industry but also to apply the resulting technology into the actual processes after R&D has been carried out. Thus, it is thought that the level of schooling in industries may be different according to the R&D intensity.

Average time in the career is higher when the R&D investment is low. The level of vocational experience of low-technology industry, whose R&D intensity was the lowest, was 22.34 years, with medium-low technology industry at 19.60, and high and medium-high technology industry at 16.13. Low-technology industry, again with the lowest level of R&D investment, had the highest added value among all industries in Korea from 1960 to 1997. Although gradually decreasing now, its percentage of the total production of manufacturing sectors in 1960 was 48.1% and in 1997, 35.6%. It seems that this is because a lot of experienced employees had been working since the early years of industrialization.

On the other hand, the high and medium-high, and medium-low technology industry sectors have grown rapidly since 1990, accounting for the major part of the manufacturing sectors by 1998 when its percentage of the total production in the manufacturing sector was 36.0%, gradually increasing to 40.9% in 2010 (Figure 3-1). As a result, many new human resources were hired, reducing the general level of vocational experience.

A comparison of the key variables among the three manufacturing industry groups reveals that there are differences in more than 6 years of work experience, and in 1-2 years of education years. These differences may lead to differences in the human capital accumulation in the manufacturing industry by R&D intensity.

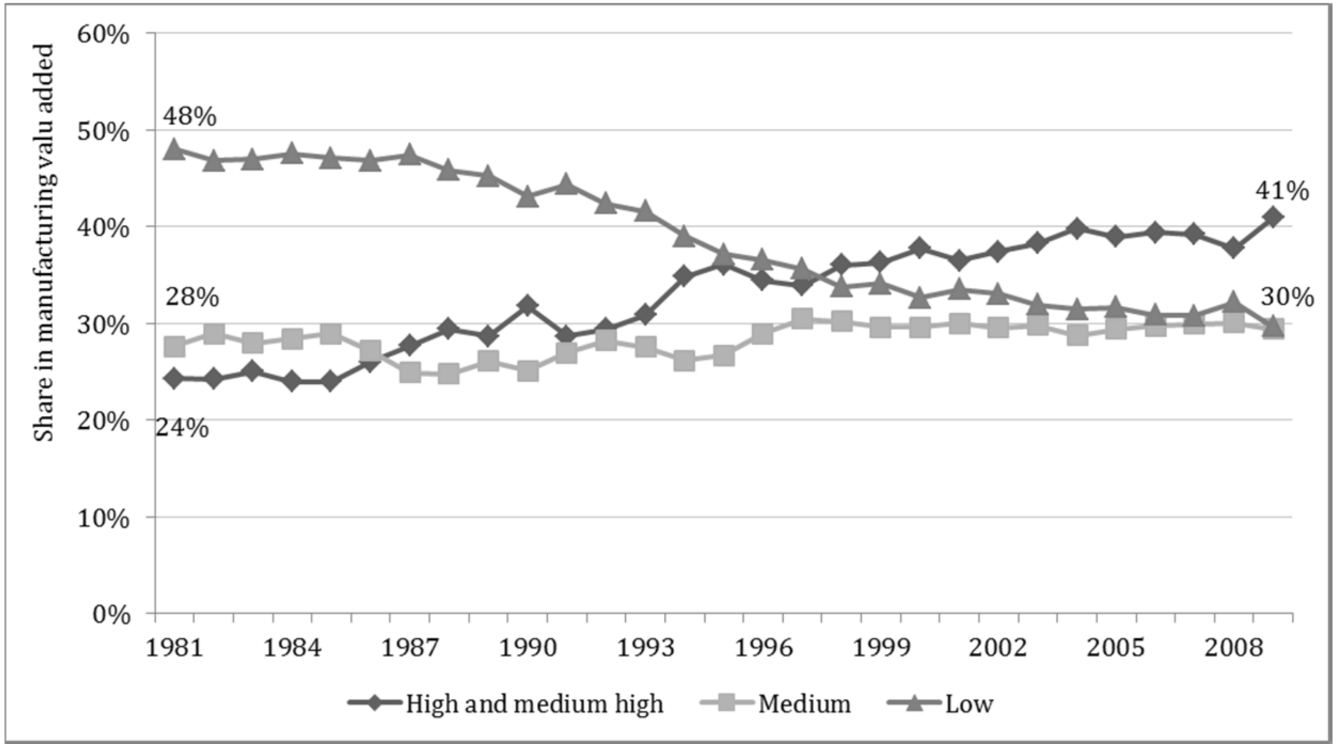


Figure 3-1 Share in manufacturing value added

Data: OECD (2005, 2010 STAN Database for Structural Analysis)

3.3 Empirical analysis result

3.3.1 Estimation of earning function

Tables 3-4 through 3-6 present the results of analysis. Table 3-4 shows the results for equation (9) using random and hausman-taylor estimation methods. Table 3-5 presents the key variables of human capital accumulation from equation (8), and Table 3-6 presents the analysis of the human capital accumulation in the manufacturing industry.

Table 3-4 presents the results of the estimations that were used for the study samples. The first column for each manufacturing group indicates the random effect estimates, and the second column indicates the Hausman-Taylor estimates. The exogenous time-variant variables—X_1—are work experience squared and dummies for company size, union, and marriage. The endogenous time-variant variables—X_2—and education, work experience, and interaction between education and work experience. The exogenous time-invariant variable, Z_1, is gender.

Table 3-4 Estimation result of earning function by industry

	High and medium-high technology industry		Medium-low technology industry		Low technology industry	
	Random Effect	H-T	Random Effect	H-T	Random Effect	H-T
Education	0.1393*** (0.0112)	0.1456*** (0.0183)	0.1547*** (0.0127)	0.1185*** (0.0179)	0.1442*** (0.0112)	0.1674*** (0.0200)
Career	0.0562*** (0.0093)	0.0451*** (0.0142)	0.0703*** (0.0094)	0.0528*** (0.0134)	0.0753*** (0.0078)	0.0641*** (0.0120)
Education * Career	0.0004 (0.0005)	0.0050*** (0.0008)	-0.0002 (0.0005)	0.0041*** (0.0008)	-0.0015*** (0.0004)	0.0020*** (0.0007)
Career^2	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0007*** (0.0001)	-0.0005*** (0.0001)	-0.0008*** (0.0001)	-0.0007*** (0.0001)
Gender	0.4402*** (0.0360)	0.3955*** (0.0985)	0.4838*** (0.0411)	0.4573*** (0.1115)	0.4970*** (0.0294)	0.3442*** (0.0647)
Marriage	-0.0386 (0.0272)	0.0007 (0.0252)	-0.1234*** (0.0323)	-0.0575* (0.0333)	-0.0679*** (0.0249)	-0.0892*** (0.0272)
1≤Work size≤20	0.1496** (0.0616)	0.1126** (0.0511)	0.1236 (0.0936)	0.1314 (0.0988)	0.2747*** (0.0514)	0.1807*** (0.0493)

21≤Work size≤100	0.1797*** (0.0599)	0.0897* (0.0495)	0.1978** (0.0939)	0.1565 (0.0993)	0.3309*** (0.0552)	0.2125*** (0.0505)
201≤Work size≤500	0.2618*** (0.0601)	0.1335*** (0.0496)	0.2002** (0.0951)	0.1558 (0.1003)	0.3987*** (0.0568)	0.1844*** (0.0531)
500≤Work size	0.3690*** (0.0598)	0.1682*** (0.0494)	0.2981*** (0.0954)	0.1821* (0.1009)	0.3987*** (0.0568)	0.2386*** (0.0548)
Union	0.0727*** (0.0208)	0.0493*** (0.0170)	0.0619** (0.0242)	0.0351* (0.0202)	0.0841*** (0.0259)	0.0815*** (0.0235)
Constant	1.8761*** (0.1713)	1.2424*** (0.2665)	1.6177*** (0.2090)	1.4717*** (0.2825)	0.1965*** (0.1725)	1.1151*** (0.2796)
Number of obs/groups	2679/818		2268/707		3265/991	
HT	513.21 [0.0000]		131.87 [0.0000]		119.71 [0.0000]	
Wald chi^2(11)		2290.29 [0.0000]		1647.15 [0.0000]		1033.20 [0.0000]
rho		0.9775		0.9794		0.9496

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. ( ) respective standard deviations, [ ] represent p-value
c. rho represent fraction of variance due to u_i

As stated in the Chapter 2, one of the outstanding differences between the pooled OLS estimation method and the hausman method is that personal characteristics are assumed to make random effects. The value of a Wald-test, which indicates the general statistical significance of the H-T model, is bigger than 0 in the models, which shows that the models are all statistically significant. In addition, individual variables are statistically significant except for a few dummy variables, including the company dummy.

In examination of the variable estimation based on H-T methodology, it turned out that the effects of schooling and career on wages are different in each industry. It also turned out that the effect of schooling was bigger than that of vocational experience or career. This is in correspondence with the results of previous studies (Jun 2002; Park and Seok, 2009), who analyzed the earnings function in Korea. The analysis shows that in 'low tech' industries, one year's increase in schooling led to a 16% increase in wages, a 14.5% increase in high and medium-high tech industries, and an 11.8% increase in medium-low tech industries. The effect of one year increase of vocational experience on wages was highest at 6.4% in high tech, at 5.2% in medium-low, and at 4.5% in high and medium-high tech industry.

The other coefficients reveal acceptable results. Work experience squared has a negative coefficient that reflects a concave relationship between earning function and work experience. Further, males were shown to have higher wages than females. In addition, it turned out that the wages of unionized workers are higher than all of the others in the three levels of industries. Only the marriage and firm size dummies are significant factors that produce differences in industries.

3.3.2 Human capital accumulation

From the estimation result, the earning rate of human capital investment and the initial human capital investment rate are calculated in each industry (Table 3-5). The earning rate of human capital investment was calculated by using the estimation variable and equation (9), and the initial human capital investment rate by using equation (8).

Table 3-5 The rate of return for post-schooling and initial investment rate of human capital

	High technology industry	Medium technology industry	Low technology industry
r_p	0.667	0.042	0.065
S_1	0.435	0.679	0.633

The rate of return for post-schooling (r_p) in the high and medium-high technology industries was 6.67%, which is the highest. This is 1.6 times higher than the earning rate in the medium-low technology industry (4.2%), which was the lowest. The earning rate for the low technology industry was 6.5%, which is about 1.54 times higher than that of the medium-low technology industry. The fact that the earning rate of human capital investment is high indicates that the accumulation of human capital is high when a measure of human capital is invested in the high and medium-high technology industries that R&D investment is most active. R&D investment is likely to result in technology innovation, and thus more production with the same amount of input. This result also indicates that higher profits are expected with smaller human capital investment. It is thought, therefore, that such effects of technology innovation may lead to more profits with the same measure of human capital.

Low-technology industry also recorded high earning rates even though the level of R&D investment was relatively low. In this type of industry, the delivery of knowledge inherent in the industry over time, rather than innovation for drastic advancement, is a vital factor of production. Thus, it may be that an efficient mechanism has been already formed to deliver knowledge in the industry, as in the example of an apprenticeship system (Polachek and Siebert, 1993). This type of mechanism contributed to a high human capital accumulation in low-technology industry.

Medium-low technology industry requires a measure of technology innovation and knowledge, some examples being shipbuilding, machinery, and equipment. This type of industry needs not only understanding of the industrial processes but also accumulation of knowledge. Although the earning rate of human capital investment is low, the amount of human capital accumulation, as well as the earning rate, counts in this regard. Thus, there should be a comprehensive interpretation with other factors considered as well. This matter will be discussed in later in this chapter.

The initial investment rate of human capital (S_1) is 0.679 and 0.633 for the medium-low and low-technology industries, respectively, showing little difference. The initial investment rate of human capital in high and medium-high technology industry is 0.350, which is lower than in the other two categories. This result indicates that a large portion of personal human capital in the medium-low and low technology industries is in human capital accumulation for the future and that workers are likely to learn as they gain experience in the field. High and medium-high technology industry is of higher R&D intensity than the medium-low and low technology industries. In the former types of industry, it is thought that since personal proficiency or the learning-by-doing effect in the industry is relatively low, the investment rate of human capital is low accordingly. This result shows that R&D investment and human capital investment are in a complementary relation.

Next, I analyzed the profits depending on the amount of human capital accumulation, wages, amount of investment, and earnings from investment based on such factors as earning rate of human capital, initial human capital investment rate, average wage, and vocational experiences in each industry (Table 3-6). The total amount of human capital accumulation can be expressed as wages and the amount of investment plus depreciation, or as the amount of human capital accumulation plus earnings from human capital investment in the former period.

Table 3-6 Result of human capital accumulation by estimation methodology

Earning function estimation method	statics	High and medium-high technology industry	Medium-low technology industry	Low technology industry
Hausman Taylor	E_t	779,184	804,490	539,122
	C_{nt}	84,382 (0.108)	177,974 (0.221)	104,404 (0.194)
	Y_t	616,884 (0.792)	546,067 (0.679)	380,806 (0.706)
	Depreciation	77,918 (0.100)	80,449 (0.100)	53,912 (0.100)
	Accumulate profit	5,645	7,448	6,734
Random Effect	E_t	742,541	750,755	522,115
	C_{nt}	616,790 (0.831)	539,184 (0.718)	400,130 (0.766)
	Y_t	51,497 (0.069)	136,495 (0.182)	69,773 (0.134)
	Depreciation	74,254 (0.100)	75,076 (0.100)	52,211 (0.100)
	Accumulate profit	4,274	10,826	5,754

The human capital accumulation depending on the level of vocational experience in each industry is presented in Figure 3-2. While the amount of human capital accumulation is similar between medium-low technology industry, and high and medium-high technology industry, the amount of human capital accumulation in low technology industry is lower than that of the other two. The total amount of human capital accumulation, when a person works for 30 years in the industry, is $804,490 in the case of medium-low technology industry, which is the highest.

Medium-low technology industry accumulates a human capital of 1.5 times more than that of low technology industry ($539,122), which is the lowest. The total amount of human capital accumulation in the high and medium-high technology industries is $779,184, which is 1.4 times more than that of the low-technology industry. The total amount of human capital accumulation is the same as the sum of the amount of human capital investment and wages paid for a person who has worked for 30 years.

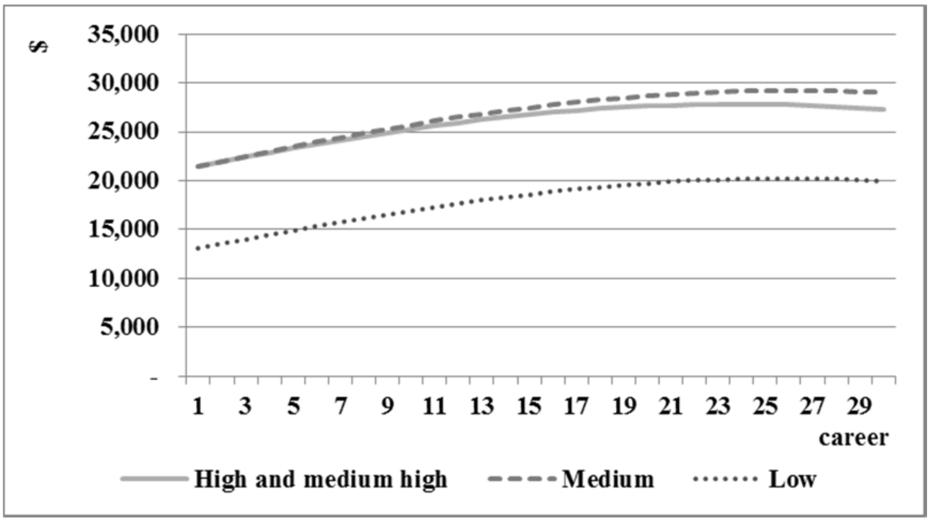


Figure 3-2 Total human capital accumulation

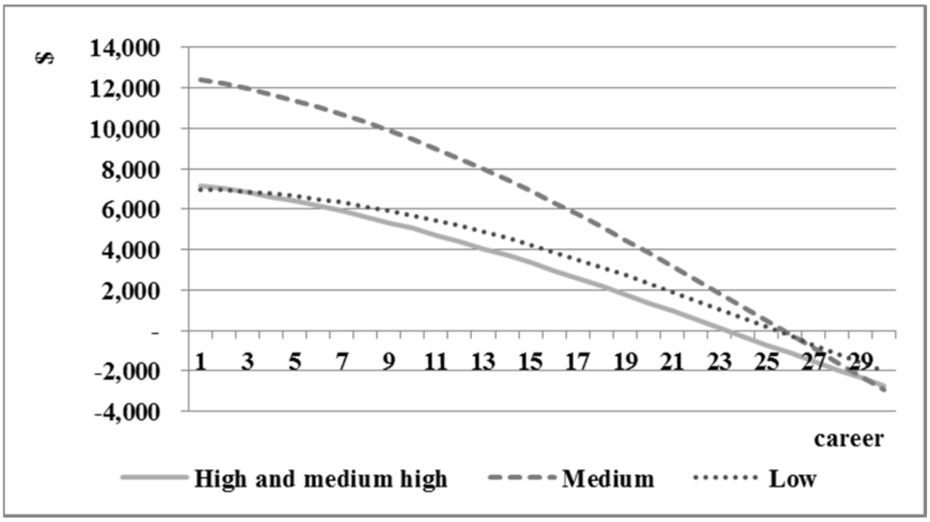


Figure 3-3 Amount of investment in human capital

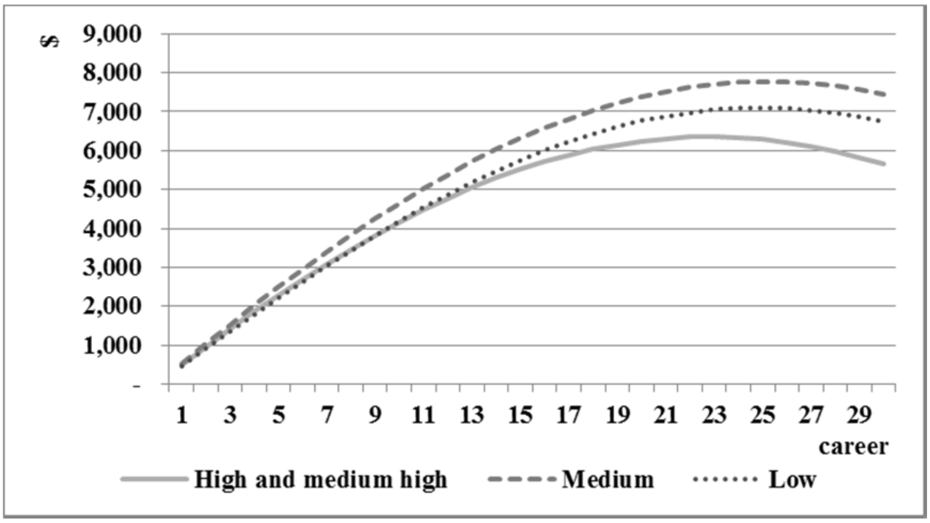


Figure 3-4 Accumulated earnings through human capital investment for 30 years

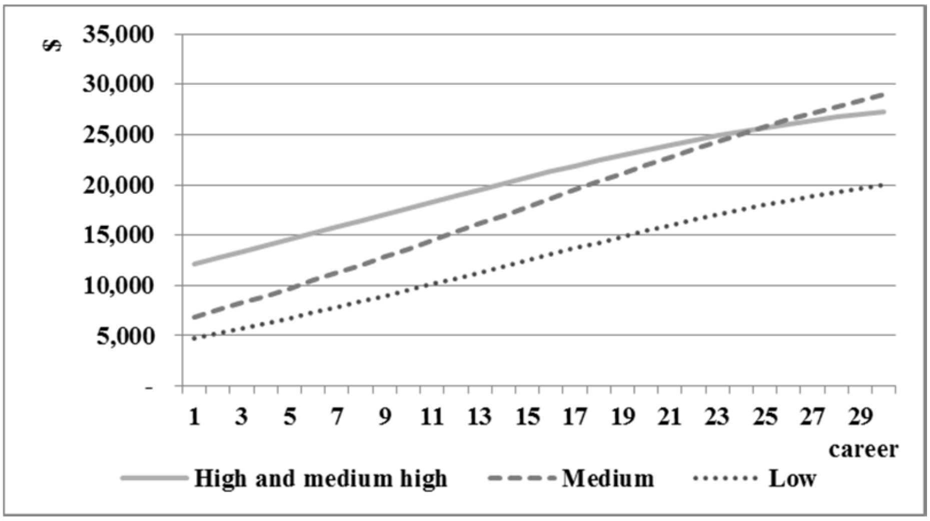


Figure 3-5 Amount of human capital that a person receives in the form of wages

Figure 3-2 indicates that the amount of human capital of a worker who has just come into a field is different, depending on the industry. The amount of human capital of a worker who has just come into the field in high and medium-high, and medium-low technology industries is higher than that in low technology industry, with the initial amount for is the first three being about \$21,400, about 1.6 times more than the initial human capital in low-technology industry (\$13,747). In addition, the initial amount of human capital in the first three, where the R&D investment is more than in low-technology industry, is relatively high. The amount of human capital reflects the characteristics of the industry in that some part of it is given in the form of wages and another in the form of investment.

The amount of investment in human capital is presented in Figure 3-3. The total amount invested in human capital in medium-low technology industry is \$177,974, which is 2.1 times more than in the high and medium-high technology industries (\$84,382), whose amount of investment is the lowest. The amount of investment in low-technology industry is \$104,404, in which the investment of human capital is 1.2 times more than in the high and medium-high technology industries. In other words, the latter two industries invest 22.1% of the human capital that the medium-low and low technology industries would invest for the accumulation of human capital in the future. High and medium-high technology industry invests only 10.8% for the accumulation of human capital in the future. Thus, the higher level of human capital investment in the medium-low technology industry clearly indicates the importance of accumulating knowledge in terms of ‘learning by doing’.

In contrast, high and medium-high technology industry cares most for technology innovation through R&D rather than human capital acquired while participating in the industry. While the rate of human capital investment in low-technology industry is similar to that of medium-low technology industry, the difference in the total amount of human capital is notable, which leads to a smaller investment in total than that of medium-low technology industry.

The net investment is the difference between investment and depreciation. New investment is negative when one’s human capital stock depreciates more quickly than it appreciates (Polachek and Siebert, 1993). Potential earnings peak when net investment is zero. Beyond this point, capital stock declines as depreciation exceeds investment. Thus, earnings decline from this point on.

The accumulated earnings through human capital investment for 30 years are presented in Figure 3-4. The total earning at $7,448 is highest in the medium-low technology industry and lowest, at $5645, in the high and medium-high technology industries. It turned out that the earning from human capital in the medium-low technology industry was about 1.32 times higher than that of the high and medium-high technology industries.

The difference in earnings is relatively small, considering the fact that the total investment stated earlier was 2.1 times more than in the high and medium-high technology industries. This is because the earning rate of human capital investment in the medium-low technology industry is lower than that in the high and medium-high technology industries. In the low technology industry, the amount of investment is smaller than that of the medium-low technology industry while the earning rate is higher, which indicates that the earnings from the human capital investment are quite sufficient ($6,734).

Figure 3-5 shows the amount of human capital that a person receives in the form of wages among the total amount of accumulated human capital in each industry. The total amount of wages received for 30 years is $616,884 in high and medium-high technology industries,

$546,067 in the medium-low technology industry, and $380,806 in the low technology industry. The total amount of wages earned in the high and medium-high technology industries is 1.6 times more than that in the low technology industry, while the total amount of wages earned by workers in the medium-low technology industry is 1.4 times more than that in the low technology industry.

The percentage total human capital given to wages is 79% in the high and medium-high technology industries, 70% in the low-technology industry, and 68% in the medium-low technology industry. In the early stage of the graph showing career to wage, the wage in the high and medium-high technology industries is higher than in the other sectors for the first 23 years, but the wage in the medium-low technology industry becomes higher than the others after a career of 23 years.

This situation occurs because the medium-low technology industry increases the investment for human capital enhancement in relation to the total human capital investment, as stated earlier. In other words, the medium-low technology industry invests a large portion in total human capital in the early stages, and as a result, the wage increases in proportion to the career, thus becoming higher than that of the high and medium-high technology industries.

It was found that all coefficients drawn through the random method to which the estimation method was adapted are only slightly different among industries compared to those of the H-T. In the analysis results based on the random estimation, the average difference of the estimator between the high and medium-high industries and the medium-low technology industry was 0.37%, which is smaller than the difference measured in the Hausman-Taylor result (2.5%).

As to the difference in the total amount of human capital accumulation also, the difference between the medium-low and the low-technology industries with the H-T was $265,368 whereas the difference was $228,640 with the random estimation method. The estimation result above shows that the earnings function in the manufacturing sectors industry is affected a great deal by personal effects. In the case of the random effect model, failure to control such personal effects results in decreasing the difference among industries with regard to the amount of human capital accumulation.

3.4 Conclusion

This chapter analyzes the effect of investment in R&D in the manufacturing sectors on the accumulation of human capital. The manufacturing sectors were classified into three different groups depending on the R&D intensity: high and medium high, medium low, and low. Based on the estimated earnings function for each industry, human capital accumulation variables, such as the earning rate of human capital and total amount of human capital accumulation, were compared among industries.

The analysis results are summarized in the following three aspects: First, the earning rates for human capital investment in each industry were found to be different, depending on the amount of R&D investment. The earning rate of human capital in the high and medium-high technology industries, whose R&D intensity was the highest, was 6.7%, the highest among the three industries. This clearly reflects enhanced production efficiency arising from technology innovation. However, the earning rate of human capital in low-technology industry, whose amount of R&D investment was the lowest, was 6.5%, which is also relatively high. This result may mean that while low-technology industry by nature requires less R&D investment, its knowledge delivery system is highly efficient as is.

Second, the analysis shows that learning by doing and R&D are complementary to each other. Out of the total amount of personal human capital, the percentage of investment for the increase in future human capital is 30.1% in the medium-low technology industry and 19.4% in the low-technology industry, both of which are a lot higher than that of the high and medium-high technology industries (10.8%). As such a difference in investment rates is reflected in the wages, the wage of the medium-low technology industry is lower than that of the high and medium-high technology industries in the early stage, but it becomes higher as the career period increases. The total amount of investment into human capital for 30 years was smallest in the high and medium-high technology industry ($84,382). In short, the results indicate that learning by doing and R&D are in a complementary relation.

Third, it also turned out that the amount of initial human capital for the advancement into each industry was also different among industries. High and medium-high technology industry and inter-industry, whose

R&D investment was high, required a higher amount of initial human capital of those with relatively little experience than did the low-technology industry. Industries that require a higher level of investment into R&D are all highly advanced businesses, in which expertise is necessary for production activity as well as R&D.

Chapter 4 Human capital accumulation structure through NRE HRD program

4.1 Introduction

For the steady growth of renewable energy industry, securing related labor is an essential factor. Plan for supplying labor force must be prepared promptly in order to accomplish renewable energy supply objectives and industrial growth objectives in the future. Insufficient human resources are treated as one of the barrier for renewable energy industry growth in Korea(Lee et al. 2009)[4].

In addition, many other countries set up the human resource training plan and tried to supply appropriate human resources (Clean Energy Council, 2009; Alan Hardcastle & Stacey Waterman-Hoey, 2009). After government emphasizes the growth of renewable energy industry, some

[4] This chapter mainly refers to Lee and Heo (2013).

studies conducted an analysis on human resource development in renewable energy industry (Lee et al. 2009, Heo et al. 2008). However, most of studies are focusing on necessity of quantification.

In the human capital accumulation model, decisions that relate to an individual's education are treated as investments that occur over the lifespan (Killingsworth, 1982; Mincer, 1974; Rosen, 1976; Shaw, 1989). Therefore, human capital that is accumulated through educational programs like HRD initiatives generates a number of tangible social effects. That is to say, production processes can be improved and social problems can be creatively approached by educated workers, and as a result, societal productivity as a whole can be improved (Barro and Lee, 1993; Barro and Sala-i-Martin, 1995; Becker, 1964; Lucas, 1993; Mankiw et al., 1992; Schultz, 1961, Chuang and Lin, 1999).

Blackburn, Hung and Pozzolo (2000) demonstrated that the accumulation of human capital expands the possibilities for innovation activity and renders manufacturing more efficient. They further showed that in an endogenous growth model, the speed of economic growth can be increased by the accumulation of human capital (Lucas, 1988; Barro and Lee, 1993; Sjögren, 1998).

From the perspective of the individual, however, this kind of social benefit can be underestimated. Investment in human capital can be made to a degree that is less than the optimal social level (Figure 4-1). Accordingly, governmental policy related to HRD should ensure that educational programs could be implemented in a way to maximize benefit not only for the individual and industry, but also for society as a whole (Blaug, 1976; Osman-Gani, 2004; Stevens, 1999; Main and Shelly; 1990). Although there have been some studies that have quantitatively evaluated the need for effective governmental-HRD policies (Gaughan and Robin, 2004; Kwon, 2011; Hatch and Dyer, 2004; Killingsworth, 1982) research that evaluates HRD initiatives on the basis of theoretical principles or the need for employees with particular education levels is scarce (Booth and Bryan, 2005).

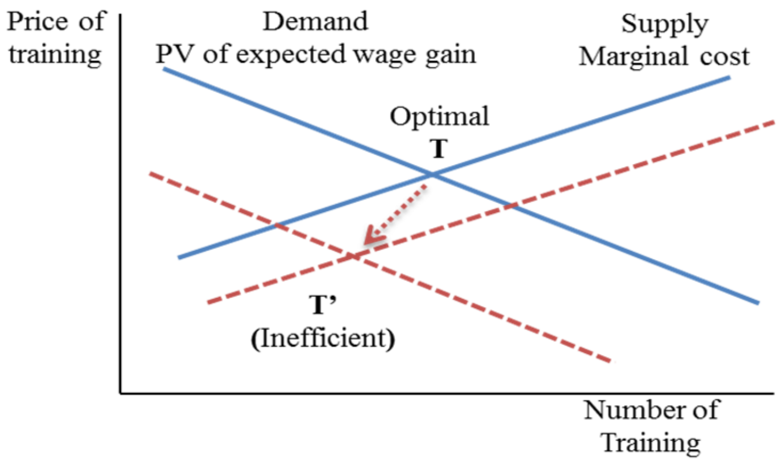


Figure 4-1 Labor market failure situation

Governmental-based HRD programs are especially needed in the renewable energy sector. However, because industrial boundaries remain nebulous and ill-defined, there exists extensive uncertainty regarding how to best optimize an individual's vocational education. As a result of the need for educated human resources, the Korean government increased its investment in producing manpower by 295% between 2005 and 2011. This investment has come in three forms: basic support, support for industries, and support for the development of advanced human resources. Despite these steps by the Korean government, their quantifiable effects have not been satisfactorily explored, and thus, remain unclear.

4.2 Operating mechanism of renewable energy HRD type

4.2.1 New and renewable energy human resource

Korea with few natural energy resources has to inevitably to depend heavily on imported energy. This situation leads Korean government to put a priority on developing new and renewable energy. The importance of new and renewable energy is emphasized not only new growth engine but also the key solution for the exhaustion problem of fossil energy and environment problem. For the steady growth of new renewable energy industry, securing related labor force is an essential factor.

New and renewable energy human resource has characteristics that distinguished form other energy industry. First, renewable energy technology is one the representative of fusion technology. Direct matching between the major and technologies is impossible in the industry. Also it lead a brad major cross-realm among undergraduate, master and PhD course. Even there are not clear definitions of majors that are related with each renewable resource.

In order to identify the major that are relater with each renewable energy, I review plan for core technology research center for renewable energy from 2005 to 2010 and category the researchers major (Table 4-1). In case of photovoltaic, electricity majors show large proportion (22%). In wind energy, mechanical engineering (47.6) and aerospace engineering (17.9), in bio energy, chemical engineering (27.1), mechanical engineering (17.8) and in fuel cell, chemical engineering (26.7), mechanical engineering (23.07) are major proportion. Each energy sources are consisted more than five main majors.

Table 4-1 Renewable energy related major

Renewable energy	Related majors
Photovoltaic	Electricity(22.0) Physics(19.5) Materials Science and Engineering(14.6), Mechanical Engineering(9.8), Semiconductor Engineering(7.3), Electronics(7.3) Architectural Engineering, Metallurgical Engineering, Industrial Engineering, Control Engineering
Wind	Mechanical Engineering(47.6), Aerospace Engineering(17.9), Metallurgical Engineering(6.0), Polymer Science (3.6), Electricity(3.6) Control Engineering(2.4) , Chemical Engineering, Structural Engineering, Design Engineering, Materials Science and Engineering
Bio	Chemical Engineering (27.1), Mechanical Engineering(17.8), Environmental Engineering (13.1), Chemistry (11.2), Agriculture (2.8), Biology (2.8), Food Science and Technology, Polymer Science and Engineering, Forestry Engineering
Fuel cell	Chemical Engineering (26.7), Mechanical Engineering(23.07), Electricity(11.36,) Materials Science and Engineering (9.66), Electronics(6.25), Chemistry(6.25), Polymer Science, Aerospace Engineering, Control Engineering, Physics

a. Data: Plan for core technology research center for renewable energy, KETEP(2005-2010),
b. ( ) represent the ratio of researchers of reach renewable energy

Another characteristic of NRE human resource have to learn technology quickly. It mean that set up the education level is difficult. Also Industry involve large volatility. In this situation the human resource development policy that are only focusing on discrepancy between supply and demand of labor. Existing studies related to new and renewable energy manpower policy were carried out mainly with emphasis on supply and demand aspects of manpower in industries, emphasizing the need of a specific policy.

In an effort to emphasize the need of new and renewable human resource development, in such studies as Lee et al(2011), KRIVET(2012) and KEEI(2012), the number of manpower was predicted that would be necessary when the new and renewable energy industry is expanded from industrial demand aspect. On the other hand, there are other kinds of Lee and Heo(2011) and Lee et al(2010) that analyzed creation of new jobs as one of the propagation effects of the new and renewable energy industry. Since the focus of existing studies was on demand and supply of industry, these studies fail to consider human capital accumulation that is inherent in individuals and the state through the decision making process of individuals who actually participate in HMD projects and related policies.

4.2.2 NRE human resource development programs in Korea

Within Korea, the current HRD policy in the field of energy consists of three categories: basic, advanced, and industry. The policies for new and renewable energy and the decision making related to educational investment throughout one's life are also categorized in a similar manner (Canton et al., 2005), as represented in human capital accumulation model.

New and renewable energy HRD was implemented in 2005 as a means to supply well-educated manpower to the new and renewable energy industry. The total amount allocated for each project and the ratio by year are as listed in the following (Figure 4-2). In 2005, \$4.1 billion was provided. By 2011, this amount had grown to \$12.1 billion[5]. In total, \$60.2 billion has been provided to support HRD in the field of new and emerging energy.

Initially, the bulk of government support was geared towards industrial HRD 73% in 2005. However, the primary target of financial

[5] Korea institute of energy technology evaluation and planning (www.ketep.re.kr)

support has since shifted to advanced HRD (Table 4-2). This reflects the initial assumption that industrial human resources required support to meet urgent demands for manpower (Fig 4-4). However, the growing importance of technology development in advanced HRD has demanded greater financial support. In contrast to industry-based and advanced HRD, basic HRD projects commenced in 2010 (Fig 4-3).

Figure 4-5 represent the renewable energy HRD budget with other energy resources. Each energy sector has different set of policy program. Energy efficiency and renewable energy sector support more industry level than other resources, 50.2% and 42.9% respectively. Next, I examined the each HRD policy mechanism.

Table 4-2 New and renewable HRD budget in Korea (Billion $)

	Basic labor force	Advanced labor force	Industry labor force
2005	-	1.1	3
2006	-	1.8	4.2
2007	-	2.6	5.9
2008	-	3.2	6.5
2009	-	4.3	5.3
2010	0.9	5.9	3.4
2011	1.9	8.2	2
Total	2.8 (-4.65%)	27.1 (-45.02%)	30.3 (-50.33%)

Data: Korea institute of energy technology evaluation and planning (2012)

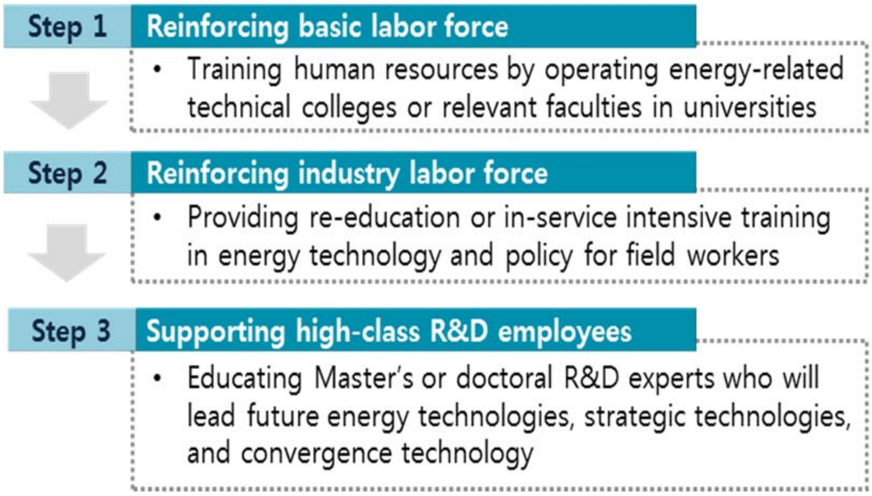


Figure 4-2 Type of human resource development program in Korea

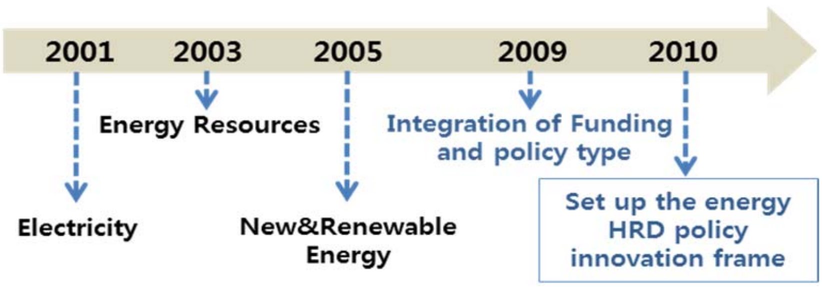


Figure 4-3 History of energy human resource development policy

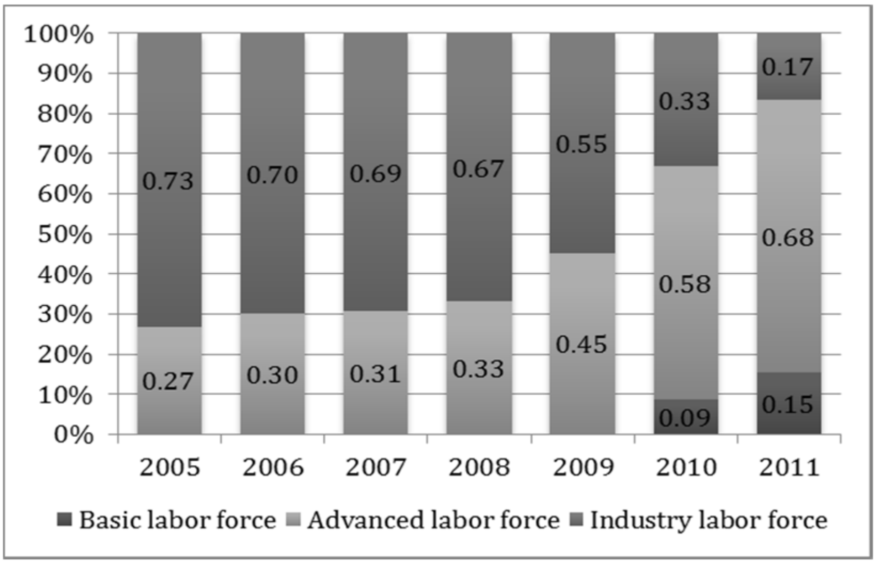


Figure 4-4 Supporting ratio of renewable HRD program

Data: Korea institute of energy technology evaluation and planning (2012)

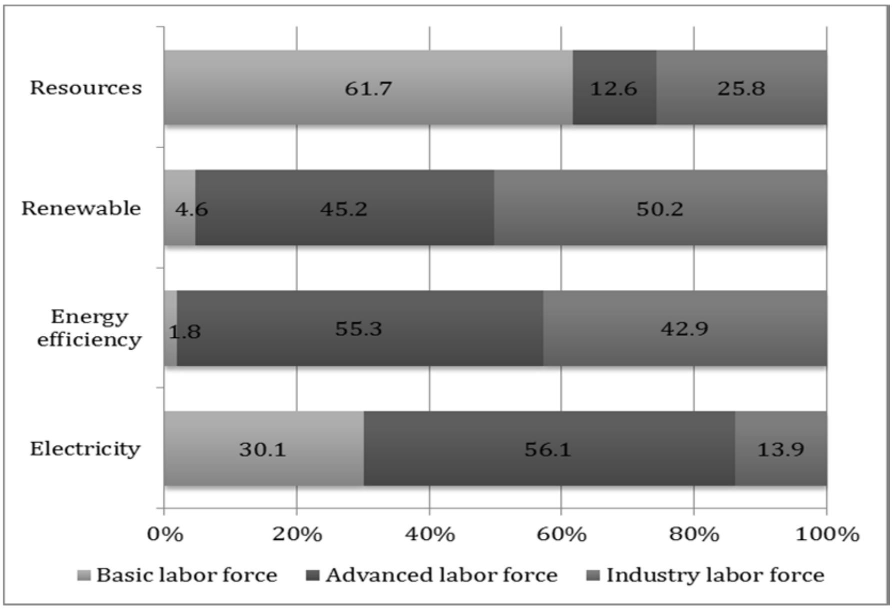


Figure 4-5 Supporting ratio of energy HRD program (2001-2011)

Data: Korea institute of energy technology evaluation and planning (2012)

(1) Basic labor force

The first type of new and renewable energy HRD policies was related to the support of college-level human resources. College-level human resources are in the greatest demand for companies that belong to industries in which the foundation is yet to be laid (Yumurtaci and Kecebas, 2011). In a study by Lee et al. (2011), 60.2% of participants indicated that college-level human resources were the most urgently needed. However, a few academic departments or programs produce industry-ready human resources in Korea. This has resulted in a situation wherein the demand for college-level human resources outpaces the supply (Lee et al., 2011, Kwon, 2011).

The following Figure 4-6, 4-7 depicts an individual's decisional process to pursue college education (Booth and Bryan, 2005). Individuals attend college when the sum of opportunity cost, the wage that one can receive after graduation of a high school, and direct costs (e.g., textbooks) is smaller than the expected payoff associated with attending.

Because new and renewable energy is an emergent industry, it is difficult to determine the wages that may be earned from working in it.

For this reason, individuals will often attend college not to prepare for a career in new and renewable energy, but with the goal of preparing to work in industries where existing wage information is available. The Korean government has mitigated the direct expense associated with attending college by incentivizing training in new and renewable energies through scholarships.

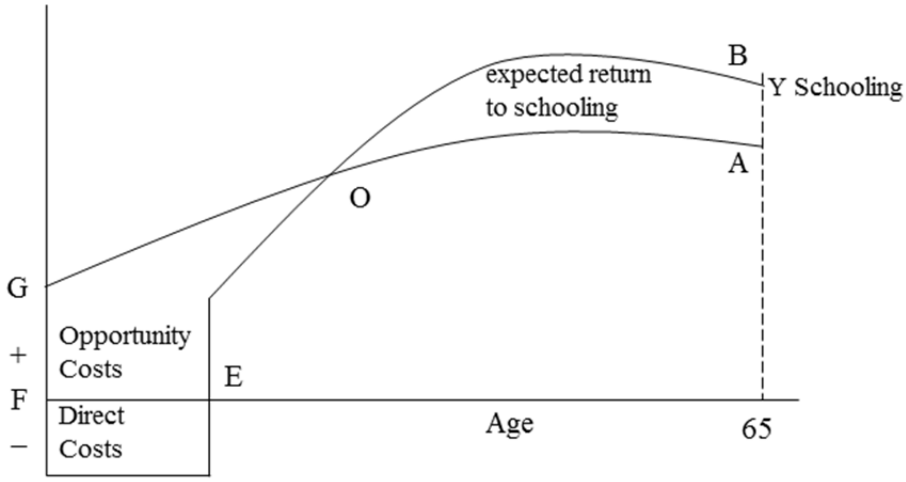


Figure 4-6 Earning profiles for high-school and university graduates

Source: Revised from Ehrenberg and Smith (2005) pp.332. Fig 9.12.

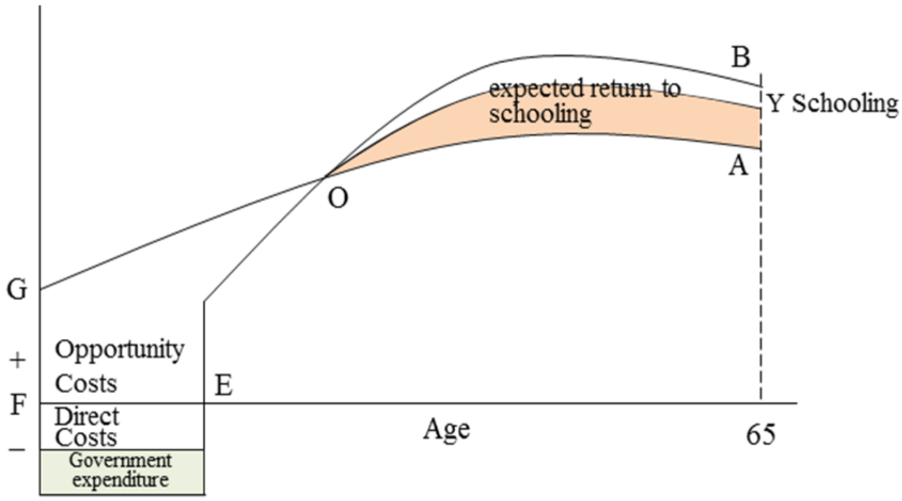


Figure 4-7 Under estimation of expected return from schooling

(2) Advanced labor force

Another type of HRD policy provides support to students in Master's or Ph.D. programs. This type of initiative is referred to as a advanced HRD program. The advanced HRD program differs from basic HRD in that it produces employees that can participate in research and development. Because the period necessary to obtain a Master's or Ph.D. degree is typically longer, both direct and opportunity costs are more substantial for individuals who undergo advanced HRD. Similar to a problem faced by those who engage in basic HRD, there is a general tendency to overestimate uncertainty in the new and renewable energy industry. As a result, individuals are similarly hesitant to invest in advanced HRD(Van Bergeijk et al., 1997)(Figure 4-8).

R&D is a critical avenue for technological innovation in many industries (Cameron, 1998, Bils and Klenow, 2000). When a technological innovation occurs, higher levels of production are possible using the same degree of labor resources and capital. There are more opportunities for innovation and production improvement in the new and renewable energy industry relative to other industries, because it is in a period of technological growth. Accordingly, advanced HRD can bring about positive external effects. These effects, particularly those associated with technological innovation, serve as the foundation for enhancing competitiveness of not only the individuals who secure training associated with them, but also the competitiveness of the industry and the nation as a whole (Canton et al.(2005), Barro and Lee (1993), Dakhli and De Clercq (2004)).

Governmental support can reduce entry barriers to advanced HRD by providing research scholarships to graduate schools, reducing the costs of R&D-related labor, and supplying other financial resources to higher-level educational programs (Stevens, 1999; Ehrenberg and Smith, 2006). Doing so would reduce the cost of educational investment by mitigating the opportunity costs associated with the pursuit of upper-level degrees. In addition, through participation in R&D, workers can accumulate on-the-job knowledge. In this way, governmental support can be used as a foundation for technology innovation by assisting the production of necessary human resources for R&D in relevant fields.

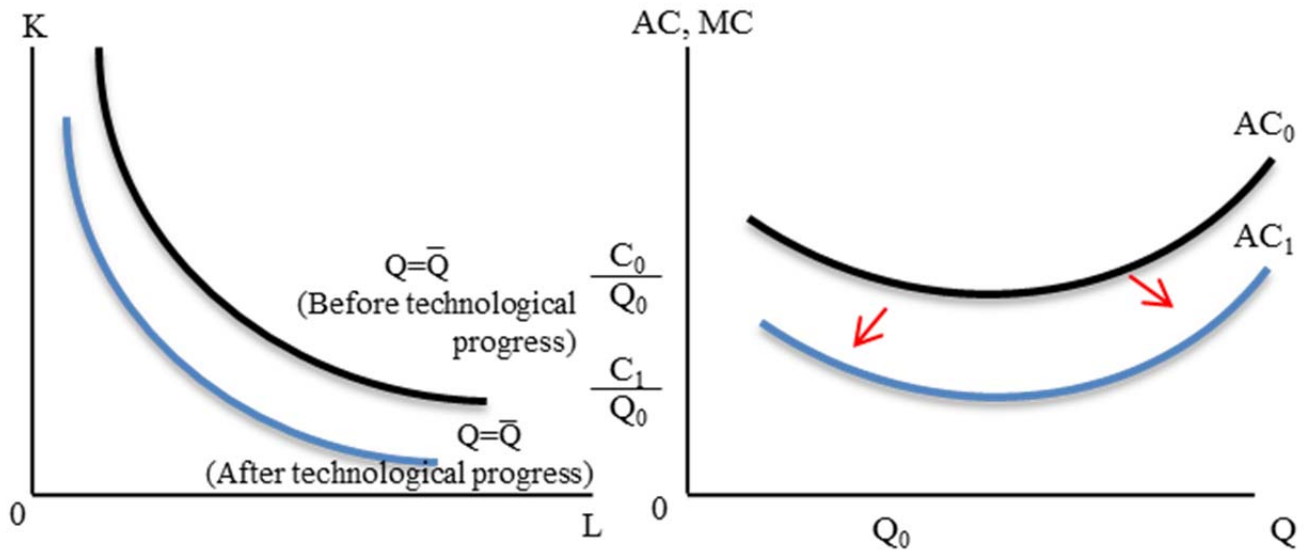


Figure 4-8 Uncertainty and under-estimate the innovation effect

(3) Industrial labor force

Another type of HRD project implements a short-term education program targeting industrial labor. In the new and renewable energy field in Korea, the supply of manpower thorough a formal college education is not well-established. This is a problematic situation, as the industry often requires manpower urgently (Lee et al., 2011, Heo et al., 2011, Lee et al., 2009). One alternative to college education for producing workers in the new and renewable energy industry is to educate individuals in comparable fields like chemical engineering and machinery. This may be particularly effective since existing companies are transitioning into new and emerging areas such as renewable energy.

Despite its benefits, the education of industrial manpower also incurs expenses for companies and employers. Companies are required to preparing lectures and absorb expenses related to teaching materials. There is also a productivity-specific limitation since workers who are undergoing education-based training are not able to participate in production activities.

Individuals incur certain costs as well. While participating in an HRD program, wages that could have been earned must be forgone. Because of this limitation, it is likely that an individual will pay for the education program only when its content is applicable to several industries. This is because knowledge obtained through industrial education that is applicable to a number of contexts can be useful beyond the industry for which the individual is initially trained. In contrast, when the knowledge provided by the educational initiative is restricted to a certain industry, the employer will incur the cost. There is no reason for an individual to incur a cost for obtaining knowledge that is needed only for the company for which the individual works (Figure 4-9).

The implementation of re-education programs for industrial manpower by the government reduces the company's costs since the government is able to create professional curricula and produce the educational programs to be administered. This reduces both financial and time-based costs of the corporation. For the individuals undergoing industry-based HRD training, this can be an opportunity to enhance one's personal competitiveness. This is particularly useful for individuals who will receive training in the new and renewable energy field (Figure 4-10).

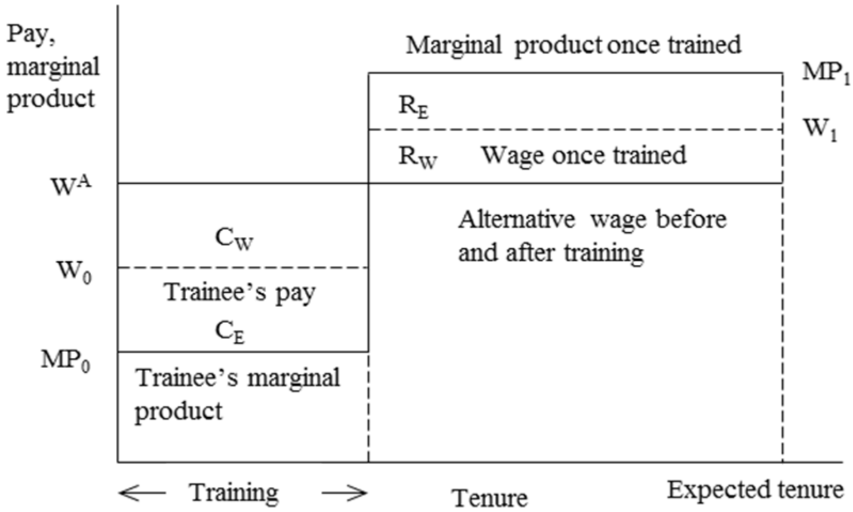


Figure 4-9 On-the-job training earning profile

Source: Revised from Ehrenberg and Smith (2005) pp.334. Fig 9.14.

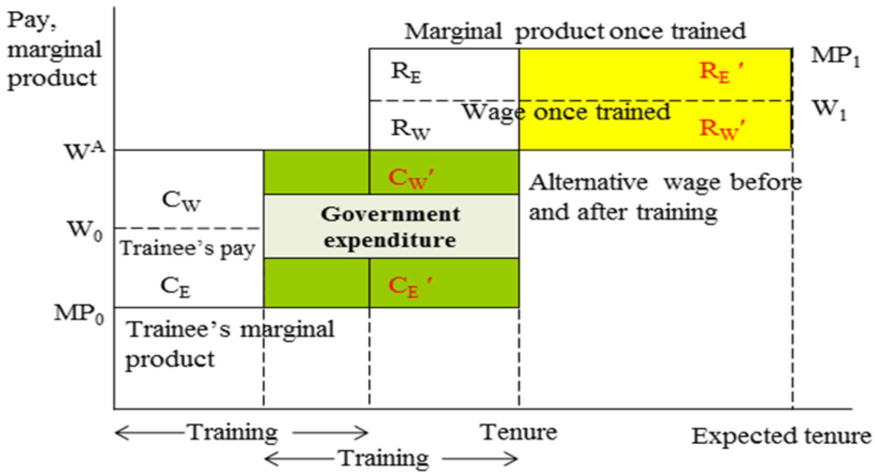


Figure 4-10 Re-training from other industry, absence of general training

4.2.3 Set up hypothesis of efficient labor market

According to Mincer(1994), Stevens(1999) and Booth et al.(2005) a wage function that is determined in an efficient labor market should satisfy a number of hypotheses. If the wage function does not satisfy these hypotheses, it is not possible to incite individuals to participate in government-sponsored HRD initiatives.

H1: There exists a positive relationship between education level and wage level.

This hypothesis suggests that a person's wage is significantly and positively related to his/her education level. Stated differently, an individual's wage should increase as his/her academic level increases. This concept serves as the basis for an individual's investment in school education despite its short-term costs. If this hypothesis were rejected, it would imply that individuals would not pursue school education despite government support for it, since wages would not increase as a result of increased education and wages cannot be earned while pursuing an education (i.e. opportunity costs are too high). Further, if this hypothesis were to be rejected, neither education-driven increases in productivity nor increases in social benefits can be expected.

H2: There exists a positive relationship between work experience and wage level.

To claim that an increase in work experience should increase one's wages suggests that an investment in human capital occurs while one works. In other words, while one performs his/her vocational duties in an industry, a certain portion of their human capital stock is invested in accordance with a human capital investment rate. This, in turn, will lead to an increase in his or her productivity. If this hypothesis is rejected, it suggests that time spent in the labor market of a given industry will not yield an accumulation of human capital. Thus, individuals will avoid moving into the new and renewable energy industry and will gravitate towards another industry where experience-based human capital can be accumulated.

H3: The relationship between wages and experience is concave in shape.

Experience-based wage increases are gains related to investment in human capital that have been made throughout one’s life. Because training has inherent costs for workers, individuals may accept a lower wage for a short period of time for the sake of higher wages in the future. Like other investments, the return on an investment in human capital tends to be greater when an investment period is longer. The rate of investment that is made while working for a job is the largest when an individual is young and shrinks over the course of one’s life. As a result, the wage function should be concave in shape to demonstrate the decreasing rate of wage increase vis-a-vis one’s experience.

4.3 Data sources

To estimate the wage function in the new and renewable energy industry, data from the Korean Labor and Income Panel Study (KLIPS)[6] was used. These data are based on questionnaire surveys conducted annually and include not only individual wage levels but also economic activity, education level, and social activities (Oh and Park, 2005; Park and Seok, 2009). The surveys were administered from 1998 to 2008 (attrition rate = 24%), making it largely generalizable for the analysis of Korean wage characteristics. These data enable the tracing of individual job characteristics of individuals.

To test the above-listed hypotheses in the context of the new and renewable energy labor market and to calculate human capital accumulation, data related to income and other individual characteristics are required. Ideally, these types of data could be secured from laborers from all the new renewable energy companies.

[6] Korea Labor Institute (www.kli.re.kr)

However, in practice, it is impossible to administer a survey to all the renewable energy companies. As such, this thesis utilizes survey data that were sampled using statistical techniques. This method is widely used for wage function analyses associated with a target nation or industry and are thus applicable for individual firms (Kim and Polachek, 1994).

Until now, there has been no industrial classification that is unique to the renewable energy industry. This is because the new and renewable energy industry shows a high degree of similarity with existing industries (Korea Energy Economy Institute, 2010). Most renewable energy companies are not independent entities. Rather, many extant companies have branched out and created a division that specializes in new and renewable energy. Further, those parts and products that are installed immediately before the final production stage of a renewable energy system are strongly related to extant products from the electronic, chemical, or machinery industries.

To classify new and renewable energy, the Korea Energy Economy Institute (2010) proposed a Dit 4 classification system for related industries. However, industrial classification of the labor panel had adopted a 3-level classification system, and thus, only allows classification of new industries (like the new and renewable industry) using the Dit 3 classification system(Appendix 1).

From the entire sample of respondents, I selected those who are working in an industry closely related to new and renewable energy and receiving wages as targets of analysis. Out of 11,756 individuals, 1,128 respondents were working in the solar energy industry; 1,324, in the wind energy industry; 642, in the bio-energy industry; 545, in the fuel cell industry; and 896, in the geothermal energy industry (Table 4-3). Among these respondents, workers in the fuel cell industry had the highest annual wages on average ($1,833) while those in the wind energy industry had the lowest average annual wages ($1,610). In contrast, the average job experience was the longest for bio energy-industry workers and the shortest for those working in the photovoltaic industry.

The average value of the gender dummy variable was 0.81–0.89 among the five industries, which indicated that across all renewable energy industries, there were far more male workers. Similarly, the dummy-coded variable for marriage had values between 0.66 and 0.69, indicating that a majority of the laborers were married. The dummy variable related to firm size indicated that only those working in the fuel cell industry worked for companies that employed more than 200 employees. The other energy industries largely consisted of comparatively smaller companies.

Table 4-3 Summary of basic statics - Photovoltaic, wind, bio, fuel cell and geothermal

	Photovoltaic	Wind	Bio	Fuel cell	Geothermal
Wage	170.38 (88.41, 101.38)	161.02 (86.73, 91.87)	157.94 (85.92, 112.04)	183.36 (90.81, 53.74)	161.51 (74.25, 74.66)
Education	12.61 (2.65, 0.24)	12.17 (3.07, 021)	11.50 (3.76, 0.27)	12.51 (2.75, 0.18)	11.91 (2.75, 0.21)
Career	17.46 (11.57, 1.63)	20.31 (13.59, 1.63)	22.17 (15.62, 1.58)	18.40 (11.61, 1.68)	20.52 (12.47, 1.63)
$Career^2$	433.11 (488.40, 71.92)	596.90 (673.31, 86.27)	717.55 (936.12, 87.86)	465.83 (525.01, 74.51)	567.83 (586.49, 82.46)
Education* Experience	200.96 (117.35, 21.21)	122.10 (124.90, 20.32)	210.53 (123.84, 19.62)	210.20 (107.52, 112.91)	222.49 (118.51, 19.74)
Gender	0.71 (0.47, 0)	0.75 (0.44, 0)	0.71 (0.45, 0)	0.75 (0.45, 0)	0.82 (0.40, 0)
Marriage	0.66 (0.47,0.14)	0.68 (0.47, 0.11)	0.69 (0.46, 0.13)	0.73 (0.44, 0.46)	0.69 (0.47, 0.10)

Firm size 1	0.29 (0.41, 0.22)	0.49 (0.44, 0.27)	0.40 (0.44, 0.25)	0.20 (0.38, 0.19)	0.47 (0.44, 0.27)
Firm size 2	0.26 (0.37, 0.27)	0.23 (0.36, 0.26)	0.26 (0.37, 0.27)	0.25 (0.38, 0.27)	0.22 (0.37, 0.26)
Firm size 3	0.16 (0.31, 0.24)	0.09 (0.23, 0.19)	0.12 (0.27, 0.21)	0.20 (0.32, 0.26)	0.08 (0.24, 0.18)
Firm size 4	0.26 (0.38, 0.19)	0.12 (0.28, 0.19)	0.36 (0.31, 0.15)	0.32 (0.39, 0.20)	0.13 (0.28, 0.14)
Firm size 5	0.01 (0.11, 0.04)	0.06 (0.24, 0.20)	0.20 (0.19, 0.11)	0.017 (0.14, 0.04)	0.07 (0.22, 0.15)
Union	0.24 (0.35, 0.22)	0.12 (0.26, 0.16)	0.39 (0.31, 0.19)	0.37 (0.41, 0.22)	0.14 (0.28, 0.16)
N	3761	4295	1997	1853	2894
n	1128	1324	642	545	896

a. (   ) respective overall and between-group standard deviations for the variables

4.4 Empirical analysis result

4.4.1 Wage function estimation

For the estimation of the wage function, four distinct methods—OLS estimation, fixed-effects model, random-effects model, and Hausman-Taylor estimation—were employed. Each method produced different results. To verify the robustness of the results associated with each method, specific post-hoc tests were carried out (Table 4-4).

First, the pooled-OLS analysis method assumes a homoscedasticity of error terms at all time points. Therefore, if all u_i are equal to 0, then the null hypotheses from the fixed-effects model are dismissed and the wage function becomes an unbiased estimator. For all five industries, u_i was equal to 0 and the null hypotheses were dismissed. This indicated that the pooled-OLS method was not appropriate.

For hypotheses tested with a fixed- and random-effects model, a Hausman test 1 was employed. The hypothesis is that some of the explanatory variables in log wage specification are correlated with the latent variable. The Hausman test 1 revealed that the fixed-effects model was appropriate than random-effect model for estimating the wage function since the null hypotheses were dismissed for all models.

Finally, with respect to the selection of the fixed-effects and H-T model, a Hausman test 2 was leveraged on the exogeneity of instrumental variables. Geothermal and fuel cell were satisfied with the exogeneity criterion. The fixed-effects model has a shortcoming in that it deletes the estimated amount of education that is an essential factor in human capital accumulation. As such, this analysis relies primarily on the Hausman-Taylor model to test hypotheses (Table 4-4). Test specifications are followed by Hausman's study (Hausman and Taylor, 1981).

Table 4-4 Test result of estimation method

	F test. all ui = 0	Hausman test 1	Hausman test 2
Photovoltaic	11.46 [0.0000]	34.07 [0.0000]	35.41 [0.0001]
Wind	43.88 [0.0000]	119.39 [0.0000]	25.33 [0.0038]
Bioenergy	27.23 [0.0000]	217.67 [0.0000]	23.34 [0.0026]
Fuel cell	10.08 [0.0000]	381.61 [0.0000]	11.14 [0.2787]
Geothermal	11.34 [0.0000]	141.43 [0.0000]	14.52 [0.1162]

[ ] represent p-value of each test.

In Chapter 4.2, three hypotheses related to the wage function were proposed. In the case of Hypothesis 1, education was shown to be positively (+) related to wages for the photovoltaic, wind, bio, fuel cell and geothermal energy industries ($p < 0.05$), but not for the geothermal energy industry ($p > 0.1$). Given these findings, Hypothesis 1 was supported in renewable energy industry.

Next, Hypothesis 2 predicted that job experience is positively (+) correlated with wage level. This hypothesis was supported in all five new and renewable energy industry cases ($p < 0.05$). This indicates that laborer wages in new and renewable industries increase in parallel with job experience, thus supporting for Hypothesis 2. Given this, it follows that individuals who have been subjected to the Korean government's HRD policy for the new and renewable energy industry have an incentive to go into a related industry.

Finally, Hypothesis 3 predicted that the relationship between job experience and wages is concave in shape. The square of job experience was shown to be negatively associated with wage levels ($p < 0.01$). This suggests that the more job experience one has, the less likely it is that the individual will invest in human capital. This provides some support for Hypothesis 3, although more data is required to verify these findings.

Although the three hypotheses were supported in varying degrees, it is useful to examine the respective effects of salient variables in the various new and renewable energy industries on wages. First, an analysis on the wage function that is based on education demonstrated that it varied considerably depending on the specific industry of which the laborer was a part. Wage increases that result from increased levels of education was most pronounced in the fuel cell industry, where wages grew by 21.0% for every additional year of education. The photovoltaic was second, with a yearly increase of 15.5% per additional year of education, followed by the wind energy industry (13.08%), the bio energy industry (9.56%), and the geothermal energy industry (6.82%).

Wage increases based on job experience was also most pronounced in fuel cell energy industry, where each additional year of job experience was associated with a 8.18% increase in wages. The photovoltaic energy industry was second, where a one-year increase in job experience yielded a wage increase of 5.68%. This was followed closely by the geothermal industry (5.540%), the wind energy industry (5.23%), and the bio energy industry (3.53%).

In the every renewable energy resources, wage increases based on job experience were less pronounced than wage increases based on education. Stated differently, a one-year increase in education had a greater effect on wages than an equivalent increase in job experience. For the solar-energy industry, wage increases based on education were as much as 2.76 times higher than wage increases based on job experience. For the wind energy industry, the wage increases based on education were 2.50 times higher than those based on job experience. Further, in the case of the fuel cell industry, one year of education produced a wage increase that was 2.62 times higher than a wage increase based on one additional year of job experience.

Past research related to wage function estimation in Korean energy industries (Lee et al., 2011, Kim, 2009) have shown that wage increases are more sensitive to education than to job experience. This trend was replicated for the analysis results. These results suggest that education level and job experience can affect wages in individual industries differently, which can likewise affect human capital accumulation in these industries in distinct ways.

Table 4-5 Earning function estimation result - Photovoltaic

	OLS	Fixed effect	Random effect	H-T
Education	0.1466*** (0.0100)	0.0436 (0.0305)	0.2032*** (0.0169)	0.1553*** (0.0167)
Career	0.1008*** (0.0074)	0.0813*** (0.0216)	0.1331*** (0.0117)	0.0568*** (0.0119)
Career^2	-0.0012*** (0.0001)	-0.0010*** (0.0002)	-0.0014*** (0.0001)	0.0039*** (0.0007)
Education* Experience	-0.0030*** (0.0003)	0.0032** (0.0012)	-0.0030*** (0.0006)	0.0039*** (0.0007)
Gender	0.5008*** (0.0262)	(omitted)	0.4927*** (0.0522)	0.2765*** (0.0780)
Marriage	-0.0348 (0.0233)	0.0276 (0.0417)	-0.0596* (0.0337)	-0.0415*** (0.0231)
firm size 1	0.0051 (0.0270)	0.0356 (0.0267)	0.0578** (0.0269)	0.1571** (0.0694)
firm size 2	0.1087*** (0.0300)	0.0724** (0.0304)	0.1088*** (0.0303)	0.1773** (0.0694)
firm size 3	0.2359*** (0.0328)	0.1150*** (0.0364)	0.2235*** (0.0349)	0.2092*** (0.0705)
firm size 4	0.4252*** (0.0341)	0.1138*** (0.0407)	0.2837*** (0.0379)	0.2389*** (0.0714)
Union	0.1194*** (0.0299)	0.0724** (0.0293)	0.0973*** (0.0293)	0.0217 (0.0145)
_cons	2.0034*** (0.1633)	2.4043*** (0.4227)	0.7769*** (0.2628)	1.2057*** (0.2447)
Number of obs/groups	3761	3761/ 1128	3761/ 1128	3761/ 1128

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. Standard errors in parentheses

Table 4-6 Earning function estimation result - Wind

	OLS	Fixed effect	Random effect	H-T
Education	0.1359*** (0.0111)	0.0430 (0.0341)	0.1832*** (0.0185)	0.1308*** (0.0186)
Career	0.0853*** (0.0083)	0.1249*** (0.0248)	0.1134*** (0.0130)	0.0523*** (0.0116)
Career^2	-0.0010*** (0.0001)	-0.0011*** (0.0002)	-0.0012*** (0.0001)	-0.0008*** (0.00009)
Education* Experience	-0.0026*** (0.0004)	0.0002 (0.0015)	-0.0023*** (0.0006)	0.0041*** (0.0007)
Gender	0.3841*** (0.0268)	(omitted)	0.3996*** (0.0571)	0.0677 (0.0819)
Marriage	0.0112 (0.0279)	-0.0378 (0.0469)	-0.0523 (0.0395)	-0.0705*** (0.0264)
firm size 1	-0.0387 (0.0373)	0.0006 (0.0357)	0.0147 (0.0369)	0.0327** (0.0228)
firm size 2	-0.0189 (0.0397)	0.0188 (0.0381)	0.0314 (0.0392)	0.0493*** (0.0250)
firm size 3	0.1067** (0.0440)	0.0729* (0.0436)	0.1487*** (0.0443)	0.0872*** (0.0286)
firm size 4	0.2774*** (0.0467)	0.0703 (0.0485)	0.2015*** (0.0482)	0.0822*** (0.0312)
Union	0.1897*** (0.0372)	0.0332 (0.0330)	0.0864** (0.0342)	0.0084 (0.0192)
_cons	2.4736*** (0.1865)	2.2843*** (0.4792)	1.3063*** (0.2971)	1.8152*** (0.2725)
Number of obs/groups	4295	4295/1324	4295/1324	4295/1324

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. Standard errors in parentheses

Table 4-7 Earning function estimation result - Bio

	OLS	Fixed effect	Random effect	H-T
Education	0.1480*** (0.0108)	0.0663** (0.0311)	0.2066*** (0.0182)	0.0965*** (0.0252)
Career	0.0945*** (0.0081)	0.1051*** (0.0230)	0.1182*** (0.0126)	0.0353** (0.0153)
Career^2	-0.0012*** (0.0001)	-0.0010*** (0.0002)	-0.0013*** (0.0001)	-0.0005*** (0.0001)
Education* Experience	-0.0025*** (0.0003)	0.0014 (0.0013)	-0.0023*** (0.0006)	0.0051*** (0.0008)
Gender	0.3275*** (0.0286)	(omitted)	0.3285*** (0.0636)	0.2258*** (0.1148)
Marriage	-0.0203 (0.0282)	0.0186 (0.0468)	-0.0265 (0.0402)	-0.0716** (0.0359)
firm size 1	0.0039 (0.0304)	-0.0436 (0.0289)	0.0063 (0.0293)	-0.0579 (0.0432)
firm size 2	0.1086*** (0.0338)	-0.0001 (0.0326)	0.0595* (0.0329)	-0.0425 (0.0458)
firm size 3	0.2274*** (0.0379)	0.0210 (0.0375)	0.1452*** (0.0375)	0.0217 (0.0506)
firm size 4	0.4308*** (0.0399)	0.0382 (0.0402)	0.1975*** (0.0397)	-0.0233 (0.0554)
Union	0.1771*** (0.0360)	0.0231 (0.0335)	0.0779** (0.0339)	0.0205 (0.0238)
_cons	2.1944*** (0.1846)	2.0657*** (0.4489)	0.9579*** (0.2959)	2.1794*** (0.3676)
Number of obs/groups	1997	1997/642	1997/642	1997/642

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. Standard errors in parentheses

Table 4-8 Earning function estimation result – Fuel cell

	OLS	Fixed effect	Random effect	H-T
Education	0.1553*** (0.0144)	0.0968* (0.0575)	0.2007*** (0.0255)	0.2100*** (0.0283)
Career	0.0962*** (0.0109)	0.1239*** (0.0340)	0.1278*** (0.0183)	0.0818*** (0.0187)
Career^2	-0.0010*** (0.0001)	-0.0013*** (0.0003)	-0.0013*** (0.0002)	-0.0007*** (0.0001)
Education* Experience	-0.0036*** (0.0005)	0.0017 (0.0020)	-0.0028*** (0.0009)	0.0036*** (0.0001)
Gender	0.3682*** (0.0378)	(omitted)	0.4589*** (0.0715)	0.4519*** (0.1283)
Marriage	0.0098 (0.0342)	-0.0808 (0.0604)	-0.1107** (0.0492)	-0.0696** (0.0303)
firm size 1	0.0031 (0.0440)	0.0598 (0.0452)	0.0660 (0.0468)	0.1271 (0.0841)
firm size 2	0.0225 (0.0458)	0.0367 (0.0504)	0.0620 (0.0508)	0.1090 (0.0832)
firm size 3	0.1258*** (0.0479)	0.0636 (0.0590)	0.1453** (0.0566)	0.1269 (0.0845)
firm size 4	0.2947*** (0.0504)	0.0843 (0.0670)	0.2633*** (0.0611)	0.1628* (0.0852)
Union	0.2663*** (0.0370)	0.1081*** (0.0389)	0.1854*** (0.0398)	0.0236 (0.0192)
_cons	2.1996*** (0.2260)	1.5836** (0.7841)	0.9599** (0.3824)	0.0637*** (0.4117)
Number of obs/groups	1853	1853/545	1853/545	1853/545

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. Standard errors in parentheses

Table 4-9 Earning function estimation result - Geothermal

	OLS	Fixed effect	Random effect	H-T
Education	0.1658*** (0.0135)	0.0571* (0.0326)	0.2176*** (0.0223)	0.0682** (0.0243)
Career	0.1085*** (0.0103)	0.0928*** (0.0260)	0.1353*** (0.0156)	0.0554*** (0.0159)
Career^2	-0.0013*** (0.0001)	-0.0011*** (0.0002)	-0.0015*** (0.0002)	-0.0008*** (0.0001)
Education* Experience	-0.0031*** (0.0004)	0.0025* (0.0014)	-0.0026*** (0.0007)	0.0041*** (0.0009)
Gender	0.4362*** (0.0370)	(omitted)	0.4363*** (0.0820)	0.2710*** (0.0978)
Marriage	-0.0866*** (0.0323)	0.0307 (0.0538)	-0.0194 (0.0464)	-0.1616*** (0.0362)
firm size 1	-0.0242 (0.0343)	-0.0081 (0.0312)	0.0310 (0.0316)	0.0551** (0.0266)
firm size 2	0.1740*** (0.0385)	0.0504 (0.0362)	0.0999*** (0.0363)	0.0870*** (0.0302)
firm size 3	0.2554*** (0.0430)	0.0415 (0.0416)	0.1574*** (0.0413)	0.0924** (0.0361)
firm size 4	0.4044*** (0.0465)	0.0516 (0.0454)	0.1780*** (0.0449)	0.0912** (0.0414)
Union	0.1181*** (0.0444)	0.0351 (0.0402)	0.0633 (0.0406)	0.0108 (0.0250)
_cons	1.7920*** (0.2263)	2.2812*** (0.4807)	0.5072 (0.3540)	1.4569*** (0.3454)
Number of obs/groups	1,504	1,504/282	1,504/282	1,504/282

a. *, **, *** significant at 10%, 5% and 1%, respectively
b. Standard errors in parentheses

4.4.2 Human capital accumulation through NRE industry

In this chapter, an attempt was made to calculate the amount of human capital accumulated by an individual in a new and renewable energy industry. Further, this chapter seeks to determine the applicability policies geared towards promoting that accumulation. When an assumption is made that an individual is representative of all workers in a given industry in terms of his/her wage level and education, the total amount of human capital that can be accumulated in the five new and renewable energy industries described above can be decomposed using the wage function estimation coefficient. To calculate the amount of positive (+) human capital accumulated through the application of Formula (1), return on investment in human capital (r_p) and the rate of investment in human capital when job experience is one year ($S_{t,1}$) were calculated using equation (9) and equation (10) respectively.

Results showed that return on investment in human capital and the initial rate of investment run counter to one another (Table 4-10). In other words, an industry that features a high return on investment in human capital has a higher investment rate than does an industry with low returns on investment. Similarly, industries that feature low in returns on investment have a low human capital investment rate relative to those industries that offer high returns on investment.

Specifically, the wind, bio and geothermal energy industries offered high returns on human capital investment at 0.376, 0.247 and 0.481 respectively. This represents a higher return on human capital investment than those seen in the solar (0.119) and fuel cell (0.093) energy industries. Despite this, the rates of investment in human capital are higher in the fuel cell (0.472) and photovoltaic (0.360) relative to the bio energy (0.122) , wind energy (0.162) and geothermal (0.104) industries. Despite fist investment are different, they reduce investment close to their retirement following the equation (5)

Table 4-10 Return on investment human capital and the initial ratio of investment of renewable energy resources

	γ_p	S_{t1}
Solar PV	0.119	0.360
Wind	0.376	0.119
Bioenergy	0.247	0.122
Fuel cell	0.093	0.472
Geothermal	0.481	0.104

On the basis of these results, it is possible to calculate the 30-year accumulation of human capital for an individual with an average degree of job experience and average wage level in his/her respective industry. Table 4-11 ~4-13 represent patterns of human capital accumulation depend on career in each renewable energy industry.

Depend on γ_p and S_{t1} each renewable energy shows different patterns. Solar and fuel cell which have high investment rates invest high proportion of their human capital in early carrier. However the amount of investment are reduced with carrier. At a retirement year, photovoltaic, fuel cell accumulate more than 2500$ of human capital. In contrast, wind and bio energy accumulate near 2000$ of human capital (Fig 4-11 – 4-15).

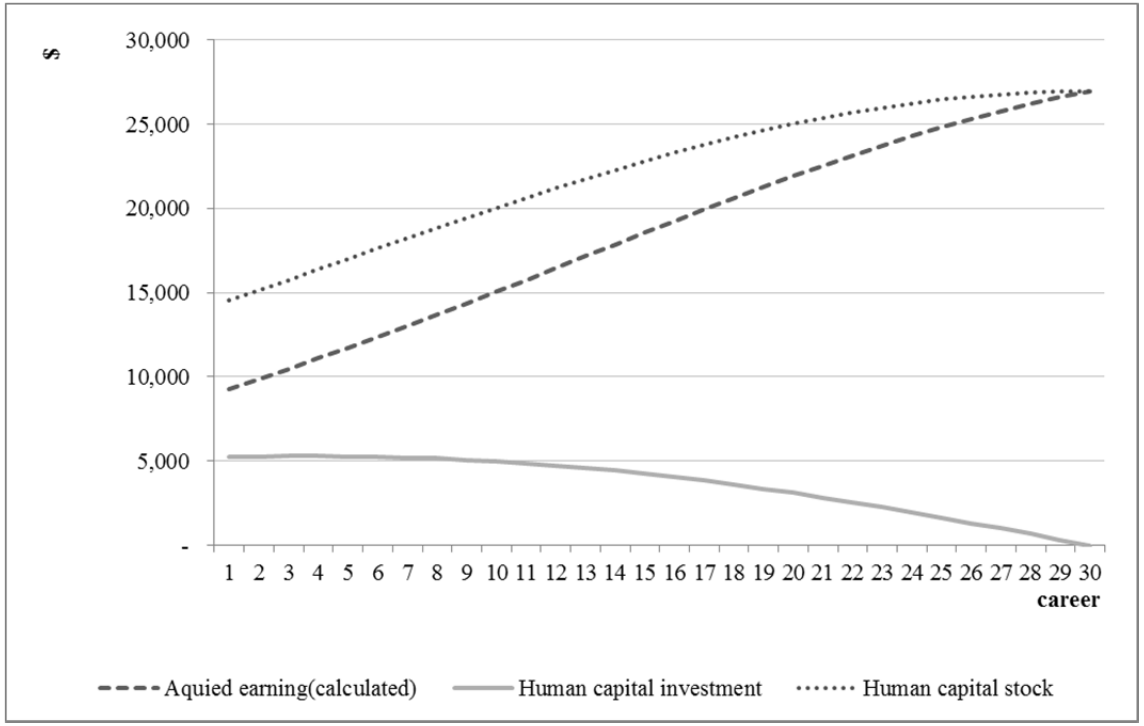


Figure 4-11 Human capital accumulation patterns of photovoltaic

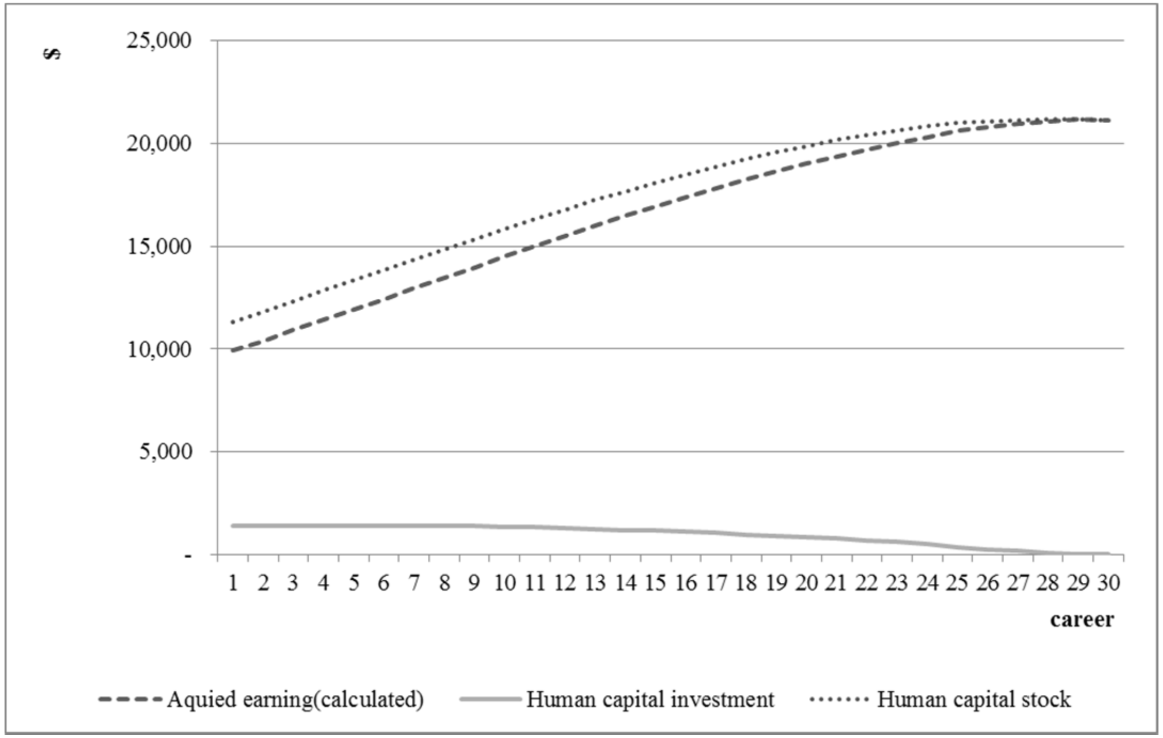


Figure 4-12 Human capital accumulation patterns of wind energy

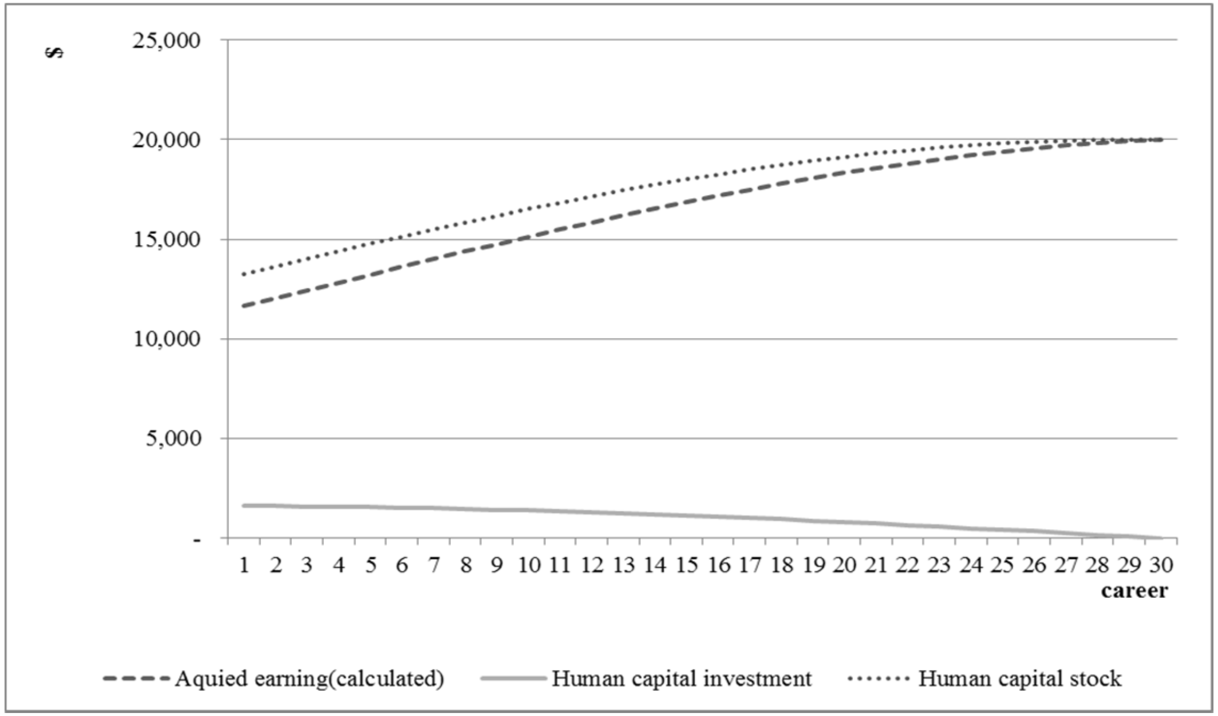


Figure 4-13 Human capital accumulation patterns of bio energy

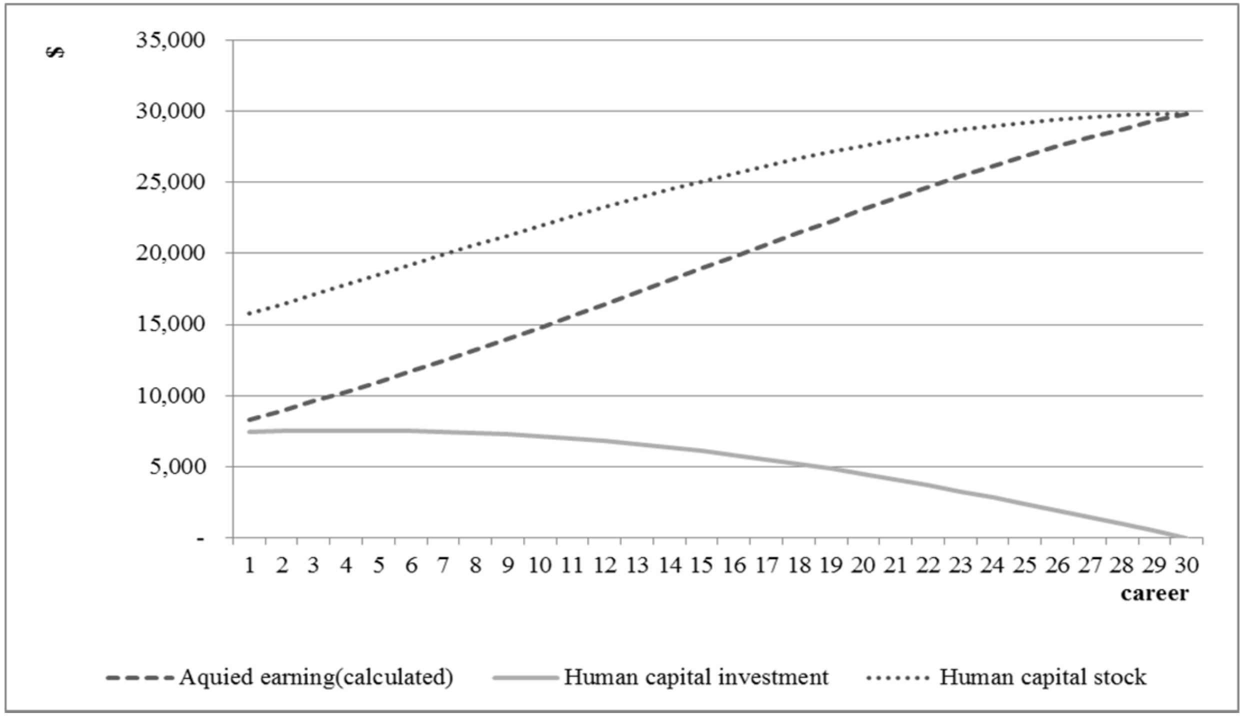


Figure 4-14 Human capital accumulation patterns of fuel cell

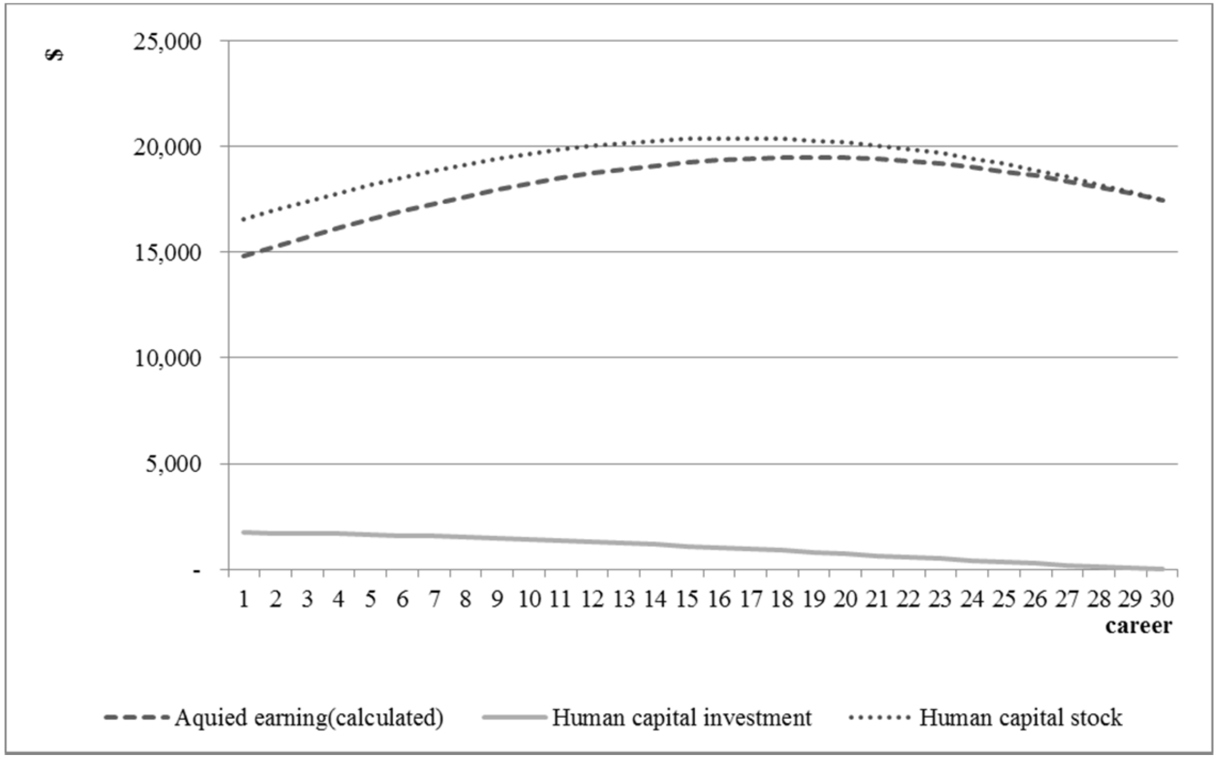


Figure 4-15 Human capital accumulation patterns of geothermal

In terms of human capital accumulation, workers in the fuel cell energy industry enjoyed the highest degree of human capital accumulation ($732,282), during their life cycle earing.

This calculation was made by considering the average age and average wage of workers in each industry. Accordingly, in an industry, the higher the workers' average wage, the lower their average job experience, and the higher their human capital accumulation. This is because a lower average age of workers in an industry implies that they will accumulate human capital for a longer time. Table 4-11 displays the average age of workers in each industry, which may drive the human capital accumulation figures reported above.

Table 4-11 Total human capital stock, acquired earning and investment

	Human capital stock	Acquired earning	Human capital investment
Solar PV	666,419	558,986	104,101
		(0.839)	(0.156)
Wind	526,697	498,056	26,007
		(0.946)	(0.049)
Bioenergy	527,661	497,838	27,184
		(0.943)	(0.052)
Fuel cell	732,282	578,135	150,486
		(0.789)	(0.206)
Geothermal	574,352	544,708	926
		(0.948)	(0.002)

a. (   ) represent the ratio from total human capital stock

4.4.3 Using human capital accumulation for HRD program evaluation

(1) Applying the index on policy decision

When using the above method to calculate the accumulation of human capital by energy source, it is likewise possible to calculate an individual's accumulation of human capital based on the government's HRD program (Table 4-12). If a governmental policy were not implemented, the human resource in question would not have gone to the industry. Therefore, the amount of human capital that an individual accumulates serves as a proxy for the amount of human capital created by governmental policy.

When examined by energy source, college-level accumulation of human capital is the highest in the fuel cell energy industry at $1,278,863. College-level accumulation of human capital was lowest for the geothermal energy industry ($665,446). HRD policies implemented at different levels yielded similar results with respect to human capital. The amount of human capital accumulated in the fuel cell energy industry was the largest, followed (in descending order) by the photovoltaic, wind, bio and geothermal energy industries.

Differences for capital from industry to industry are driven by variation in average wage amounts. The fuel cell energy industry has the highest average wages.

Similar to the previous finding, the above estimation result demonstrated that the effect of education on wages was the most pronounced in the fuel cell energy industry, followed closely, in descending order, by the photovoltaic, wind, bio and geothermal energy industries. This kind of wage market evaluation illustrates the close association between education level and human capital accumulation.

When an HRD policy is limited by budgetary constraints, the amount of human capital accumulation that was calculated above allows for a different approach, depending on the policy’s function. For example, when budgetary scales are fixed regardless of the energy industry being evaluated, the maximization of human capital accumulation can be achieved. To this end, Table 4-12 reports the accumulation ratio of human capital for college, industrial labor, Master’s degrees, and Ph.D. degrees relative to an undergraduate student whose human capital level has been standardized at 100.

Accumulated human capital for a Ph. D. student in the fuel cell energy industry is 35% higher than that for undergraduates in the same industry. In contrast, the accumulation of human capital for a Ph. D. student in the geothermal energy industry is 5% lower than that of an undergraduate student in that industry.

This indicates that when an identical budget is available for potential laborers in undergraduate, Master's, and Ph. D. programs, an undergraduate in the geothermal energy industry will accumulate more human capital than will his/her higher-educated counterparts; undergraduates, Master's graduates, and Ph.D graduates in the wind energy industry will accumulate identical amounts of human capital; and Ph. D program students in the fuel cell energy industry will accumulate the most human capital. From this perspective, human capital accumulation can serve as a guiding index for developing a budget and for selecting targets of funding support.

Full cell show the largest gab between PhD graduates and undergraduates. PhD graduates accumulate 35% more, master graduates accumulates 15% more, industry labor accumulate 5% more than undergraduates. In case of photovoltaic, the PhD graduates accumulate 23% more, master graduate accumulate 11% more and industry labor accumulate 5% more than undergraduates. In case of wind, PhD graduates accumulate 16% more, master graduates accumulate 8% more and industry labors accumulate 4% more than undergraduates. However in case of geothermal, PhD graduates accumulate 8% less, master graduates accumulate 5% less and industry labors accumulate 5% less than undergraduates.

Table 4-12 Individual's accumulation of human capital on new and renewable HRD project

	Basic labor force	Industry labor force	Advanced labor force	
			Master degree	PhD degree
Solar PV	1,017,402 (100)	1,064,368 (105)	1,125,443 (111)	1,253,702 (123)
Wind	790,255 (100)	821,551 (104)	853,555 (108)	916,244 (116)
Bioenergy	756,604 (100)	779,400 (103)	793,371 (105)	819,084 (108)
Fuel cell	1,278,863 (100)	1,348,879 (105)	1,466,338 (115)	1,725,165 (135)
Geothermal	665,446 (100)	681,571 (102)	650,239 (98)	629,196 (95)
Average	901,714	939,154	977,789	1,068,678

a. ( ) represent that degree relative to an undergraduate student whose human capital level has been standardized at 100

Utilizing the above index also allows for the calculation of human capital accumulation based on yearly policy composition. Human capital ratio can compared with new and renewable HRD budget ratio. Table 4-13 is the result for 2011 budget of new and renewable energy HRD policy.

The amount of per unit human capital accumulation is $949,218, which is higher than the average amount of human capital accumulation at the industry level ($939,154), but lower than the average amount of human capital accumulation for the Master. program participants ($977,789). There is a difference between the budget ratio by energy source and the human capital ratio. For the fuel cell and solar energy industries, the human capital ratio respectively increased by 0.054 and 0.034 relative to the budget ratio. For the wind, bio and geothermal energy industries, the human capital ratio decreased by 0.058, 0.027, and 0.010, respectively.

Table 4-13 Comparing human capital ratio with budget ratio

	Human capital accumulation ($)	human capital accumulation ratio	Budget ratio of NRE HRD(2011)
Solar PV	415,412	0.403	0.369
Basic labor force	113,949	0.120	0.112
Industry labor force	36,189	0.038	0.034
Advanced labor force	262,275	0.245	0.254
Wind	275,682	0.266	0.314
Basic labor force	18,176	0.019	0.023
Industry labor force	-	-	-
Advanced labor force	257,506	0.247	0.246
Bioenergy	118,225	0.123	0.150
Basic labor force	-	-	-
Industry labor force	78,719	0.083	0.101
Advanced labor force	39,505	0.040	0.038
Fuel cell	212,235	0.184	0.133
Basic labor force	-	-	-
Industry labor force	-	-	-
Advanced labor force	212,235	0.184	0.0.203
Geothermal	23,173	0.024	0.034
Basic labor force	-	-	-
Industry labor force	23,173	0.024	0.034
Advanced labor force	-	-	-
Total	949,218	1.000	1.000

When this approach is applied to policy decision making, the optimal allocation for human capital accumulation for each energy industry and specific project budget can be found. This can serve as a multiplier that can be used to adjust levels of financial support relative to the energy source industry that is implementing the government policy. When the accumulation level is considered through multiplication of the budget scale, changes in the amount and speed of human capital within that particular budget can be identified.

(2) Sensitivity analysis

It is expected that the index can be utilized for the effective distribution of national resources. Depend on budget ratio of renewable energy as well as policies, the total human capital through renewable energy HRD program can be different. In this part, sensitivity analyses were conducted using the index. Sensitivity analysis was carried out three parts.

- Changing renewable energy budget ratio
- Changing policy ratio in each renewable energy based on 2011 budget ratio

- Changing policy ratio in each renewable energy by 10%, 30%, 50%, 70% and 90%

At first, each standard renewable energy ratio are increased by 20%, 40%, 60%, 80%. 100% with fixing other energy resources budget ratio. Each renewable energy industry have a different human capital accumulation stock (Figure 4-16). It means that the total human capital stock will be changing with budget ratio.

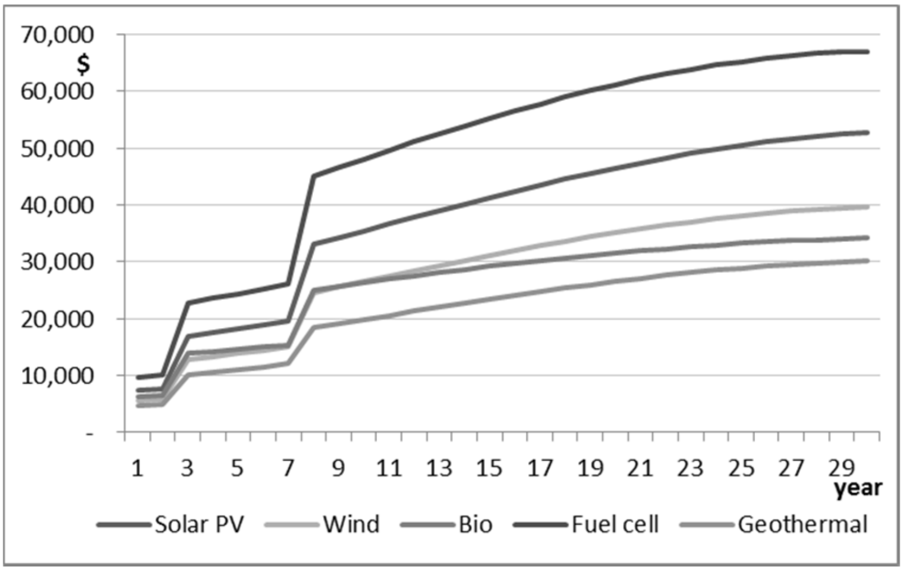


Figure 4-16 Human capital accumulation from each renewable energy

In case of photovoltaic, budget ratio increasing from 0.37 to 0.44, 0.52, 0.59, 0.66, and 0.74. Budget ratio of other renewable energy was reduced with the same ratio in 2011(Table 4-14). Case of Other resources are summarized in appendix. With the creasing HRD budget in photovoltaic human capital stock is also increasing by 1,024,416$, 1,037,020$, 1,062,228$ 1,074,832$ and 1,086,436$. It is a 1%, 4%, 5%, and 6% increasing with first human capital.

When consider the 100% increasing cases, human capital stock in case of fuel cell and solar is increasing by 7% and 6% respectively. In contrast, human capital stock was decreased by 1%, 4% and 8% in case of geothermal, bio, wind.

Especially, the wind energy HRD is 31% of total renewable energy HRD in 2011. When the budget of wind energy increases 100%, total human capital stock reduces 8%. Geothermal is the lowest of a unit of the human capital accumulation. Because it’s budget ratio is just 3.4% in 2011, there is no significant effect of the increase in the budge. Fuel cell is the highest of a unit of the human capital accumulation. When the budget rate increase 100%, budget ratio became 26%. The human capital in that case are similar when the solar budget increasing 100%, in that case photovolaic’s budget rate become 73%.

Table 4-14 Changing NRE HRD budget ratio based on photovoltaic

	Budget ratio in 2011	Photovoltaic budget ratio increasing				
		20%	40%	60%	80%	100%
Photovoltaic	**0.37**	0.44	0.52	0.59	0.66	0.74
Wind	**0.31**	0.28	0.24	0.20	0.17	0.13
Bio energy	**0.15**	0.13	0.11	0.10	0.08	0.06
Fuel cell	**0.13**	0.12	0.10	0.09	0.07	0.06
Geothermal	**0.03**	0.03	0.03	0.02	0.02	0.01
Total ratio	**1**	1	1	1	1	1
Human capital ratio	**1.00**	1.01	1.02	1.04	1.05	1.06

Table 4-15 Changing NRE HRD budget ratio based on wind

	Budget ratio in 2011	Wind budget ratio increasing				
		20%	40%	60%	80%	100%
Wind	0.31	0.38	0.44	0.50	0.57	0.63
Photovoltaic	0.37	0.34	0.30	0.27	0.23	0.20
Bio energy	0.15	0.14	0.12	0.11	0.10	0.08
Fuel cell	0.13	0.12	0.11	0.10	0.08	0.07
Geothermal	0.03	0.03	0.03	0.02	0.02	0.02
Total ratio	**1**	1	1	1	1	1
Human capital ratio	1.00	0.98	0.97	0.95	0.94	0.92

Table 4-16 Changing NRE HRD budget ratio based on Fuel cell

	Budget ratio in 2011	Fuel cell budget ratio increasing				
		20%	40%	60%	80%	100%
Fuel cell	0.13	0.16	0.19	0.21	0.24	0.27
Photovoltaic	0.37	0.36	0.35	0.34	0.32	0.31
Wind	0.31	0.30	0.29	0.29	0.28	0.27
Bio energy	0.15	0.15	0.14	0.14	0.13	0.13
Geothermal	0.03	0.03	0.03	0.03	0.03	0.03
Total ratio	1	1	1	1	1	1
Human capital ratio	1.00	1.01	1.03	1.04	1.06	1.07

Table 4-17 Changing NRE HRD budget ratio based on geothermal

	Budget ratio in 2011	Geothermal budget ratio increasing				
		20%	40%	60%	80%	100%
Geothermal	0.03	0.04	0.05	0.05	0.06	0.07
Photovoltaic	0.37	0.37	0.36	0.36	0.36	0.36
Wind	0.31	0.31	0.31	0.31	0.31	0.30
Bio energy	0.15	0.15	0.15	0.15	0.15	0.14
Fuel cell	0.13	0.13	0.13	0.13	0.13	0.13
Total ratio	1	1	1	1	1	1
Human capital ratio	1.00	1.00	0.99	0.99	0.99	0.99

Table 4-18 Changing NRE HRD budget ratio based on bio energy

	Budget ratio in 2011	Bio energy budget ratio increasing				
		20%	40%	60%	80%	100%
Bio energy	0.15	0.18	0.21	0.24	0.27	0.30
Photovoltaic	0.37	0.36	0.34	0.33	0.32	0.30
Wind	0.31	0.30	0.29	0.28	0.27	0.26
Fuel cell	0.13	0.13	0.12	0.12	0.11	0.11
Geothermal	0.03	0.03	0.03	0.03	0.03	0.03
Total ratio	1	1	1	1	1	1
Human capital ratio	1.00	0.99	0.98	0.98	0.97	0.96

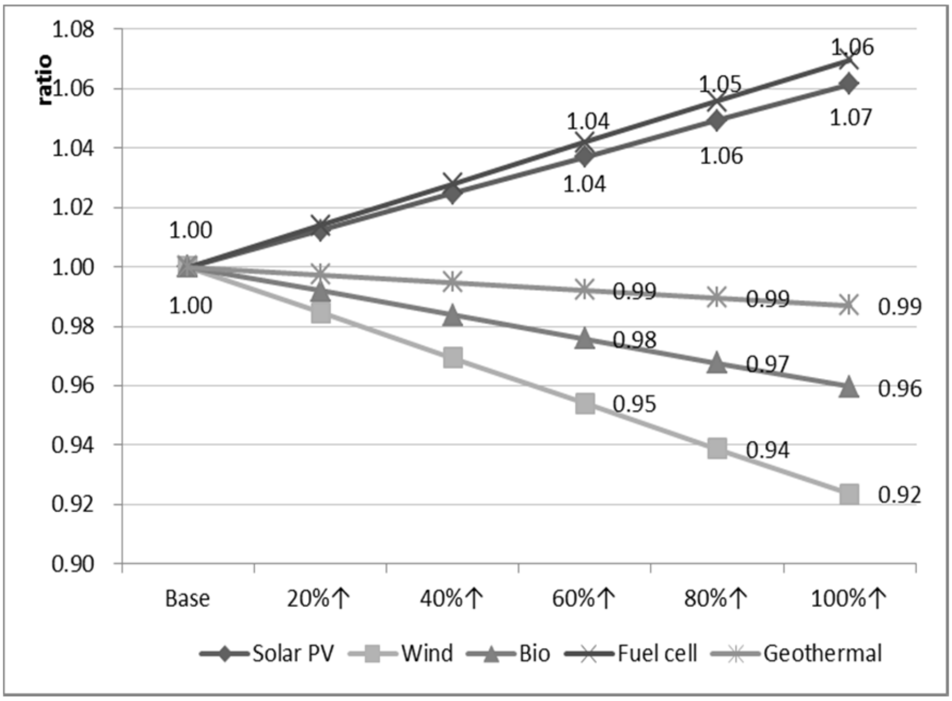


Figure 4-17 Sensitivity analysis of NRE HRD budget ratio

In a second sensitivity analysis, policy ratio in each renewable energy was changed based on 2011-budget ratio. When the budget ratio of each renewable energy resource is fixed, the policy maker can control the ratio of each programs: basic, industry and advanced. Base case assumes the 2011 police ratio as sheen in Table 4-19. Each policy program was increased by 20%, 50%, 100% -20% and -50%. If there is no policy support, HRD budget ratio were increased by 10%, 20%, 30%, 40% and 50%.

Table 4-19 represent the analysis result. Human capital stock reduced by 96%, when increasing the budget of basis level 100%. Human capital stock reduced by 99%, when increasing the budget of basis level 100%. Human capital stock increased by 60% (438,783$), when increasing the budget of basis level 100%. The patterns of human capital accumulation of each case are represented Fig 4-18-4-21.

The result can be used when the purpose of policy is increasing the human capital accumulation with budget ration of each renewable energy is fixed. For example, the geothermal energy have a only a industry labor HRD program in 2011. If the program ratio have changing industry: basic: advanced = 0.54:0.23: 0.23, has the same human capital stock when industry: advanced = 0.7:0.3 without basic level. It is a 98% of the initial level of human capital stock. The results of other energy resources are summarized in Appendix 3.

Table 4-19 Sensitivity analysis of programs of photovoltaic

	Budget ratio in 2011	Basic budget ratio increasing				
		20%	**50%**	**100%**	**-20%**	**-50%**
Basic	0.30	0.36	0.46	0.61	0.24	0.15
Industry	0.09	0.08	0.07	0.05	0.10	0.11
Advanced	0.60	0.55	0.47	0.34	0.66	0.74
Human capital ratio	1.000	0.992	0.979	0.958	1.008	1.021
	Budget ratio in 2011	**Industry budget ratio increasing**				
		20%	**50%**	**100%**	**-20%**	**-50%**
Industry	0.09	0.11	0.14	0.18	0.07	0.05
Basic	0.30	0.30	0.29	0.27	0.31	0.32
Advanced	0.60	0.59	0.57	0.54	0.62	0.64
Human capital ratio	1.000	1.017	1.026	1.043	0.983	0.957
	Budget ratio in 2011	**Advanced budget ratio increasing**				
		20%	**30%**	**50%**	**-20%**	**-50%**
Advanced	0.60	0.73	0.79	0.91	0.48	0.30
Industry	0.09	0.06	0.05	0.02	0.12	0.16
Basic	0.30	0.21	0.16	0.07	0.40	0.54
Human capital ratio	1.000	0.999	0.997	0.994	1.001	1.003

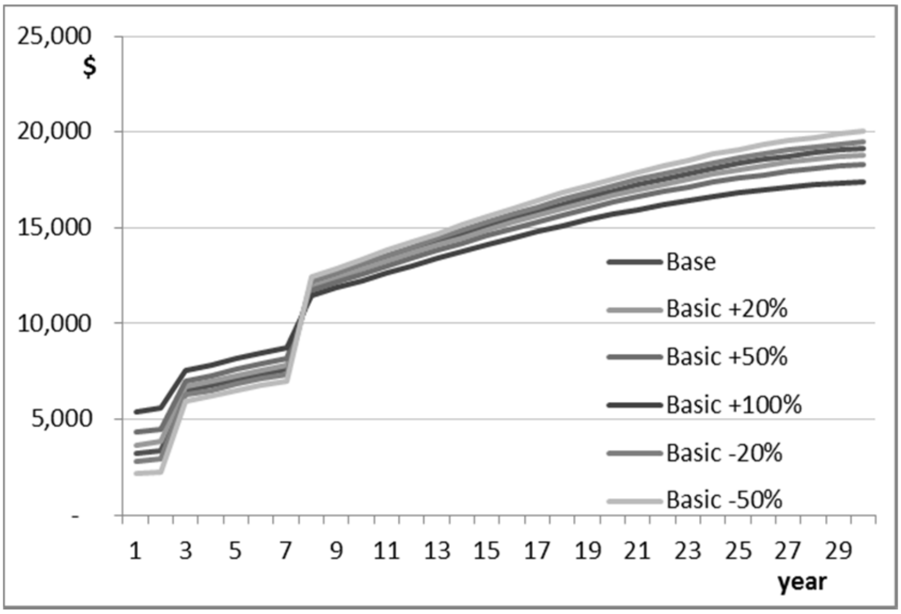


Figure 4-18 Sensitivity analysis of basic HRD ratio on photovoltaic

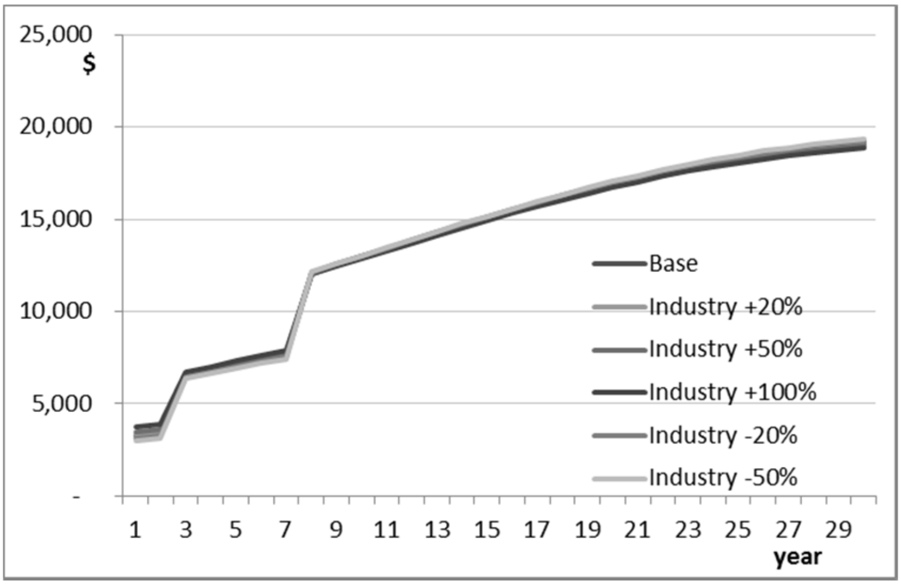


Figure 4-19 Sensitivity analysis of industry HRD ratio on photovoltaic

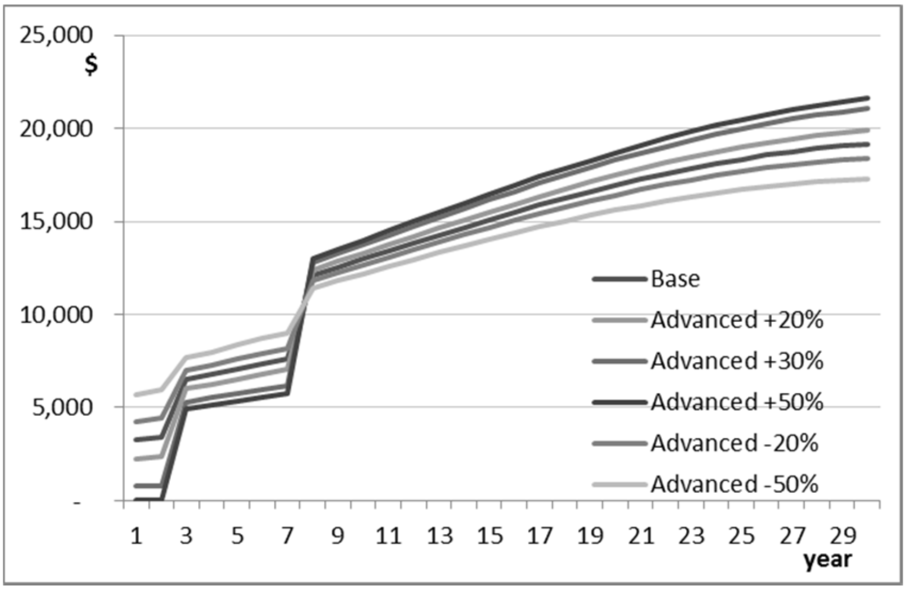


Figure 4-20 Sensitivity analysis of advanced HRD ratio on Photovoltaic

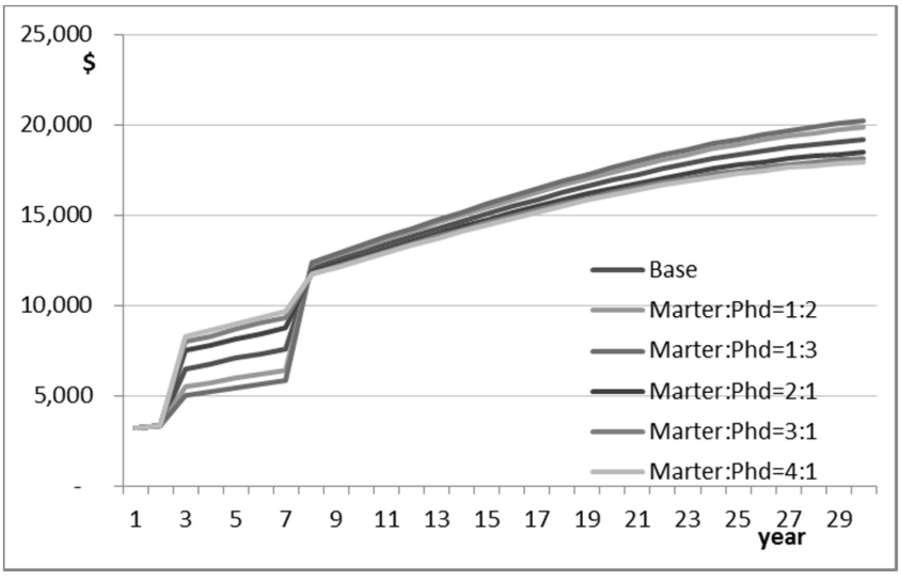


Figure 4-21 Sensitivity analysis of master and PhD support ratio

Finally, regardless of budget ratio in 2011, each policy program were assumed by 10%, 30%, 50%, 70%, 90%. Renewable energy has different pattern by programs (Fig 4-22 – Fig 4-25). When the fuel cell budget increasing to 90%, total human capital stock increase 1.5 times. In contrast, When increasing ratio of geothermal to 90%, total human capital stock decrease to 70% of base case.

These sensitivity analyses prove the applicability the human capital index. It can be applied more broadly to the establishment of HRD plans. it is expected that this study can be utilized for the effective distribution of national resources.

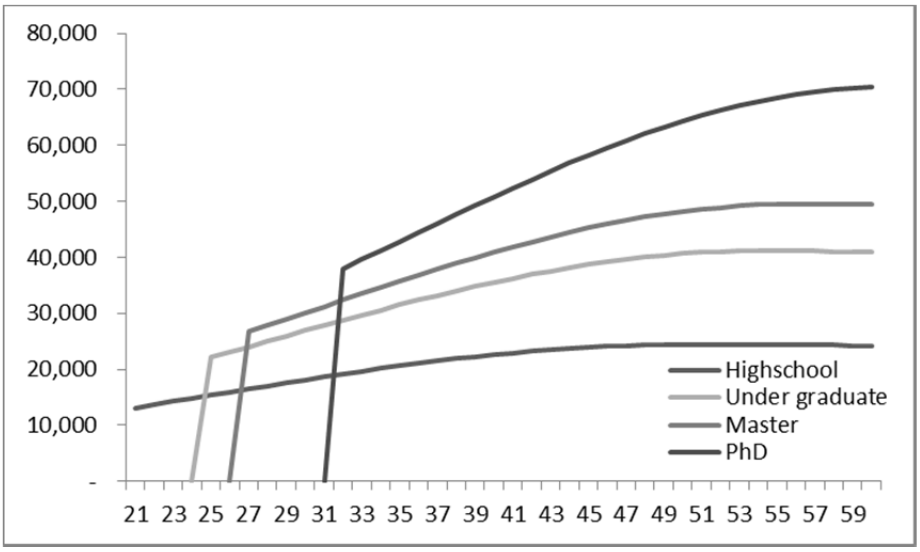


Figure 4-22 Profile of human capital stock of photovoltaic HRD programs

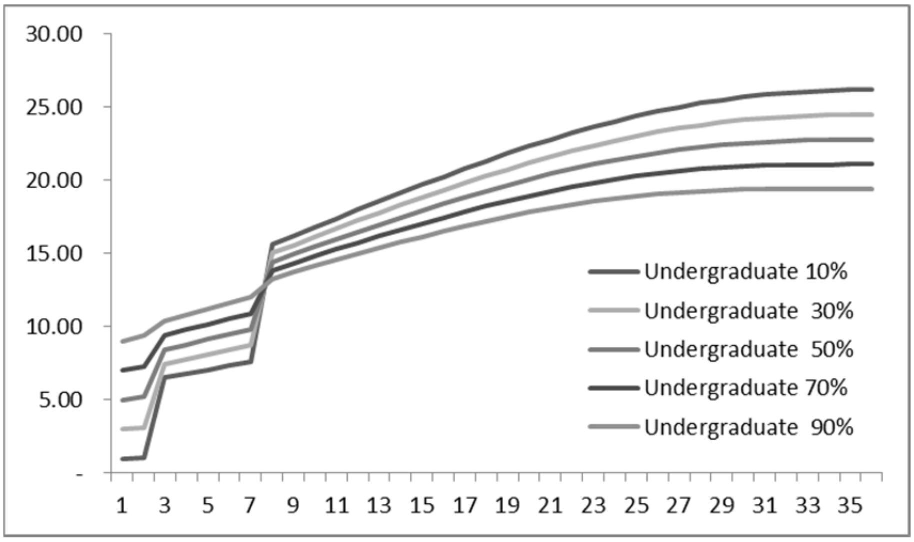


Figure 4-23 Sensitivity analysis of basic labor of photovoltaic HRD

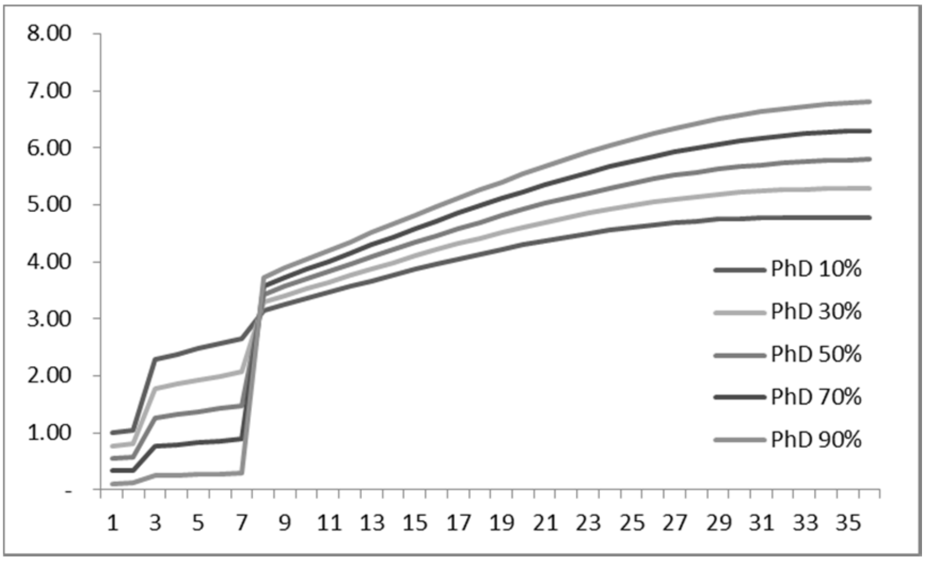


Figure 4-24 Sensitivity analysis of PhD labor of photovoltaic HRD

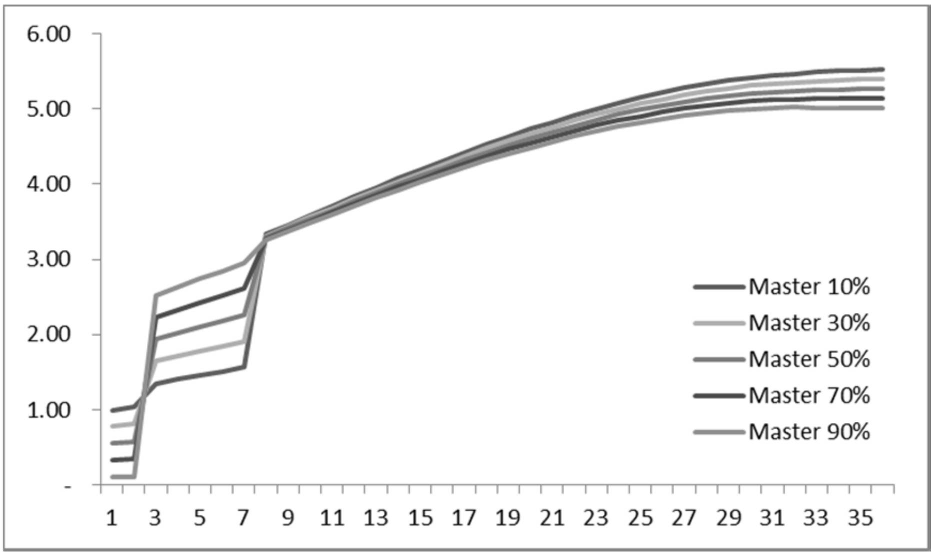


Figure 4-25 Sensitivity analysis of master and PhD support ratio

4.5 Conclusion

This chapter has attempted to quantify the amount of human capital that is accumulated through new and renewable energy industry HRD projects. To this end, the overall new and renewable energy industry was divided into the solar energy, wind energy, fuel cell energy, geothermal energy, and bio energy industries; the efficiency of wage markets in each sub-industry was examined; and the amount of human capital that was accumulated in each sub-industry was determined. Moreover, the efficacy of HRD policy was evaluated by quantifying the theoretical operation principles and human capital accumulations of basic HRD, industrial HRD, and advanced HRD.

The results of the analyses can be described as follows: First, human capital that is accumulated in different renewable energy industries varies. Of five popular energy sources, the fuel cell energy industry was shown to accumulate the greatest amount of human capital. The wind energy industry was demonstrated to accumulate the least amount. These deviations exist because there are differences in earning rates based on school-generated knowledge and on-the-job generated knowledge. Those industries that evaluate school knowledge more positively tend to accumulate higher levels of human capital. This difference affects the degree to which human capital can be accumulated through each particular HRD initiative.

Second, the three HRD policies operate on the basis of different methods for decision making. This suggests that three distinct policy portfolios are needed. This analysis has shown that individual decision making related to education was based on factors that are salient throughout one’s entire life. Applying to a school, for example, is affected by perceptions of direct costs of attendance and expected returns post-graduation.

In educating industrial-based human resources, policy design is important because the rate at which expenses are transferred to an individual or a company varies based on the character of the education. Third, in the case of advanced HRD, the positive effect of technological innovation is not being considered by individuals in their decisions to attend graduate school. Given this, the government should select an appropriate method for designing an HRD projects.

Finally, the respective wage markets of each new and renewable energy industry are operating efficiently. In other words, wage increases were shown to occur in parallel with increases in education or job experience. Related to this, as workers age, the speed with which wages increase is reduced. In the geothermal energy industry, however, there was no significant relationship between education level and wage growth. Communicating the (general) efficiency of the wage market in the new and renewable energy industry may induce individuals to invest more in their education in response to the implementation of HRD policy.

Chapter 5 Conclusion

5.1 Summary

The broader concept of human capital includes all the knowledge and production capability embodied in an individual. As the industrial society is transforming into a knowledge-based one, the acquisition and utilization of human capital, which is intangible property, is increasingly being emphasized. A number of studies on the endogenous growth model, including Romer (1986) and Lucas (1988), have shown that human capital plays a key role in economic growth. These studies have become the foundations for the implementation of human resource development and research & development projects by the government.

However, studies that quantify human capital are not sufficient because human capital has characteristics unlike those of tangible assets; it is not tangible, but is inherent in an individual and, therefore, not tradable. Further, as a factor of input in production, returns on investment on human capital vary depending on production technologies. Thus, the indices of level of education, wages, and total cost of education have been used as indirect means for estimating human capital until now. Therefore, research on analytical methods is required, which can quantify the stock and accumulation mechanism of human capital.

The ultimate aim of this thesis is to conduct quantitative analysis of human capital accumulation. To achieve the goal, the quantification method is settled. In addition, two empirical analyses are carried out using the method.

First, to examine the theoretical context, I analyzed how human capital was adapted in various fields of research such as growth models, wage disparities, human capital policies, and R&D investment. I proposed a framework that enables quantifying the outcome of investment activities throughout the life of an individual as accumulation of human capital. I proposed a framework that enables quantifying the outcome of investment activities throughout the life of an individual as accumulation of human capital. Features are based on a comprehensive examination from Mincer’s (1974) early model. This model is then leveraged to quantitatively determine human capital accumulation of the industry.

- **Effect of R&D on human capital accumulation**

Fist empirical analysis examined the effects of accumulation of human capital in accordance with R&D investment. R&D and human capital have been recognized as key factors in the growth of a nation in the knowledge-based industry and have been considered in the growth models of Lucas (1992) and Scicchitano (2010). Lately, the extent of the research has become narrower as it focuses on mutual interactions between the two factors. In this thesis, the focus was on the effects of human capital in accordance with R&D investment. In this regard, I classified Korean manufacturing industries into three categories in accordance with their R&D intensity—high-, medium-, and low-tech—and analyzed the mechanisms of accumulation of human capital of each group.

The result of examine the effect of R&D on human capital analsyis are summarized in the following three aspects: First, the earning rates for human capital investment in each industry were found to be different, depending on the amount of R&D investment. The earning rate of human capital in the high and medium-high technology industries, whose R&D intensity was the highest, was 6.7%, the highest among the three industries. This clearly reflects enhanced production efficiency arising from technology innovation. However, the earning rate of human capital in low-technology industry, whose amount of R&D investment was the lowest, was 6.5%, which is also relatively high. This result may mean that while low-technology industry by nature requires less R&D investment, its knowledge delivery system is highly efficient as is.

Second, the analysis shows that learning by doing and R&D are complementary to each other. Out of the total amount of personal human capital, the percentage of investment for the increase in future human capital is 30.1% in the medium-low technology industry and 19.4% in the low-technology industry, both of which are a lot higher than that of the high and medium-high technology industries (10.8%). As such a difference in investment rates is reflected in the wages, the wage of the medium-low technology industry is lower than that of the high and medium-high technology industries in the early stage, but it becomes higher as the career period increases. The total amount of investment into human capital for 30 years was smallest in the high and medium-high technology industry ($84,382). In short, the results indicate that learning by doing and R&D are in a complementary relation.

Third, it also turned out that the amount of initial human capital for the advancement into each industry was also different among industries. High and medium-high technology industry and inter-industry, whose R&D investment was high, required a higher amount of initial human capital of those with relatively little experience than did the low-technology industry. Industries that require a higher level of investment into R&D are all highly advanced businesses, in which expertise is necessary for production activity as well as R&D.

- **Human capital accumulation mechanism through NRE HRD**

Second empirical analysis quantified the accumulation of human capital of renewable energy and the possibility of utilizing the quantification as an index for human resource development programs. The government's project for human resource development support started from its recognition that individuals were not reaching optimal levels of investment because they tend to underestimate the benefits of investment in education. In particular, when there is considerable uncertainty regarding the growth prospects of an industry such as renewable energy, an individual's investment in education becomes limited. Therefore, in planning for the human resource development project, not just individuals who have invested in specialized training, but also the accumulation of human capital innate in each individual should be considered. Accordingly, I analyze the accumulation of inherent human capital development in accordance with human resource development project for renewable energy that has been being implemented in Korea. I classified the energy sources into wind power, bio, fuel cell, and geothermal and then analyzed them.

The results of analysis can be described as follows: First, human capital that is accumulated in different renewable energy industries varies. Of five popular energy sources, the fuel cell energy industry was shown to accumulate the greatest amount of human capital. The wind energy industry was demonstrated to accumulate the least amount. These deviations exist because there are differences in earning rates based on school-generated knowledge and on-the-job generated knowledge. Those industries that evaluate school knowledge more positively tend to accumulate higher levels of human capital. This difference affects the degree to which human capital can be accumulated through each particular HRD initiative.

Second, the three HRD policies operate on the basis of different methods for decision making. This suggests that three distinct policy portfolios are needed. This thesis has shown that individual decision making related to education was based on factors that are salient throughout one's entire life. Applying to a school, for example, is affected by perceptions of direct costs of attendance and expected returns post-graduation. In educating industrial-based human resources, policy design is important because the rate at which expenses are transferred to an individual or a company varies based on the character of the education. Third, in the case of advanced HRD, the positive effect of technological innovation is not being considered by individuals in their decisions to attend graduate school. Given this, the government should select an appropriate method for designing an HRD projects.

Finally, the respective wage markets of each new and renewable energy industry are operating efficiently. In other words, wage increases were shown to occur in parallel with increases in education or job experience. Related to this, as workers age, the speed with which wages increase is reduced. In the geothermal energy industry, however, there was no significant relationship between education level and wage growth. Communicating the (general) efficiency of the wage market in the new and renewable energy industry may induce individuals to invest more in their education in response to the implementation of HRD policy.

5.2 Implications

The implications of this thesis based on the aforementioned outcomes of the study can be summarized as follow:

First, this study contributes theoretically to the methodology of quantification analysis of human capital by proposing an analytical framework that can quantify human capital by considering investment made throughout the life of an individual. It shows that the method can reflect heterogeneous characteristics of each industry and the level of academic education by supplementing the quotient approach, which is based on the premise that all human resources are homogeneous. It has the advantage of analyzing accumulation of human capital at a national level as well as at the industry and company level.

Second, this study empirically proves that the accumulation of human capital is affected by R&D. It is meaningful that the theory of Mathur (1999) that investment in R&D can enhance returns on human capital was empirically demonstrated. It showed that the opposite relationship of the general theory that human capital of high quality can enhance the performance of R&D can be established.

Third, this study is the first study that analyzed the wage structure system of the renewable energy industry and the accumulation of human capital associated with it. As the domestic renewable energy industry is still in the infancy stage and its association with established industries is very high, separate studies on the labor market are insufficient. Moreover, in the current situation, the identification of related academic major (field of study) for each renewable energy source has not been established in a context where one-on-one matching of the academic major of the university and the industry is unfeasible. In this study, related majors for the renewable energy industry were arranged based on related data and by referencing the literature of the Korea Energy Economics Institute (2013). In the future, this study can become a benchmark for analyzing the labor market of the domestic renewable energy industry.

Forth, this study suggested an additional index that can be applied in the plan for human resource development policy of the government. Although the government plan must be implemented based on an index that can reflect the properties of each program, until now, the plan for the human resource development project has just included the basic purpose of balancing supply and demand. The method of analyzing human capital proposed in this study can express the effect of the policy in the long term by quantifying the amount of human capital inherent in each individual by industry and by the level of policy. This method suggested in this thesis can be applied usefully to the establishment of plans such as human resource development projects or R&D projects across different industries.

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Appendix

- **Appendix 1 Related industry of NRE industry**
- **Appendix 2 Sensitivity analysis of renewable energy budget ratio changing**
- **Appendix 3 Sensitivity analysis of programs based on budget ratio in 2011**
- **Appendix 4 Sensitivity analysis of programs regardless of budget ratio in 2011**

Appendix 1 Related industry of NRE industry

Table A. 1 Photovoltaic

KSIC-9	KSIC-8	
20	24	Manufacture of chemicals and chemical products
201	241	Manufacture of basic chemicals
22	25	Manufacture of rubber and plastics products
222	252	Manufacture of plastics products
221	251	Manufacture of rubber products
23	26	Manufacture of other non-metallic mineral products
231	261	Manufacture of glass and glass products
239	269	Manufacture of non-metallic mineral products n.e.c.
24	27	Manufacture of basic metals
242	272	Manufacture of basic precious and non-ferrous metals
243	273	Casting of metals
25	28	Manufacture of fabricated metal products,, except machinery and equipment
251	281	Manufacture of structural metal products, tanks, reservoirs and steam generators
259	289	Manufacture of other fabricated metal products; metal working service activities

KSIC-9	KSIC-8	
26	32	Manufacture of radio, television and communication equipment and apparatus
261	321	Manufacture of electronic valves and tubes and other electronic components
262	321	Manufacture of electronic valves and tubes and other electronic components
27	33	Manufacture of medical, precision and optical instruments, watches and clocks
273	333	Manufacture of watches and clocks
28	31	Manufacture of electrical machinery and apparatus n.e.c.
281	311	Manufacture of electric motors, generators and transformers
282	314	Manufacture of accumulators, primary cells and primary batteries
29	29	Manufacture of machinery and equipment n.e.c.
292	293	Manufacture of domestic appliances n.e.c.
41	45	Construction
412	451	Site preparation
42	46	Construction
421	461	Building of complete constructions or parts thereof; civil engineering
423	463	Building installation
424	464	Building completion

Table A. 2 Wind

KSIC-9	KSIC-8	
22	25	Manufacture of rubber and plastics products
222	252	Manufacture of plastics products
25	28	Manufacture of fabricated metal products, except machinery and equipment
251	281	Manufacture of structural metal products, tanks, reservoirs and steam generators
259	289	Manufacture of other fabricated metal products; metal working service activities
27	33	Manufacture of medical, precision and optical instruments, watches and clocks
272	332	Manufacture of optical instruments and photographic equipment
28	31	Manufacture of electrical machinery and apparatus n.e.c.
281	311	Manufacture of electric motors, generators and transformers
282	314	Manufacture of accumulators, primary cells and primary batteries
283	313	Manufacture of insulated wire and cable
289	319	Manufacture of other electrical equipment n.e.c.
29	29	Manufacture of machinery and equipment n.e.c.
291	291	Manufacture of general purpose machinery
42	46	Construction
421	461	Building of complete constructions or parts thereof; civil engineering
423	463	Building installation
72	74	Other business activities
721	743	Architectural, engineering and other technical activities

Table A. 3 Bio energy

KSIC-9	KSIC-8	
1	1	Agriculture, hunting and related service activities
11	11	Growing of crops; market gardening; horticulture
3	5	Fishing, operation of fish hatcheries and fish farms; service activities incidental to fishing
32	52	Fishing, operation of fish hatcheries and fish farms; service activities incidental to fishing
16	20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
162	202	Manufacture of products of wood, cork, straw and plaiting materials
19	23	Manufacture of coke, refined petroleum products and nuclear fuel
192	232	Manufacture of refined petroleum products
20	24	Manufacture of chemicals and chemical products
201	241	Manufacture of basic chemicals
21	24	Manufacture of chemicals and chemical products
211	242	Manufacture of other chemical products
23	26	Manufacture of other non-metallic mineral products
232	262	Manufacture of non-metallic mineral products n.e.c.

KSIC-9	KSIC-8	
25	28	Manufacture of fabricated metal products, except machinery and equipment
251	281	Manufacture of structural metal products, tanks, reservoirs and steam generators
28	31	Manufacture of electrical machinery and apparatus n.e.c.
281	311	Manufacture of electric motors, generators and transformers
29	29	Manufacture of machinery and equipment n.e.c.
291	291	Manufacture of general purpose machinery
292	293	Manufacture of domestic appliances n.e.c.
35	40	Electricity, gas, steam and hot water supply
352	402	Manufacture of gas; distribution of gaseous fuels through mains
38	90	Sewage and refuse disposal, sanitation and similar activities
381	902	Sewage and refuse disposal, sanitation and similar activities
39	74	Other business activities
390	743	Architectural, engineering and other technical activities
41	45	Construction
412	451	Building of complete constructions or parts thereof; civil engineering

Table A. 4 Fuel cell

KSIC-9	KSIC-8	
20	24	Manufacture of chemicals and chemical products
201	241	Manufacture of basic chemicals
203	241	Manufacture of basic chemicals
204	243	Manufacture of man-made fibers
22	25	Manufacture of rubber and plastics products
221	251	Manufacture of rubber products
222	252	Manufacture of plastics products
28	31	Manufacture of electrical machinery and apparatus n.e.c.
281	311	Manufacture of electric motors, generators and transformers
289	319	Manufacture of other electrical equipment n.e.c.
29	29	Manufacture of machinery and equipment n.e.c.
291	291	Manufacture of general purpose machinery
292	292	Manufacture of special purpose machinery
30	34	Manufacture of motor vehicles, trailers and semi-trailers
301	341	Manufacture of motor vehicles
42	46	Construction
421	461	Building of complete constructions or parts thereof; civil engineering
422	462	Building installation
423	463	Building installation

Table A. 5 Geothermal

KSIC-9	KSIC-8	
22	25	Manufacture of rubber and plastics products
222	252	Manufacture of plastics products
25	28	Manufacture of fabricated metal products, except machinery and equipment
251	281	Manufacture of structural metal products, tanks, reservoirs and steam generators
27	33	Manufacture of medical, precision and optical instruments, watches and clocks
272	332	Manufacture of optical instruments and photographic equipment
28	31	Manufacture of electrical machinery and apparatus n.e.c.
281	311	Manufacture of electric motors, generators and transformers
29	29	Manufacture of machinery and equipment n.e.c.
291	291	Manufacture of general purpose machinery
42	46	Construction
421	461	Building of complete constructions or parts thereof; civil engineering
422	462	Building of complete constructions or parts thereof; civil engineering

Appendix 2 Sensitivity analysis of renewable energy budget ratio changing

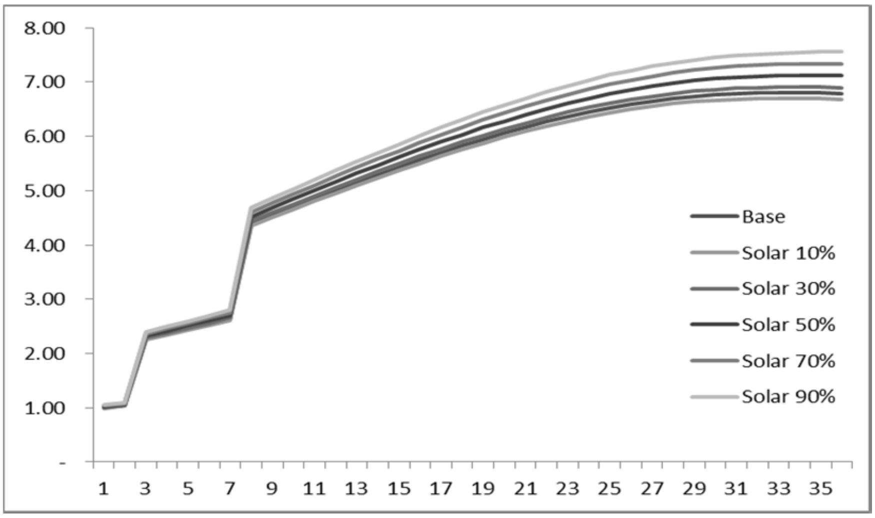

Figure A. 1 Changing renewable energy budget ratio based on photovoltaic

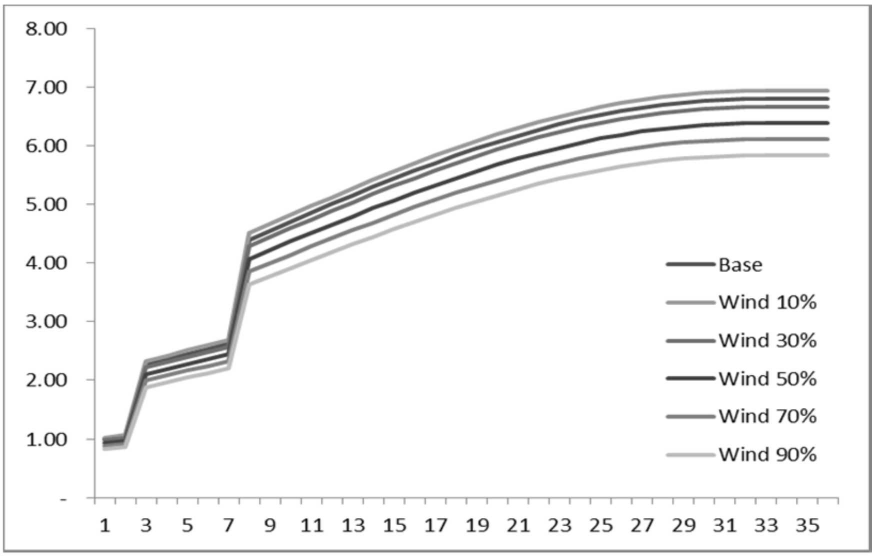

Figure A. 2 Changing renewable energy budget ratio based on wind

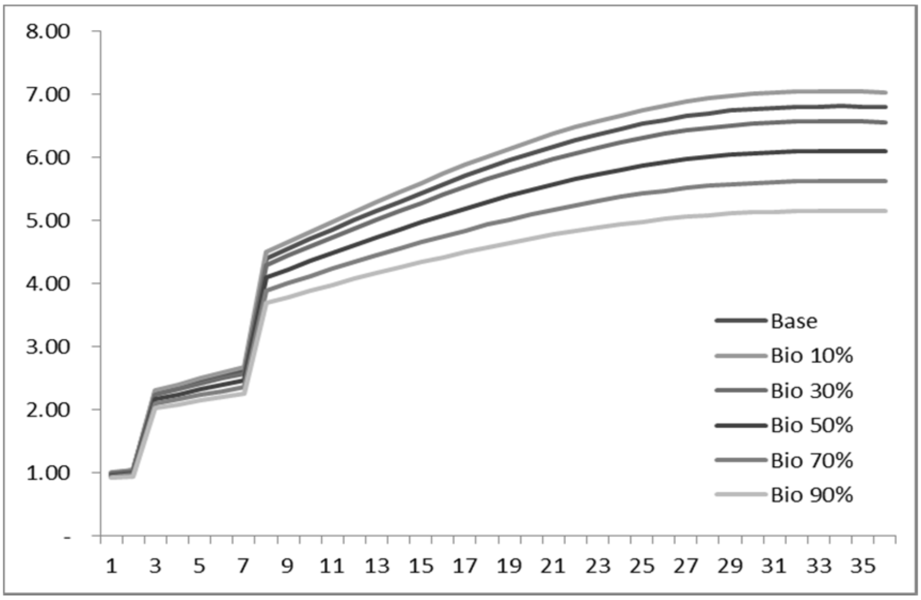

Figure A. 3 Changing renewable energy budget ratio based on bioenergy

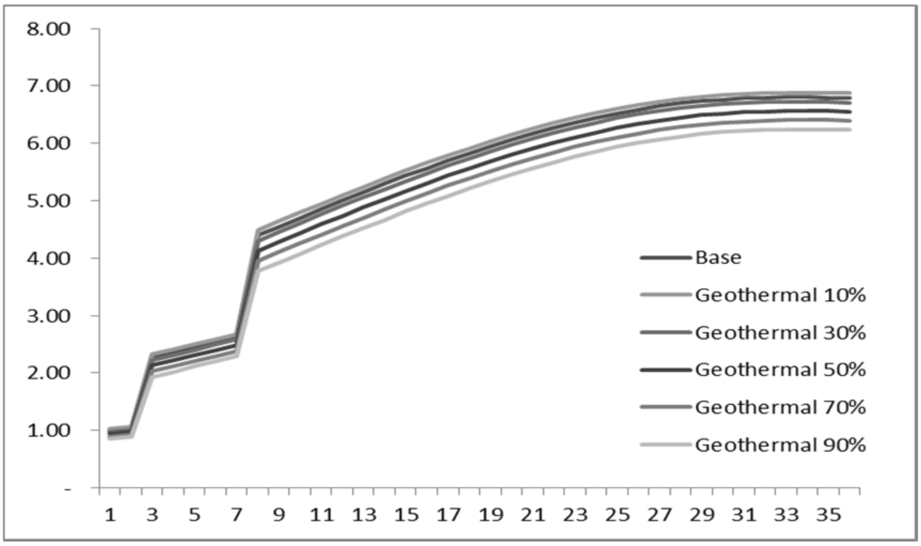

Figure A. 4 Changing renewable energy budget ratio based on geothermal

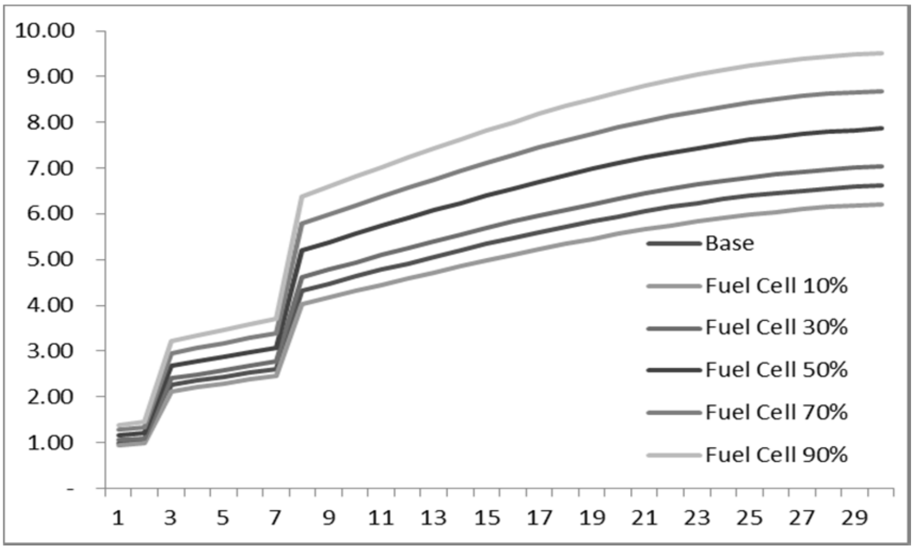

Figure A. 5 Changing renewable energy budget ratio based on fuel cell

Appendix 3 Sensitivity analysis of programs based on budget ratio in 2011

Table A. 6 Sensitivity analysis of each program of wind

	Budget ratio 2011	Basic budget ratio increasing				
		20%	50%	100%	-20%	-50%
Basic	0.07	0.09	0.11	0.15	0.06	0.04
Industry	0.00	0.00	0.00	0.00	0.00	0.00
Advanced	0.93	0.91	0.89	0.85	0.94	0.96
Human capital ratio	1.000	0.998	0.996	0.992	1.002	1.004
	Basis case	Industry budget ratio increasing				
		20%	30%	40%	50%	60%
Industry	0.10	0.20	0.30	0.40	0.50	0.60
Basic	0.07	0.06	0.05	0.05	0.04	0.03
Advanced	0.83	0.74	0.65	0.55	0.46	0.37
Human capital ratio	0.993	0.987	0.980	0.974	0.968	0.961
	Budget ratio 2011	Advanced budget ratio increasing				
		-10%	-20%	-30%	-40%	-50%
Advanced	0.93	0.83	0.74	0.65	0.56	0.46
Industry	0.00	0.00	0.00	0.00	0.00	0.00
Basic	0.07	0.17	0.26	0.35	0.44	0.54
Human capital ratio	1.000	0.990	0.980	0.970	0.960	0.950

Table A. 7 Sensitivity analysis of each program of bio energy

	Basis case	Basic budget ratio increasing				
		20%	40%	60%	80%	100%
Basic	0.10	0.20	0.30	0.40	0.50	0.60
Industry	0.67	0.54	0.47	0.40	0.34	0.27
Advanced	0.33	0.26	0.23	0.20	0.17	0.13
Human capital ratio	1.096	0.992	0.988	0.984	0.980	0.976
	Budget ratio in 2011	**Industry budget ratio increasing**				
		20%	**-20%**	**-30%**	**-40%**	**-60%**
Industry	0.67	0.80	0.54	0.47	0.40	0.27
Basic	0.00	0.00	0.00	0.00	0.00	0.00
Advanced	0.33	0.20	0.46	0.53	0.60	0.73
Human capital ratio	1.000	0.995	1.005	1.007	1.009	1.014
	Budget ratio in 2011	**Advanced budget ratio increasing**				
		20%	**50%**	**100%**	**-20%**	**-50%**
Advanced	0.33	0.40	0.50	0.66	0.26	0.20
Industry	0.67	0.60	0.51	0.34	0.74	0.80
Basic	0.00	0.00	0.00	0.00	0.00	0.00
Human capital ratio	1.000	1.002	1.006	1.011	0.998	0.996

Table A. 8 Sensitivity analysis of each program of fuel cell

	Basis case	Basic budget ratio increasing				
		20%	**30%**	**40%**	**50%**	**60%**
Basic	0.10	0.20	0.30	0.40	0.50	0.60
Industry	0.00	0.00	0.00	0.00	0.00	0.00
Advanced	0.90	0.80	0.70	0.60	0.50	0.40
Human capital ratio	0.980	0.960	0.940	0.921	0.901	0.881
	Basis case	**Industry budget ratio increasing**				
		20%	**30%**	**40%**	**50%**	**60%**
Industry	0.10	0.20	0.30	0.40	0.50	0.60
Basic	0.00	0.00	0.00	0.00	0.00	0.00
Advanced	0.90	0.80	0.70	0.60	0.50	0.40
Human capital ratio	0.985	0.969	0.954	0.938	0.923	0.907
	Basis case	**Advanced budget ratio increasing**				
		-20%	**-40%**	**-50%**	**-80%**	**-90%**
Advanced	0.90	0.72	0.54	0.36	0.18	0.09
Industry	0.05	0.14	0.23	0.32	0.41	0.46
Basic	0.05	0.14	0.23	0.32	0.41	0.46
Human capital ratio	0.982	0.951	0.919	0.887	0.855	0.839

Table A. 9 Sensitivity analysis of each program of geothermal

	Basis case	Basic budget ratio increasing				
		20%	**30%**	**40%**	**50%**	**60%**
Basic	0.1	0.2	0.3	0.4	0.5	0.6
Industry	0.90	0.80	0.70	0.60	0.50	0.40
Advanced	0.00	0.00	0.00	0.00	0.00	0.00
Human capital ratio	0.998	0.995	0.993	0.991	0.988	0.986
	Basis case	**Industry budget ratio increasing**				
		-20%	**-40%**	**-50%**	**-80%**	**-90%**
Industry	0.90	0.72	0.54	0.36	0.18	0.09
Basic	0.05	0.14	0.23	0.32	0.41	0.46
Advanced	0.05	0.14	0.23	0.32	0.41	0.46
Human capital ratio	0.996	0.988	0.980	0.973	0.965	0.961
	Basis case	**Advanced budget ratio increasing**				
		20%	**30%**	**40%**	**50%**	**60%**
Advanced	0.10	0.20	0.30	0.40	0.50	0.60
Industry	0.90	0.80	0.70	0.60	0.50	0.40
Basic	0.00	0.00	0.00	0.00	0.00	0.00
Human capital ratio	0.994	0.988	0.982	0.975	0.969	0.963

Appendix 4 Sensitivity analysis of programs regardless of budget ratio in 2011

- **Sensitivity analysis on wind**

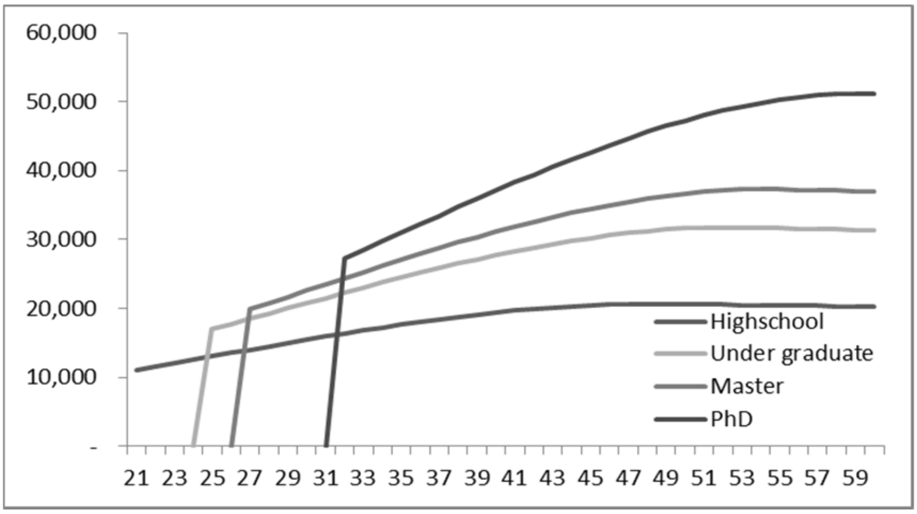

Figure A. 6 Profile of human capital stock of wind HRD programs

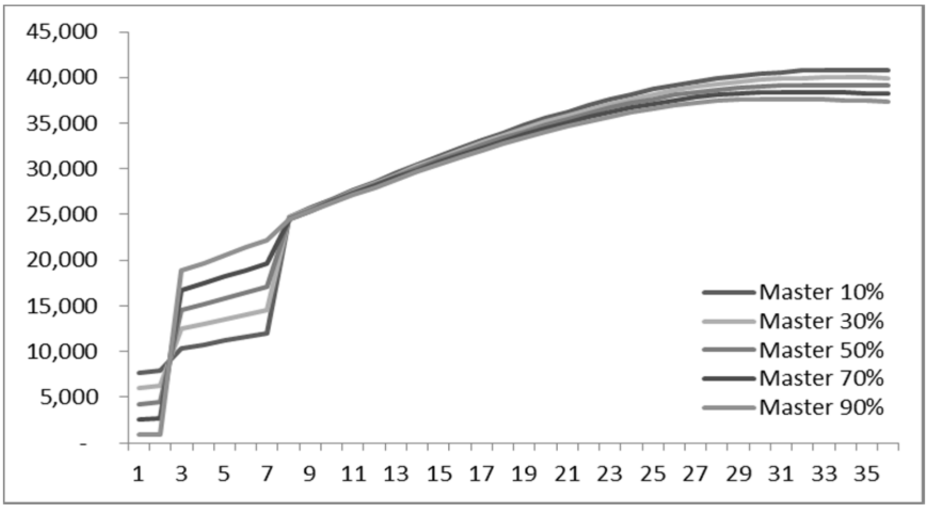

Figure A. 7 Sensitivity analysis of master labor of wind HRD

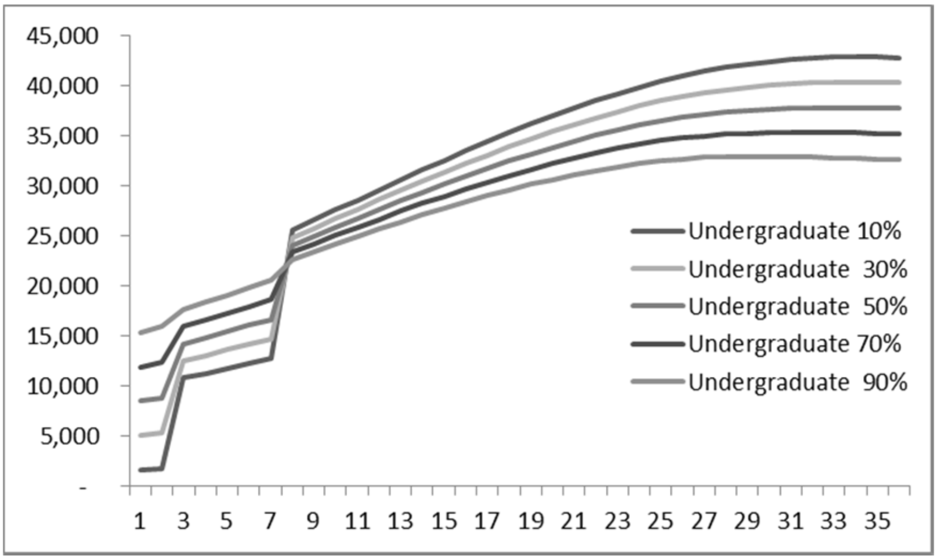

Figure A. 8 Sensitivity analysis of basic labor of wind HRD

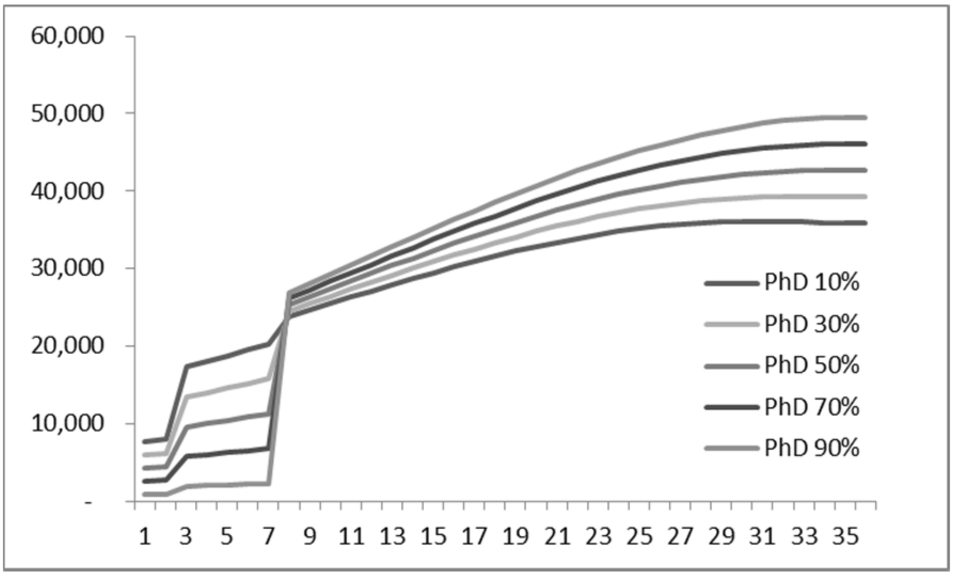

Figure A. 9 Sensitivity analysis of PhD labor of wind HRD

- **Sensitivity analysis on bio energy**

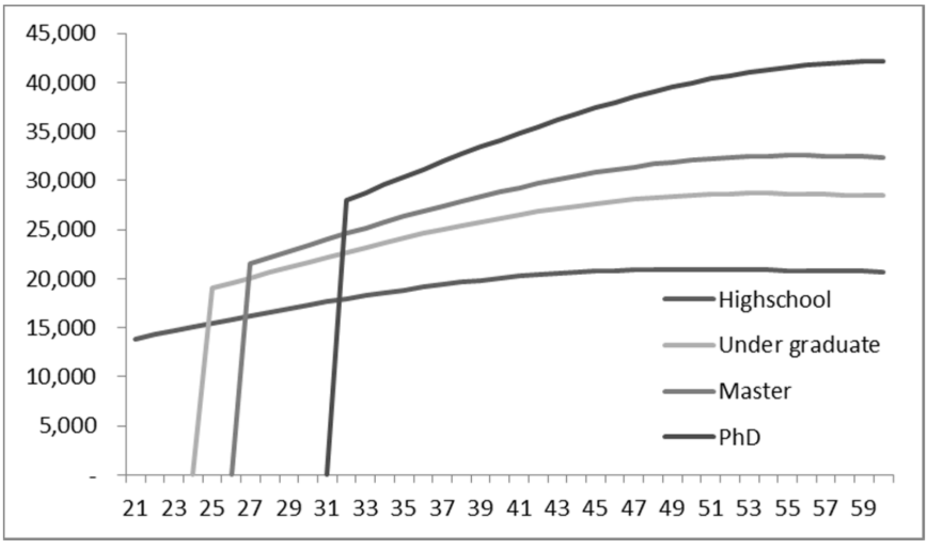

Figure A. 10 Profile of human capital stock of bio HRD

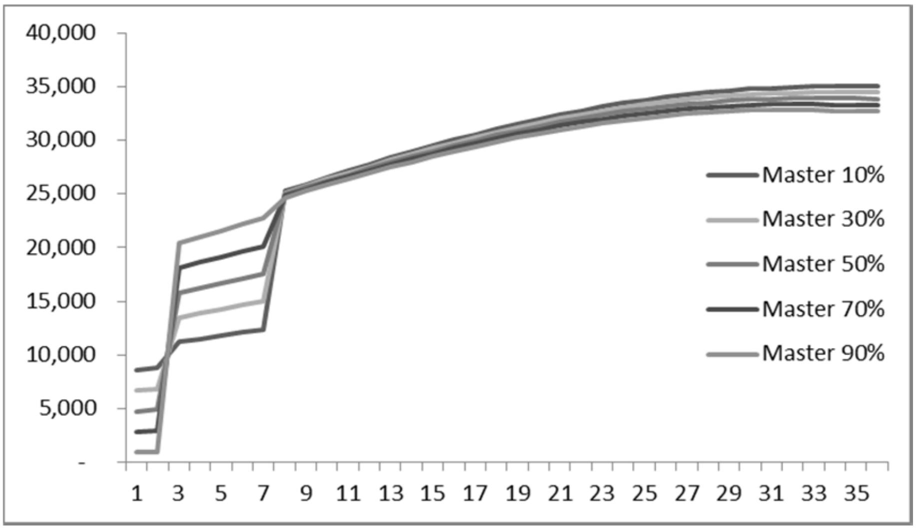

Figure A. 11 Sensitivity analysis of Master labor of bio energy HRD

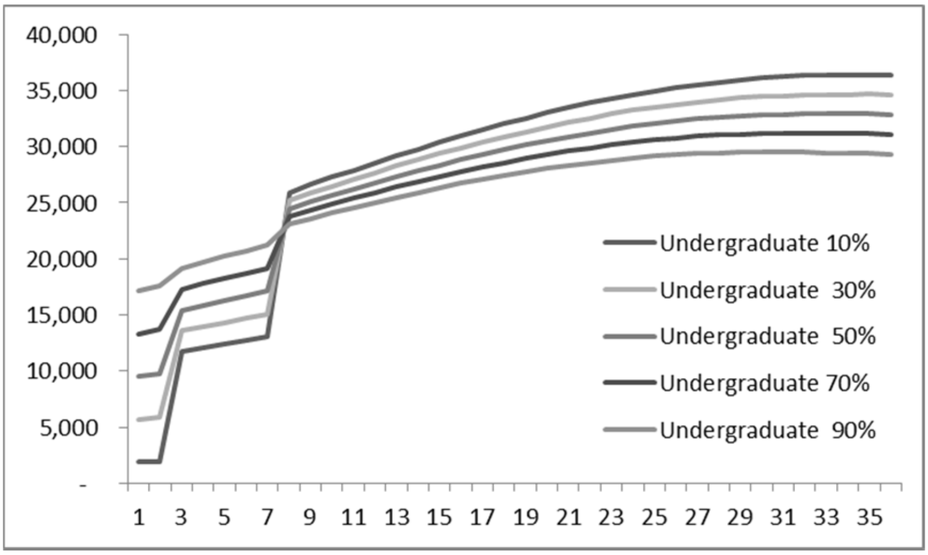

Figure A. 12 Sensitivity analysis of basic labor of bio energy HRD

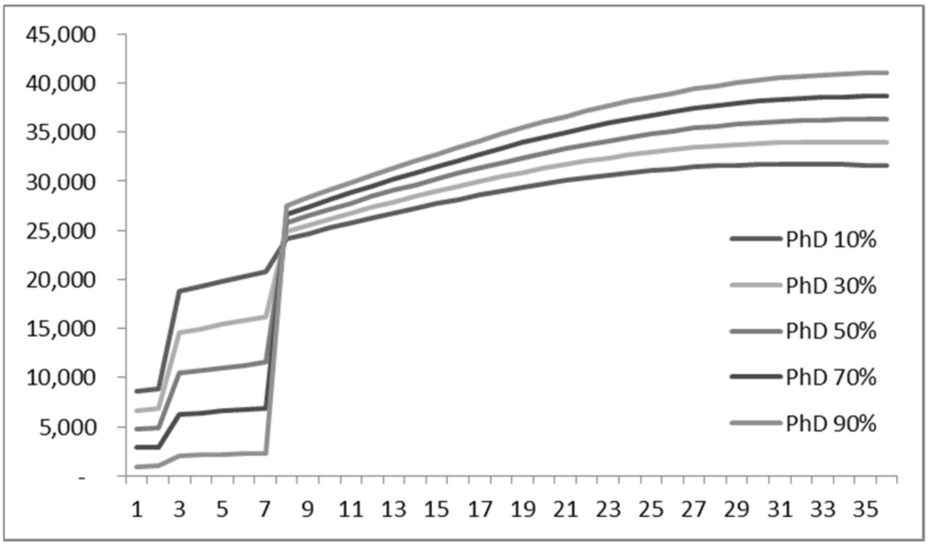

Figure A. 13 Sensitivity analysis of PhD labor of bio energy HRD

- **Sensitivity analysis on geothermal energy**

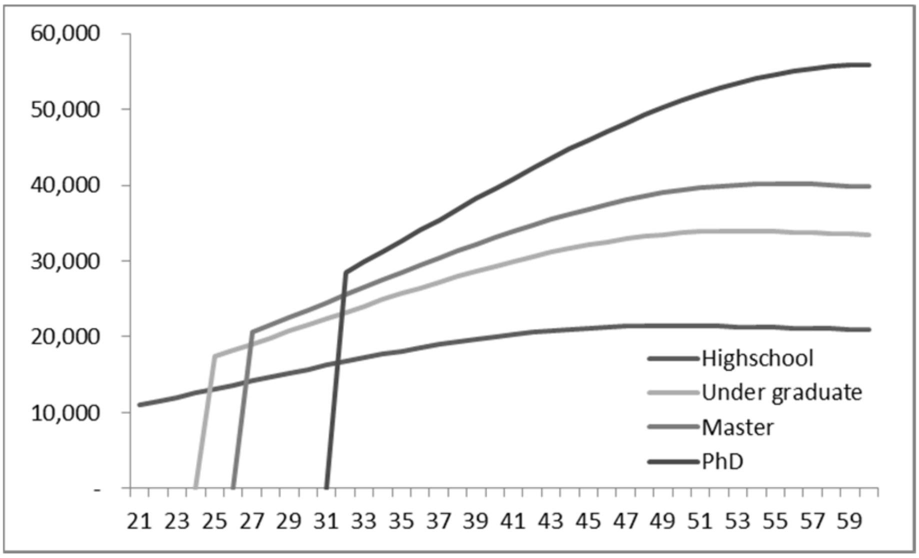

Figure A. 14 Profile of human capital stock of geothermal HRD programs

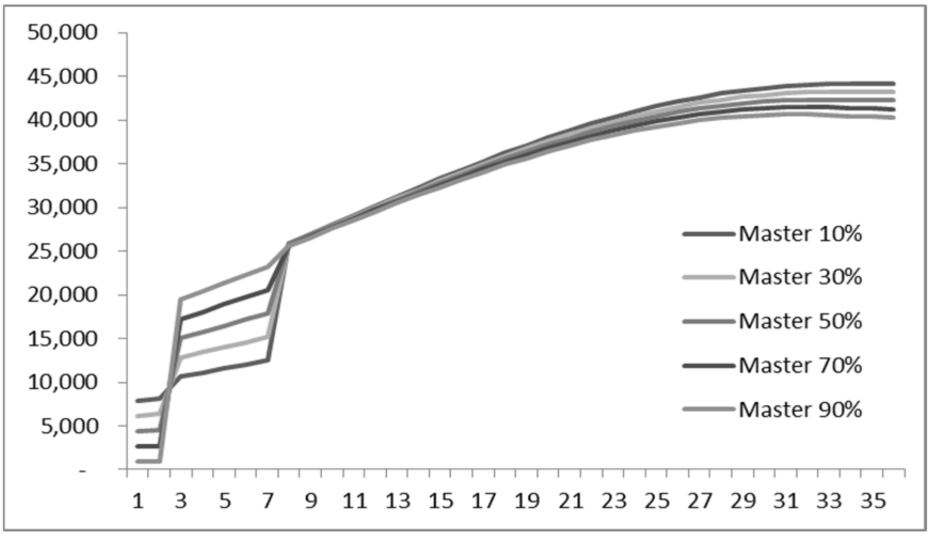

Figure A. 15 Sensitivity analysis of master labor of geothermal HRD

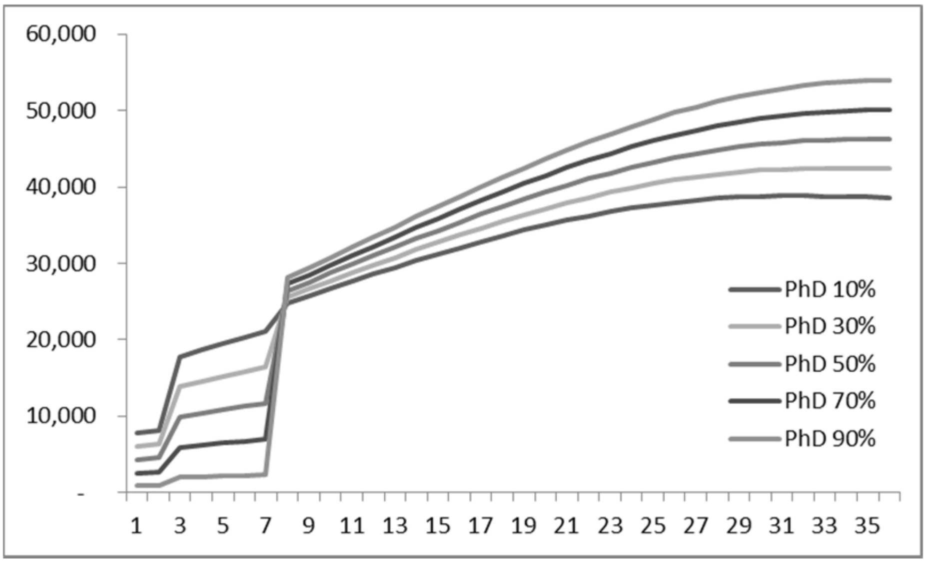

Figure A. 16 Sensitivity analysis of PhD labor of geothermal energy HRD

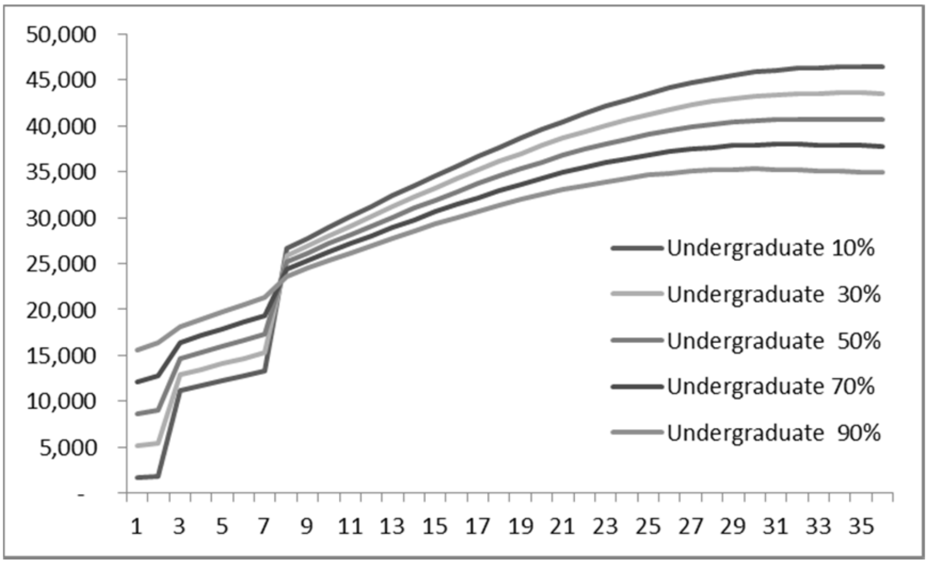

Figure A. 17 Sensitivity analysis of basic labor of geothermal energy HRD

- **Sensitivity analysis on fuel cell**

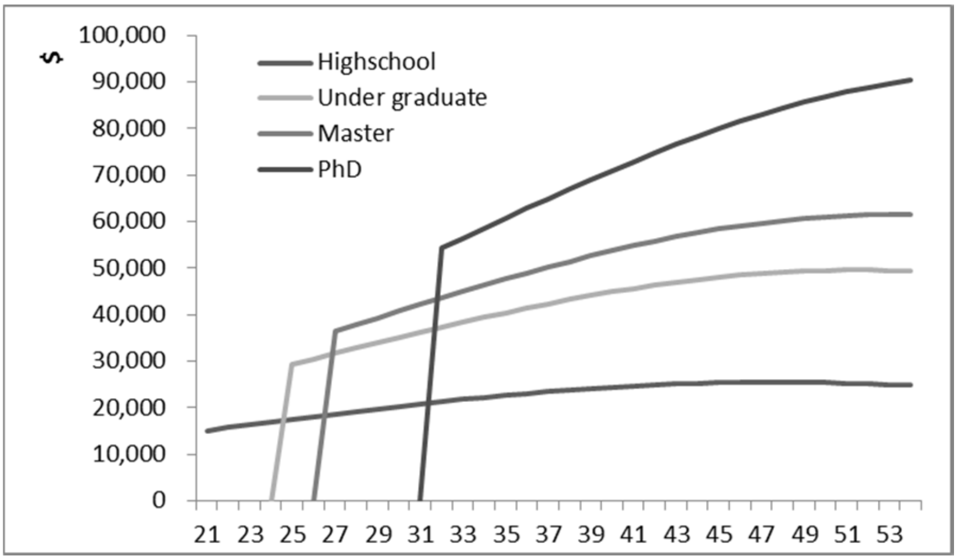

Figure A. 18 Profile of human capital stock of fuel cell HRD programs

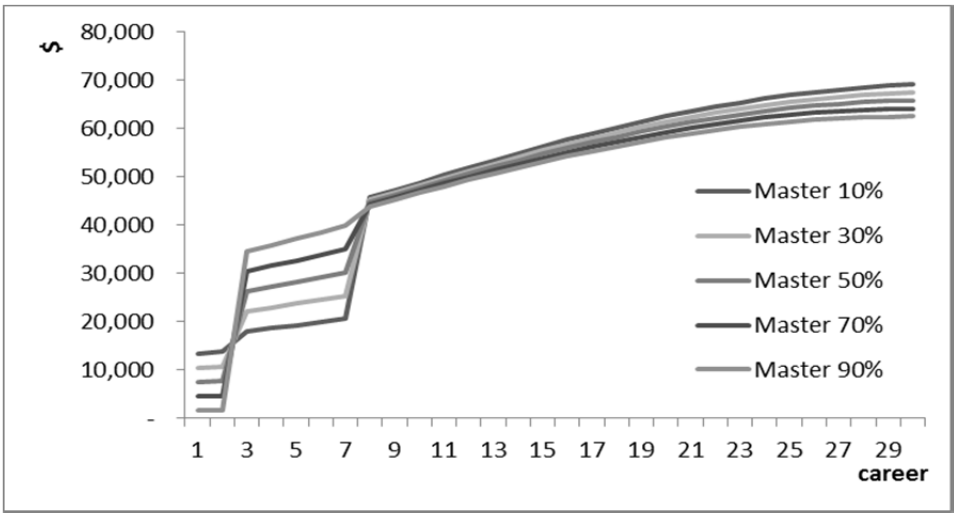

Figure A. 19 Sensitivity analysis of master labor of fuel cell HRD

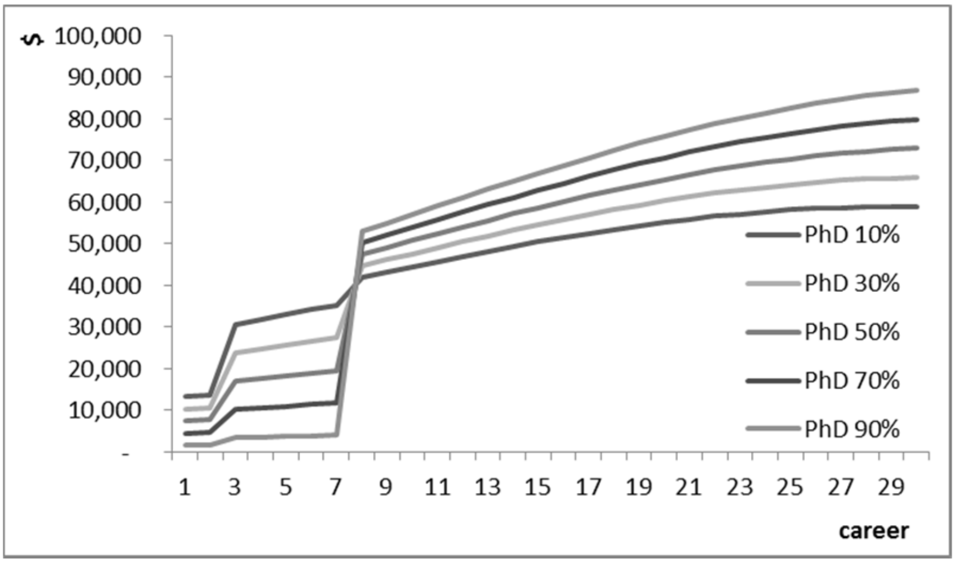

Figure A. 20 Sensitivity analysis of PhD labor of fuel cell HRD

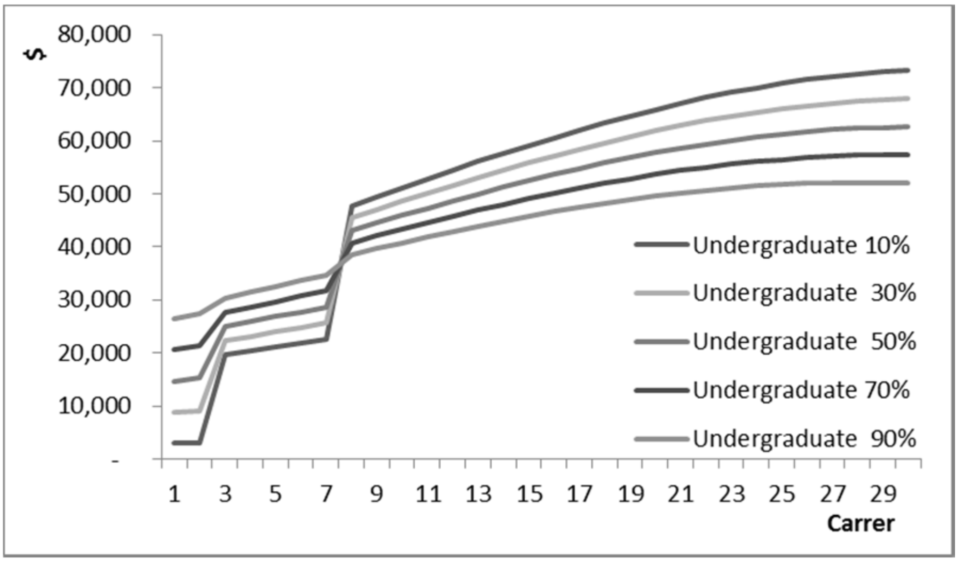

Figure A. 21 Sensitivity analysis of basic labor of fuel cell HRD

Quantitative Analysis of Human Capital Accumulation:
R&D Investment on Manufacturing Sector and Human Resource Development Program on Renewable Energy Sector

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요약 (국문 초록)

본 논문에서는 인적자본 축적의 내생적 특성을 반영하여 인적자본의 정량화 분석 연구를 수행하였다. 특히, 인적자본이 유형자산과 동일하게 투자의 수익으로 축적된다는 이론에 기반하여, 각 산업의 인적자본 수익률 및 투자 비율을 고려한 인적자본 저량의 정량적 분석 틀을 제안하였다. 나아가 제안한 분석방법을 적용하여 국가 인력양성 사업의 지표로서의 활용가능성을 제시하였다.

인적자본은 광의적인 개념으로 개인에게 체화되는 모든 지식 및 생산능력을 포함한다. 산업사회가 지식기반 사회로 이행되면서 무형자산인 인적자본의 획득과 활용이 강조되고 있다. 특히 Romer(1986), Lucas(1988) 을 비롯한 많은 내생성장 모형 연구에서는 인적자본이 경제성장에 중요한 역할을 하고 있음을 보여주었고, 이는 다양한 정부의 인력양성 및 연구개발 사업 수행의 근거가 되고 있다.

하지만 이러한 중요성에도 불구하고 인적자본을 정량화하는 연구들은 미흡한 실정이다. 인적자본은 유형자산과 달리 개인에게 내제되어 있기 때문에 거래할 수 없다 또한, 생산의 투입요소로써 그 생산기술에 따라 수익률이 달라지는 특성을 가지고 있다. 이에 지금까지 인적자본 측정의 간접적인 수단으로 학력, 임금, 총 교육비용들의 지수가 사용되어 왔다.

이러한 맥락에서, 본 연구에서는 국내외 인적자본 측정 방법 및 실증 분석 연구들을 심도 있게 분석하여 인적자본 정량화 분석 틀을 제안하고, 두 가지 실증분석 연구를 수행하였다. 먼저, 이론적 부문에서는 인적자본의 개념을 정리하고 성장모형, 임금 차이, 인적자본 정책, R&D 투자 등 다양한 연구 분야에서 인적자본의 적용을 분석하였다. 또한 Mincer(1974)의 연구를 기반으로 개인의 전 생애에 걸친

투자활동의 결과를 인적자본 축적으로 정량화하여 분석할 수 있는 틀을 제안하였다.

첫 번째 실증 분석에서는 R&D 의 투자에 따른 인적자본 축적의 영향을 분석하였다. R&D 와 인적자본은 지식기반 사회에서 국가의 성장의 주요요인으로 인식되며 성장모형에서 함께 고려되어 왔다. 최근에는 그 연구 범위가 두 요소 간의 상호작용으로 좁혀지고 있는데, 본 논문에서는 R&D 의 투자에 따른 인적자본의 영향에 초점을 맞추어 분석을 실시하였다. 이를 위하여 한국의 제조업을 R&D intensity 에 따라 세 개의 산업(High -, Medium - and Low technology industry)로 구분하였다.

분석결과 R&D 투자에 따라 각 산업에서 축적되는 인적자본 수익률은 차이를 보이는 것으로 분석 되었다. R&D 투자가 가장 높은 High technology industry 에서 인적자본 투자에 대한 수익률이 가장 높은 것으로 분석되었는데, 이는 R&D 의 투자가 기술혁신으로 이어져 동일한 인적자본을 투자하였을 때 더 큰 수익을 기대할 수 있는 것으로 판단된다. 또한 개인이 생산활동에 참여하는 30 년 동안 인적자본의 수익을 위해서 인적자본에 투자하는 비율은 R&D 의 투자가 낮은 산업에서 높게 나타났다. 이는 Medium technology industry 와 Low technology 의 경우 산업에 자체의 기술혁신이나

생산성 보다는 직접적인 경험으로 축적하게 되는 지식이 중요하여 개인 총 인적자본 저량 중 많은 부분을 투자하는 것으로 해석할 수 있다.

두 번째 실증분석에서는 신재생에너지 산업의 인적자본 축적을 정량화하고 이를 인력양성 프로그램 계획의 지표로서 활용가능성을 모색하였다. 정부의 인력양성지원 사업은 개인이 교육에 대한 투자의 결정에 사회적인 편익을 과소평가함에 따라 최적 수준의 교육투자가 이루어지지 않는 다는 문제의식에서 시작되었다. 특히 신재생에너지 산업과 같이 산업 성장의 큰 불확실 성을 가지고 있는 경우 개인의 교육투자는 더욱 위축되게 된다. 따라서 인력양성 사업의 계획에는 단순한 배출 인원뿐만 아니라 개인에 의해 내제되는 인적자본의 축적을 함께 고려해야 한다. 이에 한국에서 실시되고 있는 신재생에너지 인력양성사업의 체계를 따라 기본, 산업, 고급인력양성으로 배출된 인력에 내재되는 인적자본 축적을 태양광, 풍력, 바이오, 연료전지, 지열 에너지로 구분하여 분석하였다.

분석결과 각 신재생에너지 원 별로 인적자본의 축적을 위하여 투자하는 양은 차이를 보였다. 풍력, 지열, 바이오 에너지 산업의 근로자들은 태양광과 연료전지 산업의

근로자들에 비하여 인적자본에 투자하는 양이 적은 것으로 나타났다. 해당 산업은 농업, 토목 산업 등 노동력 자체에 초점을 맞춘 산업들의 비중이 타 에너지원에 비해 높기 때문에 지식의 축적을 위해서 산업에 투자하는 양이 크지 않은 것으로 사료된다.

또한 개별 에너지원에서 인력양성 사업 수준에 따른 인적자본 축적 양을 비교해 보면, 태양광, 풍력, 바이오, 연료전지 산업은 박사과정에 지원한 경우의 인적자본 축적이 학부에 지원하는 것보다 높은 것으로 분석되었다. 반면, 교육의 수익률이 가장 낮은 지열의 경우에만 학부 수준의 개인에게 축적되는 인적자본 양이 더 많은 것으로 분석되었다. 이는 교육수준이 높아질수록 인적자본을 축적할 수 있는 기간일 짧아지기 때문에 교육 수익률에 따라 정책에 따라 인적자본 축적의 효과가 원 별로 차이를 보일 수 있음을 의미한다.

이상의 연구 결과에 따른 본 논문의 의의는 크게 네 가지로 나누어 볼 수 있다. 첫째, 인적자본의 정량화 연구 방법론에 대한 이론적인 기여를 들 수 있다. 본 논문에서는 인적자본을 개인의 전 생애를 통해 이루어 지는 투자를 고려하여 정량화 할 수 있는 분석 방법 틀을 제시하였다. 이는 기존의 모든

인력이 homogeneous 하다는 가정을 전제로 하고 있는 지수 방법을 보완하여 각 산업 및 학력의 heterogeneous 한 특성을 반영할 수 있는 방법을 제안한 것이다. 이 방법을 적용할 경우 국가 차원의 인적자본 축적뿐만 아니라 산업과 기업 수준에서 축적되는 인적자본을 분석할 수 있는 장점이 있다.

둘째, R&D 에 의해 인적자본의 축적이 영향을 받음을 실증적으로 증명하였다. R&D 의 투자 가 인적자본의 수익을 향상 시킬 수 있다는 Mathur(1999)의 이론을 실증적으로 보여 주였다는 데 의의가 있다. 이는 우수한 인적자본에 의해 R&D 성과가 향상 될 수 있다는 보편적인 이론에 역의 관계 역시 성립할 수 있음을 보여준 것이다.

셋째, 신재생에너지 산업의 임금 구조 체계와 인적자본 축적 분석한 최초의 연구이다. 국내 신재생에너지 산업은 발전 초기이고 기존 산업과의 연관성이 매우 높아 별도의 노동시장 관련 연구가 미흡하다. 더욱이 대학의 전공과 산업의 1:1 매칭이 불가능한 여건에서 각 신재생에너지 원 별 관련 전공조차 파악이 되어 있지 않은 실정이다. 본 연구에서는 관련 자료들을 바탕으로 각 신재생에너지 산업 연관 전공들을 정리하고, 에너지경제연구원(2013)등의 문헌을 참고하여 연관 산업을 기준으로 신재생에너지 노동시장을 구분하였다. 향후

국내 신재생에너지 산업의 노동시장 분석에 기준 연구로서 역할을 할 수 있을 것이다.

마지막으로, 인력양성 정책의 계획에 적용할 수 있는 추가적인 지표를 제시하였다. 정부 프로그램의 계획 및 평가는 각 프로그램의 성격을 반영할 수 있는 지표를 바탕으로 이루어 져야 한다. 하지만 지금까지 인력양성 사업의 계획은 수요와 공급의 불균형을 맞추는 일차적인 목표를 가지고 수행되었다. 본 연구에서 제안한 인적자본 분석 방법은 각 산업별 및 정책 수준별로 개인에게 내제되는 인적 자본량을 정량화 할 수 있다. 이에 따라서 인력양성 사업의 평가 및 장기적인 관점에서 정책의 효과를 정량적으로 분석하는데 유용하게 사용될 수 있을 것이라 기대된다.

주요어: 인적자본축적, 패널 추정, R&D 투자, 한국 제조업, 신재생에너지, 인력양성사업

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