Ph. D. Dissertation in Economics

Study on the effect of innovation on employment structure and economic growth: A computable general equilibrium approach

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- 연산일반균형모형을 중심으로 -

August 2015

Graduate School of Seoul National University

Technology Management, Economics, and Policy Program

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Abstract

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In the 1990s and the early part of the 2000s, many countries in the world have gone through the ‘jobless growth’ in which employment stalled while economy grew. In many countries since the global financial crisis, there has also been occasions where the unemployment rate has increased instead of falling although the economy has bounced back. Likewise, South Korea has been going through this ‘jobless growth’ since the middle of the 2000s. There are various claims in the circles of economics as to the cause of such phenomenon, one of which is that it’s due to technological innovation. That is, as technologies progress, productivity and output increases, but the demand for jobs

decreases and has a bad influence on employment. Particularly, in the case of South Korea, which has reached the highest degree of intensity in its investment in R&D as continuous investment therein has increased, points are being raised that this is the cause of the 'jobless growth'.

Not only the quantitative aspect of employment but also the qualitative aspect is an issue, and, while technological innovation increases the demand for skilled laborers, it stunts the demand for unskilled laborers. That is, it brings about skill-biased technology change. Especially, Brynjolfsson and McAfee (2014) claimed in their book 'The Second Machine Age' that, as information communication technology advances, new technologies and machines replace jobs faster, technological innovation causes skill-biased technology change and capital-biased technology change, and leads to income polarization. However, the recently raised arguments are only considering the direct influences that innovation has on employment. The innovation affects employment through various routes. Especially, when diversity of products increases through innovation, it leads to indirect influences in which new demand is created and the employment increases. Therefore, the influence of innovation on employment and growth should be examined with its indirect effects as well as direct. Hence, in this study, using the computable general equilibrium model, which is capable of concurrently considering various aspects of economy, it was intended to examine what influence innovation has on employment structure and economic growth. For this, knowledge-based Social Accounting Matrix and knowledge-based computable general equilibrium model have

been constructed.

The result of the study utilizing the knowledge-based computable general equilibrium model is summed up as follows. Viewed from the employment aspect first, additional innovative activities turned out to increase the total demand of labor, increasing the demand for unskilled, skilled, and high-skilled labor all together. The demand for the high-skilled labor especially showed the highest increase rate. When examined by the industry, the high-tech manufacturing which invests heavily in R&D also showed the greatest rate of employment increase. In sequence, when viewed from the aspect of economic growth, additional innovative activities turned out to have a positive influence on economic growth, which led to the increase in all production elements' added values. In the case of capital, high-skilled labor, and knowledge, however, while their weights in added values have increased, unskilled and skilled labors' weights in added value turned out to have decreased by the capital-biased technology change and the skill-biased technology change. Accordingly, the foregoing turned out to have a bad influence on income distribution and deepened income polarization. Meanwhile, when viewed by the industry, due to the additional innovative activities, the output of the manufacturing industry turned out to show a higher increase rate than that of the service industry.

Keywords: Innovation, Employment structure, Economic growth, Skill-biased technological change, Capital-biased technological change, Computable general equilibrium model
Student Number: 2009-23211

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Chapter 1. Introduction

1.1 Research background

South Korea has accomplished tremendous economic growth over the past half century. High-speed growth was achieved through labor-intensive light industry in the 1960s, and heavy chemical industry and electronics industry in the 1970s and 1980s. From the 1990s, development of IT industry and its convergence with existing industries led economic growth. However, as economic growth rate declines in the 21st century, a new source of growth is required. Accordingly, innovation-driven economic growth through ongoing R&D has been implemented since the early 2000s. For this reason, R&D in Korea has continued to increase as shown in Figure 1, ranking the sixth worldwide as of 2013, and Korea has maintained the R&D intensity at the highest level in the world.

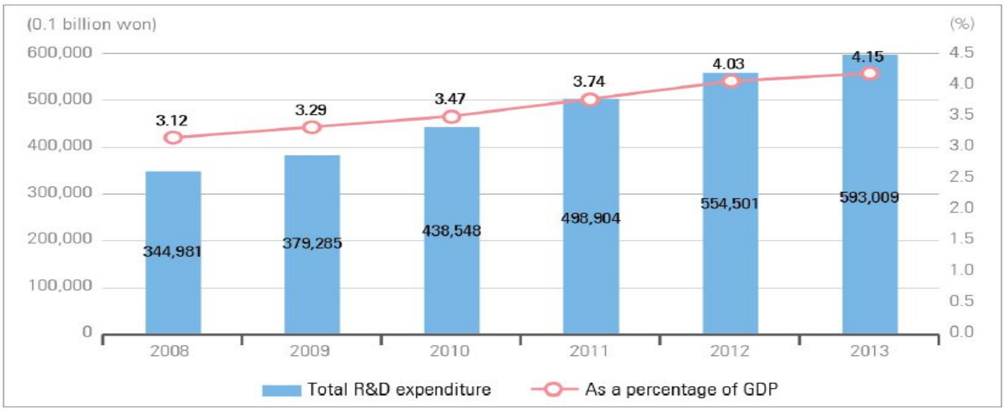


Figure 1. R&D Investment and R&D intensity in Korea

Source: KISTEP (2015), Survey of Research and Development in Korea

However, despite such efforts, innovation-driven economic growth has resulted in both shining achievements and a darker side. In particular, since the dawn of the 21st century, "jobless growth" has been suggested as a huge problem of innovation-driven economic growth. In other words, despite economic growth, the employment rate did not increase, and the number of the unemployed rather increased. Numerous theories have been proposed regarding the cause of the phenomenon. Brynjolfsson and McAfee (2014) indicated that technological innovation is the cause of "jobless growth." They argued that although increased productivity through innovation helps economic growth, it has an adverse effect on employment as machines based on new technology replace people's jobs. Nevertheless, in recent years, the Korean government has sought achieve economic growth through the creative economy. In other words, it has tried to establish a sustainable economic system with a virtuous cycle of improved growth potentials and job creation through innovation, the so-called innovation-driven economic growth system. Thus, theoretical and empirical examination of the effect of innovation on employment is a crucial issue, and considering the Korean government's efforts to improve capacity for innovation, the examination of overall innovation, employment, and economic growth and the relationships among them in the Korean economy poses a very important challenge at present.

1.2 Research motivation and purpose

The effects of innovation on employment have been studied since the early years of the industrial revolution. As workers lost their jobs to newly developed machines while the process of industrial revolution unfolded, the relationship between innovation and employment drew increasing attention. Despite the confusion in the early period of the industrial revolution, high economic growth rate eventually prevailed through innovation, resulting in many people becoming employed again (Goldin & Katz, 2008; Bessen, 2015). However, with the recent advent of automated robots in addition to the progress in IT, unskilled labor workers that mainly engage in simple work tasks are losing jobs in large numbers. Consequently, Brynjolfsson and McAfee (2014) argued that we need to pay attention to the negative effect of technological innovation on employment. They pointed out that, while wages have increased with productivity for nearly 200 years, mid-level wages have not kept up with productivity recently, and median income has decreased by about 10% in the last 10 years, despite the increase in GDP. They argued that this indicates skill-biased technological change (SBTC) and capital-biased technological change. In addition, Frey and Osborne (2013) concluded that approximately 47% of all jobs are likely to be turned over to robots in the future, based on the analysis on the jobs are likely to be replaced by robots and artificial intelligence systems. However, some argue that a similar development occurred in the period of the industrial revolution and, therefore, that it does not pose a significant threat. Bessen (2015) argued that new technology reduces factory labor but creates jobs requiring new skills. He contended that that, rather than simply taking away jobs, technological innovation displaces jobs to where new technical knowledge is required. In addition, he argued that technological change has created more jobs than it has taken away. In a study on the effects of technological advance on jobs in the past few centuries, Katz and Margo (2013) also argued that, although new expertise is required for new types of jobs, jobs themselves never disappeared. In other words, they argued that, from a long-term perspective, employment rate has been quite stable, and people have always created new jobs that require new technical capacity in the face of new technological progress.

Such discussions show that the debate on innovation and employment has been sparked again due to the advancement in robot technology and information and commutation technology in recent years. Thus, the present study aims to examine the nature of the issue of innovation and employment, a recent controversy, and investigate effects of innovation on overall employment and economic growth based on the structural understanding of the issue. To this end, computable general equilibrium (CGE) modeling, which can determine both direct and indirect economic effects, has been used. Furthermore, this study investigated complex effects of innovation on employment and economic growth by incorporating SBTC and capital-biased technological change, which are emergent issues for the model. Figure 2 shows the overview of this study illustrating the above aspects.

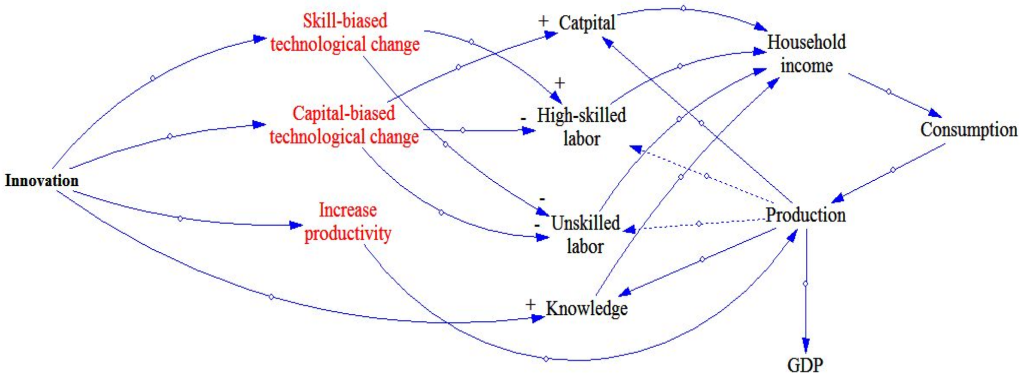


Figure 2. Conceptual outline of this study

1.3 Outline of the study

The organization of this study is as follows. Chapter 2 describes the theoretical background of this study. It summarizes the literature to date on the relationship between innovation and employment based on previous studies, and discusses the significance of this study. Chapter 3 presents the methodology used in this study. First, the method to build a knowledge-based social accounting matrix is described; then the method to build knowledge-based CGE is described in detail. Chapter 4 discusses the results of the analysis on effects of innovation on employment and economic growth using the knowledge-based CGE model. Finally, Chapter 5 concludes the study by synthesizing study results and presenting related policy implications.

Chapter 2. Theoretical Background

2.1 Innovation and employment

Research on the relationship between innovation and employment has been conducted since the early Industrial Revolution. In the textile industry in the early 19th century, skilled labor working in handicraft lost jobs because of the supply of new machines, which led to destruction of machinery in protest (Luddite Movement), as workers attributed job losses and reduced wages to such machines. Despite such concerns, economists argued that new jobs are typically created by the so-called compensation effect through various ways, even though employment decreases temporarily due to technological innovation. In other words, they argued that employment reduction driven by innovation causes falling wages, and in turn, promotes labor-intensive technology and industry (Venables, 1985; Layard, Nickell, & Jackman, 1991; 1994). Conversely, arguing that cost savings from innovation results in increase in wages, which in turn, promotes spending and industry development, research on various compensation effects has been conducted (Pasinetti, 1981; Boyer, 1988; 1990).

In addition to the debate on compensation effects, a plethora of empirical studies on innovation and employment has been conducted. Moreover, in the recent turn toward the digital age, as robots and automation devices are combined with IT technology, many cases of machines taking away human jobs have occurred, and consequently, research on innovation and employment has attracted renewed attention. Thus, this chapter will examine previous studies on innovation and employment.

2.1.1 Compensation mechanism

Vivarelli (2012) explained the compensation effect by six theories, as shown in Figure 3. The first theory is the increase of employment in capital goods industry. That is, innovation requires new equipment and facilities, and employment increases in the industries producing the new equipment and facilities (Say, 1964). The second theory is the increase of employment due to decrease in price. When production costs decreases because of innovation, the price of consumer goods falls, which creates new demand, leading to increase of employment (Heffernan, 1981; Nickell & Kong, 1989). The third theory is the increase of employment due to wage reduction. Labor-saving technology development reduces the negotiating power of labor. The lower wages increase employment (Neary, 1981; Layard & Nickell, 1985). The fourth theory is the increase of employment as a result of increase in new investment. When the gap between cost of production and market price of goods increases because of technology development through innovation, additional profit occurs. The additional profits bring increased investment, which promotes new product development and employment expansion (Hicks, 1973; Stoneman, 1983). The fifth theory is the increase of employment due to emergence of new products. When new products and services emerge from innovation, employment to produce them increases (Freeman & Soete, 1994; Vivarelli & Pianta, 2000). Finally, cost savings from innovation cause increased profits, which results in wage increase. The increased wages lead to more consumption, ultimately increasing employment (Pasinetti, 1983; Boyer, 1990).

However, a number of counter arguments against the theories of the compensation effect exist. Marx (1969) refuted the compensation effect, arguing that whenever machines are introduced, far more workers are replaced than the number of new jobs created. Moreover, Malthus (1964) and Sismondi (1971) argued that the negative effect of decrease in demand due to laid off workers is greater than the increased demand by decrease in price of products. In addition, they argued that, in the event of insufficient total demand, wage reduction does not directly translate into increase of employment.

Fierce debate on the compensation effect has persisted over the last century and is ongoing. This state of affairs is because results vary across periods and countries, as well as industries and technologies, making it difficult to conclude which side is correct. Furthermore, the general conclusion on innovation and employment is harder to reach because most studies to date have investigated a given aspect of compensation effect from a partial equilibrium perspective.

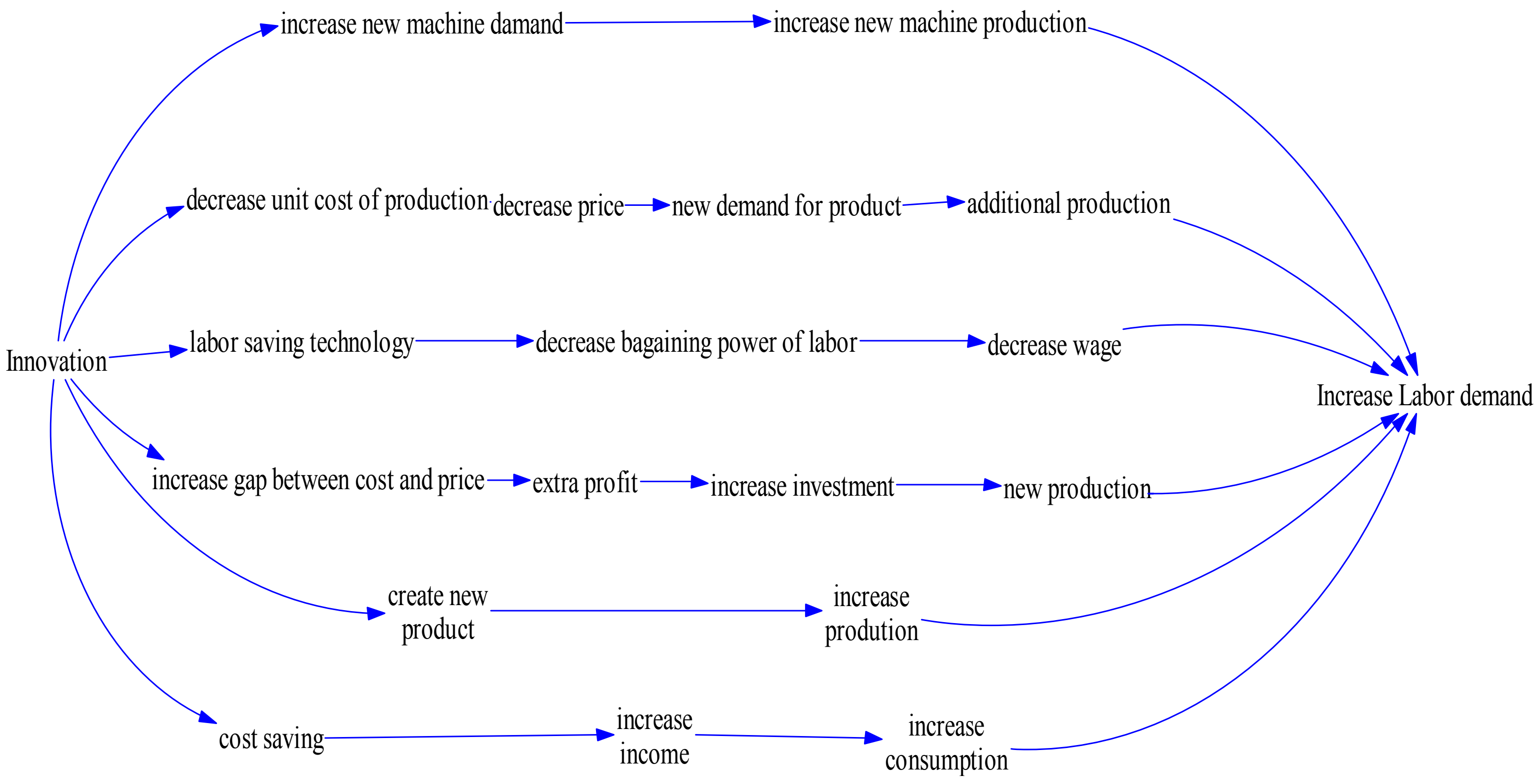


Figure 3. Causal loop diagram of compensation mechanism

2.1.2 Innovation and employment: The empirical evidence

Empirical research on the relationship between innovation and employment has been conducted by a large number of researchers. However, their results are still debated. This is because innovation is difficult to measure. Although innovation is often measured by R&D, patents, and studies, these are merely an aspect of innovation. Moreover, because the overall effect of employment due to innovation differs across the scope of analysis, countries, and industries, and a variety of factors that influence employment, it is difficult to determine the role of innovation in employment in a comprehensive, conclusive manner. For these reasons, the controversy continues to date, and many empirical studies are still underway. The empirical studies that have been conducted to date can be summarized as follows.

Concerning results of studies on company level innovation and employment, most of these have investigated the direct effect of innovation on employment. This is because correlation analysis was performed using companies' in-house data on innovation and employment. In an analysis using the data from 1984 for the U.K. manufacturing industry, Machin and Wadhwani (1991) showed that employment increased in the companies that introduced more ICT technology. In addition, in an estimation of the relationship between introduction of new technology and employment growth rate, Blanchflower, Milward, and Oswaald (1991) also demonstrated a positive correlation between introduction of new technology and increase of employment. In an analysis of U.S. manufacturers, Doms, Dunne, and Roberts (1995) found a positive correlation between the number of new technologies introduced and employment. Van Reenen (1997) performed an analysis using panel data of 598 manufacturers from 1976 to 1982. The study results showed that innovation benefits employment. Based on analysis of German manufacturers, Smolny (1998) argued that innovation has a positive effect on employment. In Blanchflower and Burgess's (1998) study using data from the U.K. and Australia, positive correlation between innovation and employment was found in both countries. According to Greenan and Gullec's (2000) study with French manufacturers from 1986 to 1990, innovative companies were found to create more jobs than those that are not. A study with Italian manufacturers from 1992 to 1997 by Piva and Vivarelli (2005) showed employment growth rate was positively correlated with companies' investment in innovation. In a study with Italian manufacturers from 1995 to 2003, Hall, Lotti, and Mairesse (2008) did not find evidence that process innovation replaces employment, but found an overall positive effect of innovation on employment. Harrison, Jaumandreu, Mairesse, and Peters (2008) investigated company data from about 20,000 companies in Germany, France, the U.K., and Spain from 1998 to 2000, and found that while process innovation has an effect of replacing employment, product innovation is has an employment-friendly effect. Lachenmaier and Rottmann (2011) conducted generalized method of moments (GMM) analysis with German manufacturers from 1982 to 2002, and found a positive effect of innovation on employment. Coad and Rao (2011) conducted a study with U.S. high tech manufacturers from 1963 to 2002, and found that employment growth rate was positively correlated with companies' R&D levels and patents. In addition, Bogliacino, Piva, and Vivarelli (2011) found a positive correlation between R&D and employment in the companies in service industry and high-tech manufacturing. Zuniga and Crespi (2013) analyzed manufacturers in Argentina, Chile, and Uruguay, and found that employment rate was higher in the companies that conducted R&D. In addition, it was found that the effect was stronger in high-tech industry.

However, no empirical studies reported positive outcomes of innovation in employment. In an analysis of micro data from 16 industries in Germany in the 1980s, Zimmermann (1991) argued that technological change was an important factor in decrease of employment. Brouwer, Kleinknecht, and Reijnen (1993) studied the relationship between employment growth rate and R&D intensity in 859 German manufacturers from 1983 to 1988 using the sample selection model. The study results showed that R&D intensity had a negative effect on employment. In a study with Norwegian manufacturers from 1982 to 1992, Klette and Førre (1998) demonstrated that net employment growth was lower in companies with a proportion of R&D expenditure compared to sales over 1% than in companies with the same proportion less than 1%.

As illustrated, a large number of empirical studies were conducted with company-level analysis, mainly in Europe and the U.S., frequently showing a positive effect of innovation on employment. Such company-level quantitative analysis can consider only direct effect because it utilizes company's innovation data and employment data. Therefore, the positive effects of companies' innovation activities are likely to be overestimated (Pianta, 2005). This is because companies that are more innovative are more likely to have higher market share and create and sustain more employment accordingly. Moreover, the companies that produce greater excess profits or growth tend to have more innovation activities, and they often undertake additional hiring. However, innovation activity of specific companies may result in decrease or increase of employment in other companies or other industries. Therefore, indirect effects must also be examined. For this reason, industry-level analyses instead of company-level analyses are also conducted in various ways.

Empirical studies that investigated the relationship between innovation and employment at the industry level are as follow. Meyer-Krahmer (1992) investigated the relationships among technological change, economic growth, and employment change using a macro model. In the study, direct and indirect effects of technological change were examined using input–out (I–O) analysis. The study results showed an overall negative effect was found, although varying across industries. Vivarelli, Evangelista, and Pianta (1996) investigated the effect of innovation on employment in Italian manufacturers. The study results showed that process innovation has an adverse effect on employment, whereas the industries with a high proportion of product innovation or engineers were employment-friendly. Antonucci and Pianta (2002) conducted a study using innovation survey data from eight European countries (Italy, France, Germany, Denmark, Netherlands, Finland, the U.K, and Sweden). The study results showed that innovation has a negative effect on employment in general. However, product innovation was found to have a positive effect on employment. Evangelista and Savona (2002) studied the effect of innovation on employment in the service industry using Italy Innovation survey data from 1993 to 1995. The study results showed that, in large corporations, capital-intensive industries, and financial industries including banks and insurance companies, innovation influenced employment negatively, whereas in small businesses or science- and technology-based industries, innovation influenced employment negatively. Bogliacino and Pianta (2010) studied the relationship between innovation and employment at the industry-level in eight European countries (Germany, France, Italia, Norway, Netherlands, Portugal, Spain, and the U.K.) from 1994 to 2004. The study results showed that product innovation creating a new product or a new market is employment friendly, while process innovation was employment saving. Bogliacino and Vivarelli (2012) investigated 25 manufacturing and service industries in 15 European countries from 1996 to 2005 using GMM. The study results showed that R&D promoting product innovation had a job creation effect.

The analysis on the industry-level relationship between innovation and employment has an advantage that indirect effects as well as direct effects of innovation on employment can be examined. In other words, analysis can incorporate the employment effect occurring as reduced price due to innovation influences demand, as well as the employment effect occurring from introducing new products or equipment (Pianta, 2005). Taken together, these empirical studies suggest that product innovation benefits employment and that process innovation negatively affects employment. Additionally, regarding industry-specific effect, employment tended to increase in industries with plenty of science technology based R&D, whereas employment tended to decrease in traditional industries.

On the other hand, other studies investigated the relationship between innovation and employment using a macro model. These studies examined the effect of incorporating compensation effect theory into the model. Sinclair (1981) studied compensation effect using U.S. data and investment/saving-liquidity preference/money supply equilibrium (IS-LM) methodology. The study results showed that when demand elasticity and elasticities of substitution between factor inputs were sufficiently high, innovation had a positive effect on employment. In addition, compensation effect though wage reduction was observed; however, compensation effect through price reduction was not. Nickell and Kong (1989) investigated compensation effect through price reduction focusing on nine industries in the U.K. The study results showed that, in seven out of nine industries, cost reduction from labor-saving technology led to price reduction, resulting in positive effect on employment due to high demand elasticity. Vivarelli (1995) investigated process innovation, product innovation, and compensation effect in Italy and the U.S. using three-stage least squares regression. In both countries, compensation effect by price reduction was most effective. In addition, innovation was more employment friendly in the U.S. than Italy. Simonetti, Taylor, and Vivarelli (2000) conducted a macro analysis using three-stage least squares regression on data from the U.S., Italy, France, and Japan from 1965 to 1993. Study results showed that compensation effects by price reduction and increased income were most effective. Moreover, product innovation was more effective on employment in the countries with more advanced technology.

On the other hand, a great deal of research on the effects of innovation on employment has been also conducted in Korea. Kang (2006) found that, despite a short-term decrease in employment due to technological innovation in the 1980s, employment in the 1990s increased as a result of technological innovation in both mid- term and long-term. In addition, technological innovation was found to expand employment in the manufacturing industry, but has no significant impact on employment in the service industry. Kim (2008) investigated the effect of technological innovation on employment and employment structure in 10 large-category industries from 1993 to 2007. The study results showed that increased total factor productivity through technological innovation decreased domestic employment in the long term, but increased the proportion of skilled employment. Mun and Chun (2008) studied the effect of companies' innovation activities on employment. The study results showed that companies' innovation activities have a positive effect on employment. In particular, product innovation was found to increase employment more than process innovation did. Lee et al. (2010) investigated the relationship between technological innovation and employment using company data from 2000 to 2009. The study results showed that employment inducement effect was excellent in science-based companies, and R&D had a stronger employment inducement effect in venture companies and small businesses than in large corporations. Kim (2012) investigated the effect of increased productivity as a result of technological innovation on employment. The study results showed that when technical level increases, employment in manufacturing industry increased in the short term, then decreased in the long term, and employment in service industry increased in both short and long terms. The overall employment effect was found to increase in both short and long terms.

Table 1. Summary of empirical researches about innovation and employment (Firm level)

Study	Nation	Period of Research	Results
Machin and Wadhwani (1991)	UK	1984	Positive correlation between ICT technology introduction and employment
Blanchflower, Milward, and Oswaald (1991)	UK	1984	Positive correlation between new technology introduction and employment growth
Zimmermann (1991)	Germany	1980-1984	Negative correlation between technological change and employment
Brouwer, Kleinknecht, and Reijnen (1993)	Germany	1983-1988	Negative correlation between R&D intensity and employment growth
Doms, Dunne and Roberts (1995)	USA	1987-1991	Positive correlation between technology introduction and employment
Van Reenen (1997)	UK	1976-1982	Positive correlation between innovation and employment
Smolny (1998)	Germany	1980-1992	Positive correlation between innovation and employment
Blanchflower and Burgess (1998)	UK, Australia	1990	Positive correlation between innovation and employment
Klette and Førre (1998)	Norway	1982-1992	Negative correlation between R&D intensity and net employment growth
Greenan and Gullec (2000)	France	1986-1990	Create more jobs in innovative companies, but negative effect on aggregate employment in industry level
Piva and Vivarelli (2005)	Italy	1992-1997	Higher employment growth rate in innovative companies

Harrison, et al. (2008)	Europe	1998-2000	Labor-friendly in product innovation, labor-saving in process innovation
Hall, Lotti, and Mairesse (2008)	Italy	1995-2003	Positive correlation between product innovation and employment
Lachenmaier and Rottmann (2011)	Germany	1982-2002	Positive correlation between innovation and employment
Coad and Rao (2011)	UAS	1963-2002	Higher employment growth rate in innovative companies
Bogliacino, Piva, and Vivarelli (2011)	Europe	1990-2008	Positive correlation between R&D investment and employment in service and high-tech industries, but negative correlation in traditional industry
Zuniga and Crespi (2013)	South America	1998-2009	Higher employment growth rate in own R&D companies
Mun and Chun (2008)	South Korea	2002-2003	Positive correlation between innovative activity and employment, and Labor-friendly in product innovation
Lee et al. (2010)	South Korea	2000-2009	Positive correlation between R&D investment and employment

Table 2. Summary of empirical researches about innovation and employment (Industry level)

Study	Nation	Period of Research	Results
Meyer-Krahmer (1992)	Germany	1980s	Negative correlation between innovation and employment
Vivarelli, Evangelista, and Pianta (1996)	Italy	1985	Labor-friendly in product innovation, labor-saving in process innovation
Antonucci and Pianta (2002)	Europe	1994-1999	Negative correlation between innovation and employment, but product innovation is labor-friendly
Evangelista and Savona (2002)	Italy	1993-1995	Positive correlation between innovation and employment in technology based industries, but negative correlation in capital intensive and financial industries
Bogliacino and Pianta (2010)	Europe	1994-2004	Labor-friendly in product innovation, labor-saving in process innovation
Bogliacino and Vivarelli (2012)	Europe	1996-2005	Positive correlation between R&D investment and job creation
Kang (2006)	South Korea	1980-2004	Negative correlation between innovation and employment in the 1980s, but negative correlation in the 1990s
Kim (2008)	South Korea	1993-2007	Negative correlation between technological innovation and employment
Kim (2012)	South Korea	1990-2011	Positive correlation between technological advances and employment in service industries, but negative correlation in manufacturing industries

2.1.3 Product innovation and Process innovation

Innovation is largely divided into product innovation and process innovation. Schumpeter (1934) conceptualized product innovation as development of a new product or a performance-enhanced product, and process innovation as introduction of new production methods or new method to commercialize products. In other words, product innovation refers to producing a new or better product, and process innovation refers to producing a product or service in a new way.

New products or services are created by radical innovation or by imitation or improvement of existing products, which leads to improved quality of products or increased diversity of products. This creates new demand, and increases production of new products, leading to employment growth (Pianta, 2000). However, new products may replace old products.

On the other hand, process innovation improves production efficiency through labor and capital saving, which serves to lower product price (Edquist, Hommen, & McKelvey, 2001). Such process innovation can be divided into two types. The first is technological process innovation. This refers to development of a new product used in a production process. Industrial robots and IT equipment are typical examples of technological process innovation. In fact, in the case of industrial robots, when they first appear, they are classified as product innovation, but as soon they are used for production of other products, they become process innovation. The second is organizational process innovation. This refers to organizing business activities, such as production or R&D, being conducted in a new way. It is differentiated from technological process innovation because technical components are not included. Just-in-time production or lean production are typical examples of organization process innovation.

It may be meaningless to differentiate product innovation and process innovation. This is because, as explained earlier, product innovation can become process innovation, and the two can occur simultaneously. In a description of a dynamic model of product innovation and process innovation, Utterback and Abernathy (1975) argued that product innovation frequently occurs in the period of industry or product formation (i.e., the fluid phase), while process innovation frequently increases in the transition phase, when product innovation decreases. However, in the present study, product innovation and process innovation are differentiated because their effects on employment differ from each other.

In general, process innovation increases productivity through labor savings and reduced capital input per unit production. Therefore, process innovation potentially has an effect of reducing employment. However, due to the compensation effect, process innovation does not always reduce employment (Edquist et al., 2001).

Regarding product innovation, on the other hand, new workers are required in addition to new machinery and equipment because a new product is produced. Therefore, the primary effect of product innovation on employment is positive (Vivarelli, 1995). However, if a new product replaces another product, and the workers producing the latter lose jobs, it may not be concluded that the employment effect in the overall economy is always positive. Thus, regarding the effect of innovation on employment, indirect as well as direct effects must be considered.

2.1.4 Skill-Biased Technological Change

Developed countries have undergone advancement of employment structures in which the proportion of skilled workers or white collar occupations increase as their economy developed. The technological developments that brought such change in employment structure are referred to as skill-biased technological change (SBTC). In countries that have undergone SBTC, employment of skilled workforce increased, while employment of low-skilled workforce, and their wages, decreased. This occurs because of complementary between capital inherent in new technology and workforce with advanced technology. In other words, new technology requires workers with the appropriate skills, and those without such skills lose jobs (Griliches, 1969). Consequently, demand for skilled workforce increases with technological advance. Empirical research that supports this claim has been actively conducted domestically and internationally. Berman, Bound, and Griliches (1994) investigated the changes in the demand for skilled labor in manufacturing industry in the U.S. and found that the demand for skilled labor was higher when R&D intensity and high tech technology ratio were higher. Doms, Dunne, and Troske (1997) investigated U.S. manufacturing industry, and found that the companies using more new technologies employed more workers with higher level of education, and paid higher wages. Dunne, Haltiwanger, and Troske (1997) analyzed data from U.S. manufacturers from 1972 to 1988; results showed a positive correlation between R&D and skilled labor. Machin and Van Reenen (1998) investigated the relationship between R&D intensity and skilled workforce in the U.S. and six other OECD countries (Denmark, France, Germany, Japan, Sweden, and the U.K.). The study results showed that the increase in technological change represented by R&D intensity and skilled workforce were closely related in all seven countries. David, Katz, and Krueger (1997) investigated the relative change in labor demand and wage gap by education level. Study results showed that relative demand for college graduates increased. In addition, advances in computer technology were found to increase relative demand for skilled labor. In analysis of company data from the 1980s, Haskel and Heden (1999) found that the companies investing more in computers employed a larger proportion of skilled labor. Falk and Seim (2001) conducted an analysis with companies in the service industry from 1994 to 1996 and found that the companies using more information and communication technology had a higher proportion of employees with higher levels of education. Based on an analysis of company data in the U.S., Bresnahan, Brynjolfsson, and Hitt (2002) argued that use of information and communication technology is the factor that causes SBTC. In a study of the Italian textile industry, Baccini and Cioni (2010) found that technological innovation has a negative effect on unskilled labor jobs, and little influence on high-skilled labor. On the other hand, Piva and Vivarelli (2001) argued that R&D and skill bias are not correlated, and Piva, Santarelli, and Vivarelli (2006), who studied the Italian machinery industry, found that technological change has a negative effect on both unskilled and high-skilled labor.

Empirical research on SBTC has also been conducted in Korea. Choi (1997) investigated technological advances and the change in labor market, and found that technological advance resulted in increase in employment and wages of those with higher levels of education, but the effect varied across different periods, showing a larger increase in relative demand for those with higher level of education in times of rapid economic growth. In addition, Park (2007) investigated the effect of R&D on employment structure by examining the effect and spillover effect of R&D on employment of science and technology workforce. The study results showed that the proportion of employment of science and technology workforce steadily increased in the manufacturing sector. Moreover, the more technologically intensive industries showed a higher proportion of employment rate for science and technology workforce, as well as faster increase in that proportion, than the industries with lower technology intensity.

2.1.5 Capital-Biased Technological Change

Brynjolfsson and McAfee (2014) argued that technology causes not only SBTC but also capital-biased technology change. In particular, they argued that, with advances in robot and automation technology through technological innovation, robots would replace people's jobs in the future. This means that the influence of capital becomes even greater as robots as capital intrude on the domain of human labor. Consequently, the proportion of labor wages in GDP decreases.

In the past, the proportion of labor in GDP has remained relatively constant. However, in recent decades, labor share is in decline. The declining labor share may have a variety of causes. Kim (2013) argued that market concentration indicating the degree of imperfect competition of product market, and the bargaining power of labor unions indicating the degree of imperfect competition of labor market, influence workers share of GDP. Hong (2013) investigated the factors affecting labor share of manufacturing industry in Korea, using panel data from 18 manufacturing industrues from 1991 to 2009. The study results showed that increased trade dependence increased labor share, whereas decreased bargaining power of labor unions, capital-biased technological progress, and globalization of production decreased labor share. Bentolila and Saint-Paul (2003) investigated the factors that influence labor share, using panel data from 12 OECD countries from 1972 to 1993. Study results suggested that prices of imported goods, capital-biased technological progress, and union bargaining power on wages influenced labor share. Guerriero and Sen (2012) investigated determinants of labor share, using data from 89 countries from 1970 to 2009. The study results suggested that the extent of trade liberalization and technological advance increased labor share, and foreign direct investment decreased labor share. Karabarbounis and Neiman (2013) argued that labor share has declined in many countries since the early 1980s, as shown in Figure 4. They argued that this decline in market share took place as relative price of capital goods decreased due to the advance in the information and communication industry and use of computers.

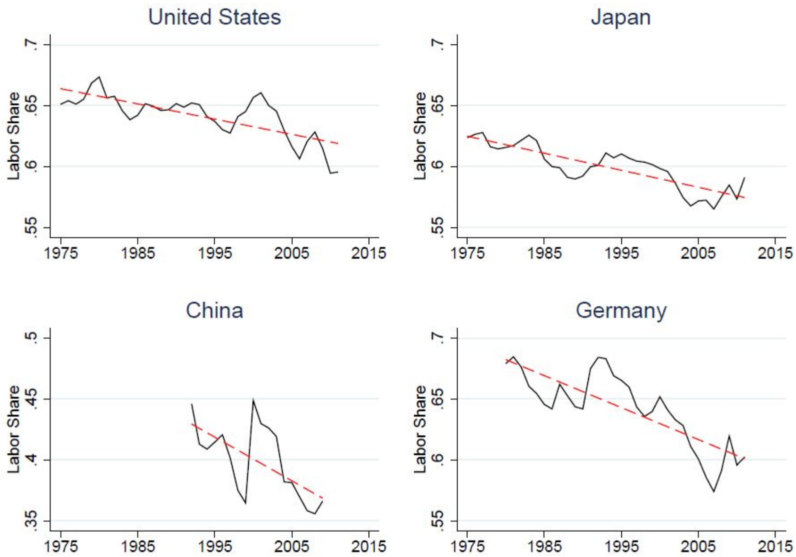


Figure 4. The share of labor income in each country

Source: Karabarbounis & Neiman (2013)

These suggest that technological innovation results in capital-biased technological change, leading to increased share of capital income for products and services derived or refined from technological innovation. The problem is that this capital-biased technological change generates polarization. Piketty (2014) argued that capital-related inequality is always larger than labor-related inequality. Based on synthesis of data from various countries and periods, he found that, while the top 10% in labor income generally accounts for 25–30% of the total labor income, the top 10% in capital income accounts for over 50% of the total wealth. In addition, Park (2014) investigated the effect of changes in income on income distribution by income type using Korean data, and argued that income distribution is more likely to suffer when capital income increases. Accordingly, when share of capital income increases due to capital-biased technological change, income polarization is more likely to intensify.

On the other hand, polarization is intensifying within capital, depending on its type. Shin and Lee (2006) argued that IT capital has a much higher return than non-IT capital, and Brynjolfsson and Hitt (1995) argued that IT capital stock generates excess returns. Accordingly, polarization may also occur depending on the type of capital.

2.2 Innovation and Employment in Digital Age

The previous chapter provided the summary of previous studies on the relationship between innovation and employment. This chapter will summarize *The Second Machine Age* by Brynjolfsson and McAfee (2014), which is gaining keen interest. This book covers a story of innovation and employment expected to unfold in the radically different world that is presently beginning to emerge. In particular, it raised an issue about job shortage in the digital age, and viewed that the progress in information and communication through technological innovation has an effect on employment unlike conventional economists' views. Let us consider the job problem that new technology will bring about with the content of the book.

2.2.1 Ability of New Machines

Discussing the division of labor between human and computer, Levy and Murnane (2004) argued that complex pattern recognition and complex communication are domains in which humans excel compared to computers. Many people agreed with the argument at the time, and technology was also far behind in these areas. However, in the 10 years since then, technology has grown rapidly and begun to surpass people's abilities in many areas. Furthermore, even in the areas where humans outperform computers, technology is intruding on humans' domains. Examples include the advent of Google's driverless car. In the past, driving was perceived as a uniquely human non-machine domain because it requires complex pattern recognition; however, a paradigm shift in future transportation became inevitable due to the advent of Google's driverless car, and jobs in the transportation section thus face and impending threat. In addition, as technology in the fields requiring complex communication such as Apple Inc.'s Siri and Google's translation service advances, jobs in these fields are also under threat. The reason rapid technological advances in such diverse areas were possible is that the technologies in the digital age have the following characteristics.

The first characteristic is exponential growth. Various technologies in computer and information and communication industries, including hard drive cost-effectiveness, internet speed, and super computer speed have been growing exponentially in accordance with Moore's Law. Exponential growth has the power to create a huge difference over time, even though it does not create a large difference at the beginning. Consequently, an enormous spillover effect has occurred as the computer and information and communication industry enters a more mature stage. The second characteristic is digitalization of everything. Recently, a lot of information has been digitalized, and its amount, speed or transmission, and diversity are growing rapidly. Digital information has a large spillover effect because it is non-competitive and marginal cost of reproduction converges nearly to zero, unlike analog information. Moreover, the advance of internet has made access to such digital information much easier, which means that time and cost for information access is much reduced compared to the past. Speed of innovation has increased because such digital information not only is the lifeline of new science but also serves to foster innovation. The third characteristic is recombinant innovation. Innovation has significance as a means by which productivity improvement takes place, and currently, recombination beyond the innovation is occurring. In particular, information and communication technology as generic technology is expanding to many industries, resulting in innovation, and various ideas are recombined and new fields are being created far more rapidly than ever before. As this recombinant innovation is combined with digitalization, use of a large amount of data sets became possible, accelerating innovation.

2.2.2 Technological Advance and Inequality

Increased productivity comes from innovation of technology in general and production technology, and occurs on a greater scale when a large number of innovations to complement generic technology show up. Similar, productivity became improved greatly in the mid-20th century when the technology of the first machine age was at its peak. The second machine age will also show high product improvement as complementary innovation thrives. This product improvement will ultimately benefit economic growth.

Although digital technology is creating huge wealth during rapid advance, not all workers benefit from this progress. Mid-level wages are lagging behind productivity, and middle incomes are in decline despite continuing economic growth. This digital technology has become a cause of increased inequality, with three groups of winners and losers. The first winner group is those with more human capital. Digital technology increased the demand for skilled labor, while reducing the demand for less-skilled labor. In other words, SBTC occurred. Accordingly, wages and demand for high-skilled labor increased, whereas wages and demand for unskilled labor decreased because their work was easily automated and often replaced by machines. This increased income inequality in general. The second winner group is those with physical capital. Until recently, despite the changes in production technology, the proportion of labor in total GDP had remained constant. However, in the past 10 years, labor share in GDP has continued to decline. This is because, as information and communication technology and automation systems advance, the value of labor declined while the value of capital increased. Due to the capital-biased technological change, the gap between rich and poor is becoming increasingly greater. The third winner group is the superstars in respective fields. In many fields, the gap between the amounts of money that the top and the second tiers in a field take away is growing larger. In other words, winners take all increasingly. The winner-takes-all phenomenon expanded further due to digitalization, improved electronics, communication, and transportation, as well as increased importance of networks and standards.

The current information technology favors skilled labor over less-skilled labor, and increases revenue for the owners of capital rather than labor, and makes it more advantageous to “superstars” over all others. Consequently, inequality and polarization are intensifying. However, some argue that it is not problematic because the abundance created by technology is more than that is needed to compensate for the gap created by the technology. However, because numerous problems that technological unemployment can cause exist, the gap may overshadow the abundance over time.

2.3 Knowledge-Based Computable General Equilibrium

Computable general equilibrium (CGE) models are equation systems that describe general economic equilibrium by introducing specific assumptions on production technology, preferred relationships, reserves of factors of production, governments' economic policy, etc., to the abstract general equilibrium model, and a useful tool to analyze the economic effect of economic policy or institutional change (Choi, 2002). They are used in various fields as they allow comprehensive analysis of spillover effect of specific economic policies on the macro economy. Currently, they are most actively used in the fields of energy and environment, international trade, and tax. In these fields, general equilibrium theory is often used because macroeconomic understanding of spillover effect is important. Recently, CGE models related to R&D have been developed. However, due to the difficulty in building and modeling R&D data, not many studies have been conducted to date, and in particular, domestic studies are virtually nonexistent. The studies conducted using a knowledge-based CGE model to date are as follows.

Diao, Roe, and Yeldan (1999) conducted a policy simulation using the CGE model to quantitatively investigate the significance and mechanism of various policy alternatives that influence the long-term growth rate of the country based on endogenous growth theory. They based their model on growth models of Romer (1990) and Grossman and Helpman (1991), and analyzed the Japanese economy with data from 1992 Global Trade Analysis Project (GTAP) and major economic data of Japan. The study results showed that the effect of trade liberalization policy on resource reallocation to domestic R&D activities was insignificant, but that the policy had a significant spillover effect of foreign technical knowledge, and ultimately increased productivity of companies. In addition, regarding R&D promotion policy, two types were analyzed, including the direct funding policy to fund the cost of R&D activities and the indirect funding policy to fund the rent for capital goods for R&D of final goods producers; it was found that effects of both policies were insignificant. Ghosh (2007) analyzed the effect of alternative policies on productivity and economic growth in Canada using endogenous growth theory. In this study, the model assumed that domestic R&D activities improve productivity of the companies in R&D sector and final goods producing companies, and the spillover effect of knowledge from abroad influence only the productivity of R&D companies. The study results showed that direct funding for R&D activities was most effective in improving productivity of the Canadian economy. Although the funding for users of R&D capital had a positive effect, the effect was relatively small, and the trade liberalization policy showed the smallest effect in productivity improvement. In other words, it showed that government policies can influence long-term economic growth by promoting private

R&D through market incentives. Lecca (2008) conducted a comparative analysis of economic effect of R&D grants depending on the status of spillover effect, establishing a CGE model with 2005 economic data of the Sardinia region of Italy. In this study, industries were divided into four groups – light industry, heavy industry, energy industry, and service industry – and along with labor and capital, knowledge was incorporated as a basic factor of production for production activities. The study demonstrated that government policies have a positive effect on economic growth by promoting companies' use of more resources on R&D. However, the study also found that the policy for improvement of long-term economic growth by increasing the knowledge stock of the region was not as effective as expected, and the policy did not greatly improve the ability to utilize foreign technical knowledge, either. On the other hand, it was found that, as spillover effect of technical knowledge from abroad has a positive impact, the region can benefit from an open economy if it has the capacity to take advantage of the knowledge embodied in imported goods.

Bye, Fæhn, and Heggedal (2009) investigated how innovation incentives should be designed to improve economic growth and social utility in a small open economy in Norway. In the study, industries were classified into R&D industry that develops patents, capital goods production industry using patents (variety-capital industry), and final goods industry, as in Romer (1990). In the model, economic growth is achieved endogenously through companies' productivity and love-of-variety effects. Productivity of R&D production companies increases by spillover effect of accumulated domestic knowledge stock, and the increased knowledge stock improves productivity of final goods companies through love-of-variety effects. On the other hand, spillover effect of foreign knowledge increases factor productivity, and the same factor productivity value was exogenously given to all production companies. The study results suggested that funding policy for purchase of R&D capital goods did not have a large effect on economic growth and social utility because domestic demand for R&D capital goods is inelastic in the final goods production sector. Consequently, positive effects of policies for funding R&D directly or for funding the production of R&D capital goods were highlighted. On the other hand, the study also pointed out that promoting economic growth does not always improve social utility.

Verbic, Majcen, and Cok (2009) investigated the effect of R&D policy on economy, using the CGE model in which education and R&D are considered as economic growth factors. In this study, three-tiered human capital stock by education level, physical capital, and R&D stock were included as factors of production. Economic growth was set to be determined endogenously by development of human capital stock of household, human capital stock specialized by sector, and R&D stock, in addition to the increase of total factor productivity over time. The total factor productivity was set to increase in proportion to the ratio of R&D goods and service production to GDP, and extent of openness of economy. The study results showed that increasing the same amount of R&D in proportion to the amount reduced in corporate tax is most effective in R&D expenditure. In addition, it was found that the measure to increase government’s R&D by

20% is the most effective measure from the economic growth standpoint.

Bor, Chuang, Lai, and Yang (2010) simulated the effect of public R&D on the economy using the recursive dynamic CGE model. In this model, labor force was classified into eight attribute groups: managers and supervisors, professionals, technicians and specialized assistants, clerks, service workers, salespeople, technical and machine operators, non-technical personnel, and manual workers. In addition, the model was set up such that basic factors of production that combine three factors of production of land, labor, and capital were produced, which in turn were used to produce final goods along with intermediates. Capital investment was classified into physical capital investment and R&D, and R&D was again classified into public R&D and private R&D. The study results showed that, in general, economic benefits resulting from public R&D outweighed its drawbacks. Inputs of public R&D showed short-term and mid-term positive effects. However, in the long term, the effect of increased R&D disappeared, and growth of GDP decreased over time due to the crowding-out effect. Findings implied that technical advances due to R&D maintain long-term economic growth through improved human capital or labor productivity.

As discussed so far, the studies conducted using knowledge-based CGE models generally investigated the effect of different types of R&D on economic growth. However, research on the effect of innovation on employment using knowledge-based CGE virtually is nonexistent.

2.4 Contribution of the Study

A plethora of research has been conducted on the relationship between innovation and employment as discussed above. However, the research to date on the relationship between innovation and employment has the following limitations. First, it is difficult to measure innovation. Previous studies measured innovation using R&D, patents, and papers. However, the present study estimated knowledge capital stock and used it as a proxy variable for innovation, and the knowledge capital stock was set to cumulate over time. The cumulated knowledge capital stock was used as a factor of production. Use of the stock as a proxy variable of innovation instead of flow can better represent the characteristics of innovation. Second, because various factors influence employment, it is difficult to discern the effect of innovation on employment (Vivarelli, 2012). Most studies to date provided results of quantitative analysis on innovation and employment using company data. However, research with company data is difficult to use to produce comprehensive results as a company's employment is often determined by various external factors, yet company data cannot incorporate indirect effects. Therefore, for accurate understanding of the effect of innovation on employment, research should be able to incorporate both direct and indirect effects in the entire economy (Pianta, 2000).

The CGE model to be applied in this study can offer a comprehensive view of the relationship by encompassing various components including production and consumption, resource allocation among sectors, pricing system of the entire economy, savings and investment, and imports and exports, into multiple macroeconomic equations that explain the equilibrium point of the entire economy (Choi, 2002). Thus, the CGE model is construed as suitable for this study due to its capability to analyze direct and indirect economic effects simultaneously. In particular, the knowledge-based CGE model can consider not only the primary effect of innovation but also impacts of various spillover effects derived from innovation, because the model incorporates R&D investment and knowledge as separate factors of production. Moreover, research on the effect of technological innovation on employment considering various paths of the relationship is virtually nonexistent to date. Thus, because CGE models have advantages over other analytic methodologies in analyzing complex interactions, it is expected that this study will provide a more solid basis for establishing innovation policies.

The review of studies to date indicated that effects of innovation varied across scope of analysis, countries, and industries. Accordingly, to examine the effects of innovation on employment in Korea, data from Korea need to be used in the present analysis. Although various studies on innovation and employment have been conducted in Korea, the studies on their relationship using a CGE model are virtually nonexistent. Thus, this study can be a new stepping-stone for conducting various studies on innovation and employment in the country in the future. In addition, in this study, the social accounting matrix was created by collecting data on overall economic activity of the national economy, including production and consumption, imports and exports, production relations among sectors, taxation, and factor income in the entire economy of the country from a macroeconomic perspective (Noh, 2006). Accordingly, the data used in CGE research has the character of “complete enumeration” of a given national economy. This means that bias in results due to the bias in data collection can be minimized. Thus, this study makes it possible to determine the scope of innovation policy assessment at the macroeconomic level by interlinking the innovation-related data that fit the situation of the country with other macro data. Moreover, this study can benefit various studies related to innovation policies as it creates a knowledge-based social accounting matrix that details labor, household, and innovation.

Chapter 3. Methodology

3.1 Construction of knowledge-based Social Accounting Matrix

This chapter describes the process of creating the social accounting matrix and household classification used in this study. The social accounting matrix used the input–output table from the Bank of Korea for 2010 as base data, and household classification used data from Household Income and Expenditure Survey by the Korea National Statistical Office as base data.

First, basic concepts of the social accounting matrix will be explained, and then the Household Income and Expenditure Survey data and input–output table data will be explained. Then, finally, the process of creating the social accounting matrix and household classification used in this study will be described in detail.

3.1.1 Social Accounting Matrix

A social accounting matrix is a matrix that can indicate economic cycle comprehensively. Each row of the matrix indicates income, and the sum of rows indicates total amount of income. The structure of the social accounting matrix is shown in Table 3. For example, in Table 3, for the 3rd household on the 5th row, the sum of income from labor and income from capital is the total income of the household. In addition, each row of the matrix indicates expenditure, and the sum of rows indicates the total expenditure.

For example, the 6th row in Table 3, *government*, gives expenditure for domestic goods and foreign goods, and expenditure for savings. Their sum is the total expenditure of government. Therefore, each element S(i, j) of the social accounting matrix indicates the income that account i receives from account j, and the expenditure that account j makes to account i at the same time. As this shows, in the social accounting matrix, income and expenditure of each economic actor should match in accordance with double-entry bookkeeping.

Social accounting matrices are created in various ways depending on the purpose of study, and a wide range of social accounting matrices also exist in Korea. However, production activity, factors of production, system, investment, tax, and overseas section are generally included.

Table 3. Structure of social accounting matrix

		Production		Value added		Institutions		Invest ment	Tax				ROW		Total
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	
Production	Domestic (1)	S(1,1)				S(1,5)	S(1,6)	S(1,7)					S(1,12)		S1
	Imported (2)	S(2,1)				S(2,5)	S(2,6)	S(2,7)							S2
Value added	Labor (3)	S(3,1)													S3
	Capital (4)	S(4,1)													S4
Institutions	Household (5)			S(5,3)	S(5,4)										S5
	Government (6)					S(6,5)			S6,8)	S(6,9)	S(6,10)	S(6,11)			S6
Investment	Physical capital (7)					S(7,5)	S(7,6)								S7
Tax	Indirect tax (8)	S(8,1)													S8
	Capital income tax (9)	S(9,1)													S9
	Labor income tax (10)	S(10,1)													S10
	Tariff (11)		S(11,2)												S11
ROW	Export (12)													S(12,13)	S12
	Import (13)		S(13,2)					S(13,7)							S13
Total		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	

Source: Yang et al. (2012)

3.1.2 Input–Output Table

The Input–Output Table of Korea is released by the Bank of Korea based on its survey, and is a statistics table as a comprehensive summary of all transactions on goods and services produced for a year. It is used as a basis for national and industry policy making as well as industry analysis.

The Bank of Korea published the first input–output table in 1960, and since then, it has been created every 3–5 years until 2005, when it began being created annually.

The basic structure of the input output table (–O table) is shown in Table 4. The horizontal direction of input output table indicates allocation structure, showing products of which industry are used for intermediate and final consumption of which industry. In addition, vertical direction of the I–O table indicates input structure, and shows production cost spent for producing products of each industry. Accordingly, the sum of a row indicates total amount of input, and the sum of a column indicates the total amount of output, and the total amount of input and the total amount of output are always identical.

The I–O table has endogenous and exogenous sections. The intermediate consumption and intermediate input that mean transaction between industries are in the endogenous section, and final consumption and added value are in the exogenous section. The endogenous section means that its values are determined passively based on the numbers for the exogenous section that are provided from outside the model; this is the most difficult part of creating an I–O table, and the most important part in analysis and use of the created table. On the other hand, values of the exogenous section are determined outside the model regardless of the endogenous section, and examining the impact of the variation in values of the exogenous section on national economy is the basic framework of I–O analysis.

In addition, I–O tables are essential data for creating social accounting matrixes. In particular, the endogenous section is also the most important part of the social accounting matrix, and the same values are brought to the matrix and used. The values of the exogenous section are also used in the social accounting matrix, and sometimes integrated and used for specific study purposes.

Table 4. Structure of I-O table

		Endogenous	Exogenous				Import	Total supply
		Intermediate demand	Consumption	Investment	Export	Final demand		
Endogenous	Intermediate input	X(i,j)	C(i)	I(i)	E(i)	Y(i)	M(i)	X(i)
Exogenous	Compensation of employees	R(j)						
	Operating surplus	S(j)						
	Depreciation of fixed capital	D(j)						
	Gross Value added	V(j)						
Total output		X(j)						

3.1.3 Household Income and Expenditure Survey

The Household Income and Expenditure Survey (HIE Survey) is conducted to provide data for measurement and analysis of the changes in income and consumption level by surveying incomes and expenditures of households and household conditions. The survey was conducted for the first time when the Bank of Korea and the Bureau of Statistics conducted a joint household survey with 120 households of salary earners in Seoul. The HIE Survey is conducted every month, and results are published quarterly by making estimations based on three-monthly data for each household. In addition, the survey also provides annual data by making estimations of 12-monthly data for each household. Specifically, annual mean income and expenditure for each household are calculated, annual weight for each household is calculated considering number of responses, and household characteristics representative of each household for the year are generated.

The most important thing in the HIE Survey is sampling and weighting. Samples are first stratified into seven cities and nine provinces, and each province is further divided into the Dong group (of urban areas) and the Eup-Myuns group (of rural areas), resulting in 25 strata in total. Sample size for each of the 25 areas is estimated using past sampling errors. The total sample size included 999 plots and 8,700–8,800 eligible households. The households selected using this method were surveyed for about three years, and one third of the entire sample is replaced every year.

The survey items in the HIE Survey are largely divided into income and expenditure.

Sub-items of each item have been slightly modified, and the current survey uses the items of the 2009 version. Sub-items are shown in Table 5.

Table 5. Income and expenditure items in household budget survey

Income (26)	Current income(22)	Wage and salary income(6)
		Business income(5)
		Property income(4)
		Transfer income(7)
	Noncurrent income(3)	
Expenditure (418)	Consumption expenditure(394)	Food and soft drinks (129)
		Alcoholic beverages and cigarette (8)
		Clothing and footwear (29)
		Housing, water, electricity, gas and other fuels (22)
		Household equipment and housekeeping services (53)
		Health (13)
		Transportation (23)
		Communication (7)
		Entertainment and culture (44)
		Education (24)
		Restaurants and hotels (8)
		Other miscellaneous goods and services (32)
	Non-consumption expenditures(24)	

3.1.4 Knowledge-Based Social Accounting Matrix[1]

The social accounting matrix of this study was generated as shown in Table 6 according to study purpose. Production activities were divided into domestic goods and imported

[1] Knowledge-based social accounting matrix was generated in reference to Yang, Jung, and Lee (2012) and Oh et al. (2014).

goods, and factors of production were divided into labor, capital, and knowledge. Systems were divided into household and government, and taxes were divided into indirect tax, corporate tax, income tax, and customs. Finally, overseas section was divided into import and export.

The social accounting matrix used the 2010 I–O Table by the Bank of Korea as its source data, and also used tax-related data in the 2010 Statistical Yearbook of National Tax. In addition, it used the data on household and government savings in the national accounts. Regarding the I–O table, the table based on the manufacturer's suggested retail price was used.

The biggest difference between the social accounting matrix discussed earlier and the knowledge-based social accounting matrix is that the latter includes knowledge in factors of production and R&D investment under investment. These were added, as R&D was capitalized in accordance with the recommendations in the Revised System of National Accounts 2008. Specifically, the row and the column of intermediates transactions of "research institutions" and "R&D in companies", respectively, under R&D become knowledge and R&D investment, respectively. Therefore, the values were not introduced from outside, but the divisions of the value for intermediates in the I–O Table were used. However, because the value for transactions of intermediates was capitalized, the value for value added increased, resulting in the increase of the value for GDP.

Table 6. Structure of knowledge based SAM

			Activity	Production factors			Institution		Investment			Tax				ROW		Total
			Intermediate	Labor	Capital	Knowledge	Household	Government	Physical capital	Knowledge capital		Indirect	Corporation	Income	Tariff	Export	Import	
										Private	Public							
Activity	Intermediate		S(1,1)				S(1,5)	S(1,6)	S(1,7)	S(1,8)	S(1,9)					S(1,14)		S1
Production factors	Labor		S(2,1)							S(2,8)	S(2,9)							S2
	Capital		S(3,1)							S(3,8)	S(3,9)							S3
	Knowledge		S(4,1)															S4
Institution	Household			S(5,2)	S(5,3)	S(5,4)												S5
	Government						S(6,5)					S(6,10)	S(6,11)	S(6,12)	S(6,13)			S6
Investment	Physical capital						S(7,5)	S(7,6)										S7
	Knowledge capital	Private					S(8,5)	S(8,6)										S8
		Public					S(9,5)	S(9,6)										S9
Tax	Indirect		S(10,1)															S10
	Corporation		S(11,1)															S11
	Income		S(12,1)															S12
	tariff		S(13,1)															S13
Row	Export																S(14,15)	S14
	Import		S(15,1)						S(15,7)									S15
Total			S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	

Based on the above information, S(1,1) means transactions of intermediates, indicating the transactions of domestic goods and the transactions of imported goods. In this study, industries were classified into 28 industries based on integrative large categories. However, because the 28th industry is the “Other” category, it was integrated into the 27th industry, resulting in a total of 27 industries.

S(2,1), S(3,1), and S(4,1) indicate input factors of production for production activities. Among them, S(2,1) indicates labor input, S(3,1) capital input, and S(4,1) knowledge input. S(2,1), S(3,1), and S(4,1) are all 1×27 matrices. S(10,1), S(11,1), S(12,1), and S(13,1) indicate the sources of government income, tax. These accounts are all 1x27 matrices. S(10,1) indicates indirect tax, S(11,1) corporate tax, S(12,1) income tax, and S(13,1) customs. S(6,10), S(6,11), S(6,12), and S(6,13) indicate tax paid to government. These used the values of sums of rows of S(10,1), S(11,1), S(12,1), and S(13,1) (i.e., S10, S11, S12, and S13), in accordance with the principles of double-entry bookkeeping.

S(15,1) and S(1,14) are trade-related accounts. S(15,1) indicates imports, and S(1,14) exports. They are 1×27 and 27×1 matrices, respectively. S(5,2) indicates household income from labor, and S(5,3) household income from knowledge. They are both 1×1 matrices. S(5,2) used the sum of S(2,1), S(2,8), and S(2,9) (i.e., the value of S2), and S(5,3) used the sum of S(3,1), S(3,8), and S(3,9) (i.e., the value of S3). S(5,4) used the sum of the row of S(4,1) (i.e., the value of S4). S(1,5) indicates household consumption expenditure , and S(7,5) indicates R&D investment. S(8,5) and S(9,5) indicate the household’s R&D investment. S(6,5) indicates the household’s government transfer payments, which is a balancing item serving to make the values of rows and columns in agreement in accordance with the principles of double-entry bookkeeping. This value is used to make income and expenditure of government in agreement.

On the other hand, S(1,6) indicates the government's consumption expenditure, and S(7,6), S(8,6), and S(9,6) indicate government's physical capital investment, government's public R&D investment, and government's private R&D investment, respectively. S(1,7) indicates physical capital investment of each industry, and S(1,8) and S(1,9) indicate R&D investment of each industry. S(2,8) and S(2,9) indicate labor input of R&D workforce, and S(3,8) and S(3,9) indicate R&D-related capital input.

Proportions of R&D investment by each industry are shown in Table 7. In the case of the Republic of Korea, manufacturing industry makes a huge R&D investment in the electrical and electronics industry, automobile industry, and chemical and medical industries, and also in the business service industry. In this data, R&D investment in public administration and the defense industry is zero, which is because the data released by government does not include data on the defense sector. Moreover, because its value is not large, the value was not included in this study.

Table 7 shows also the proportion of private R&D funding and public R&D funding, indicating significant difference in proportion across industries. S(14,15) and S(15,7) are balancing items for trade. S(15,7) indicates trade balance, using the total imports subtracted by the total imports. S(14,15) indicates the total exports, using the sum of S(1,14).

Table 7. Proportions of R&D investment in each industry and Proportions of private and public R&D investment

	Industry	%	Private	Public
1	Agriculture, forestry, and fisheries	0.1	0.66	0.34
2	Mining and quarrying	0	0.98	0.02
3	Food, beverages and tobacco prod.	0.4	0.98	0.02
4	Textile and apparel	0.26	0.9	0.1
5	Wood and paper products	0.12	0.18	0.82
6	Printing and publishing	1.28	0.55	0.45
7	Petroleum and coal products	1.29	0.55	0.45
8	Chemicals, drugs and medicines	5.68	0.75	0.25
9	Non-metallic mineral products	0.32	0.7	0.3
10	Basic metal products	1.13	0.94	0.06
11	Fabricated metal products	0.76	0.95	0.05
12	General machinery and equipment	8.42	0.55	0.45
13	Electronic and electrical equip.	12.25	0.7	0.3
14	Precision instruments	2.76	0.62	0.38
15	Transportation equipment	6.58	0.6	0.4
16	Furniture and other manufactured prod.	0.92	0.59	0.41
17	Electric, gas, steam and water supply	4.56	0.63	0.37
18	Construction	3.2	0.65	0.35
19	Wholesale and retail trade	2.44	0.76	0.24
20	Accommodation and food services	0		
21	Transportation and warehousing	2.44	0.75	0.25
22	Communications and broadcasting services	2.15	0.72	0.28
23	Finance and insurance	2.69	0.6	0.4
24	Real estate and business services	11.12	0.8	0.2
25	Public administration and defense	0		
26	Educational, health and social work	0.47	0.5	0.5
27	Social, personal and other services	28.68	0.81	0.19
	Total	100	0.72	0.28

3.1.5 Household Classification

In this study, household were classified into 20-quantiles based on total income, using micro data of 2010 HIE Survey by Korea National Statistical Office. Each household has the structure shown in Table 8. Because this is the social accounting matrix for households only, the sums of rows and columns in areas other than households do not agree.

Table 8. Structure of household SAM

			Activity	Production factors			Institution		Investment			Total
			Intermediate	Labor	Capital	Knowledge	Household	Government	Physical capital	Knowledge capital		
										Private	Public	
Activity	Intermediate						H(1,5)					H1
Production factors	Labor											H2
	Capital											H3
	Knowledge											H4
Institution	Household			H(5,2)	H(5,3)	H(5,4)						H5
	Government						H(6,5)					H6
Investment	Physical capital						H(7,5)					H7
	Knowledge capital	Private					H(8,5)					H8
		Public					H(9,5)					H9
Total			H1	H2	H3	H4	H5	H6	H7	H8	H9	

What each element of Table 8 indicates is nearly identical to the elements of social accounting matrix described above. H(1,5) indicates household's consumption expenditure, and H(7,5) indicates household's physical capital investment. H(8,5) and H(9,5) indicate households' R&D investment. Households make investment through household savings. H(6,5) indicates households' transfer payments to government. The sum of these five accounts is the total expenditure of households. On the other hand, H(5,2) indicates wage income from labor, H(5,3) indicates capital income from capital, and H(5,4) indicates income from knowledge. The sum of these three accounts is the total income of households.The value for each account is obtained in the following manner. H(1,5) was obtained using the proportion of consumption expenditure of industries for each quantile. To obtain the proportion of consumption expenditure of industries for each quantile, first, household consumption expenditure items in the HIE Survey and 27 industry classification of macro social accounting matrix need to be matched to each other. Matching was performed by comparing items in the HIE Survey and items of basic areas in the I–O table. Consumption expenditure for each industry in each household income quantile can be obtained by multiplying the S(1,5) value in the macro social accounting matrix by the proportion based on matching.

Proportions of H(7,5), H(8,5), and H(9,5) were obtained using savings data of the HIE Survey. In the case of H(5,2), H(5,3), and H(5,4) as household incomes, proportions were obtained using household income data from the HIE Survey. In the case of H(5,2), household earned income for each quantile was calculated using the percentage of earned income, and in the case of H(5,3) and H(5,4), household capital income for each quantile was calculated using the proportion of the sum of business income and property income. Finally, H(6,5) was used as an adjustment item to make household income and expenditure agree.

3.1.6 Classification of Labor

In this study, labor was classified by education level to examine the change of labor by skill level. In other words, labor for production of final goods and knowledge production was split into three types, as shown in Figure 5. In terms of final degree of education, masters or doctoral degree holders were classified as high-skilled, college graduates as skilled, and high school graduates or lower as unskilled. This classification is because the college enrollment rate is high in Korea.

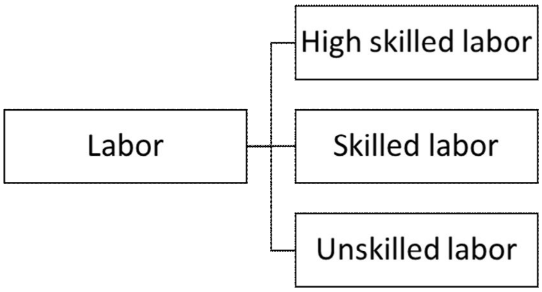


Figure 5. Segmentation of labor

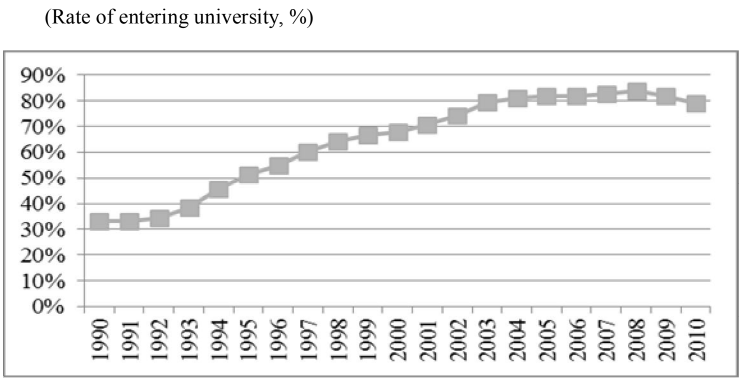


Figure 6. Rate of entering university in South Korea

Labor was classified in this study using the 2010 HIE Survey micro data and 2010 Wage Structure Statistics by the Ministry of Employment and Labor. Each type of labor has a structure as shown in Table 9. As this is the social accounting matrix for labor only, the sums of rows and columns in areas other than labor do not agree.

Table 9. Structure of labor SAM

<table>
<tr><td colspan="2" rowspan="3"></td><td>Activity</td><td>Production factors</td><td colspan="2">Investment</td><td rowspan="3">Total</td></tr>
<tr><td rowspan="2">Intermediate</td><td rowspan="2">Labor</td><td colspan="2">Knowledge capital</td></tr>
<tr><td>Private</td><td>Public</td></tr>
<tr><td>Production factors</td><td>Labor</td><td>L(2,1)</td><td></td><td>L(2,8)</td><td>L(2,9)</td><td>L2</td></tr>
<tr><td>Institution</td><td>Household</td><td></td><td>L(5,2)</td><td></td><td></td><td>L5</td></tr>
<tr><td colspan="2">Total</td><td>L1</td><td>L2</td><td>L8</td><td>L9</td><td></td></tr>
</table>

What each element of Table 9 indicates is nearly identical to the elements of the social accounting matrix described previously. L(2,1) indicates labor input for final goods production, L(2,8) indicates labor input for private knowledge production, and L(2,9) indicates labor input for public knowledge production. The sum of the three accounts indicates the total labor input. Labor input utilized the proportion of labor with different education level by industry on the basis of Employment and Labor Statistics of Korea; labor input for R&D utilized the proportion of different education levels in private R&D and public R&D based on the Survey of Research and Development by Korea Institute of S&T Evaluation and Planning (KISTEP). The 2010 distribution of researchers by sector and degree is shown in Table 10. In private companies, 40% of the R&D workforce was college graduates, accounting for the largest proportion. On the other hand, in public research institutions, about 38.6% of the R&D workforce were master's degree holders, 48.9% doctoral degree holders. In college, 36.5% of the R&D workforce were master's degree holders and 57.7% doctoral degree holders.

Table 10. South Korea's researcher distribution by R&D fund institution and education degree in 2010

Education level	Public R&D Centers	Universities	Private firms	Total
High school graduates	0.001	0.002	0.036	0.039
Bachelor degree	0.006	0.009	0.297	0.312
Master degree	0.022	0.073	0.235	0.330
Doctor degree	0.028	0.116	0.175	0.319

On the other hand, L(5,2) indicates wage income from labor, and was classified using the proportions of education level in each income quantile based on the HIE Survey.

The results of classification are shown in Figure 7. Highly educated high-skilled labor was largely distributed in the higher classes with high wage. In addition, income of the highest class was found to account for more income than all other classes did.

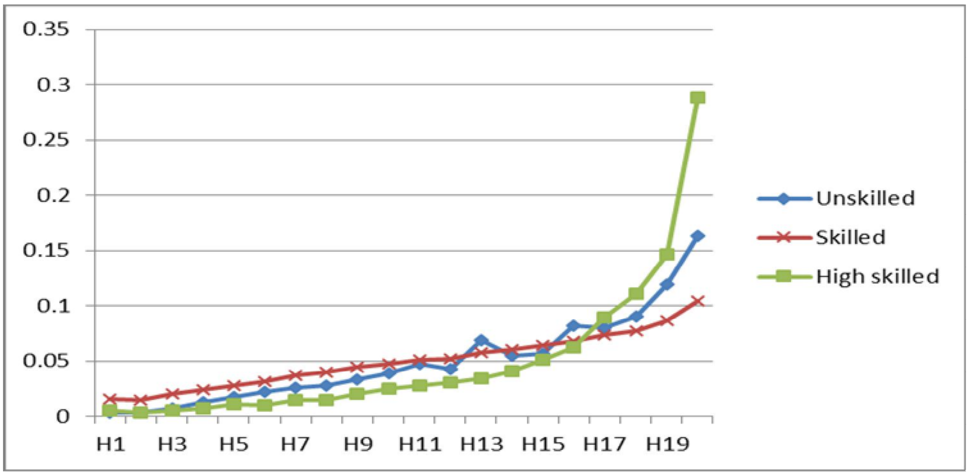


Figure 7. Portion of each labor by household income group in 2010

3.1.7 Integrated SAM

The social accounting matrix used in this study was completed by classifying households into 20 quantiles and labor into three sectors in the knowledge-based social accounting matrix. The integrated social accounting matrix is shown in Table 11. The numbers in Table 11 indicates the size of matrix of each account.

Table 11. Structure of integrated knowledge-based SAM

			Activity	Production factors			Institution		Investment			Tax				ROW		Total
			Intermediate	Labor	Capital	Knowledge	Household	Government	Physical capital	Knowledge capital		Indirect	Corporation	Income	Tariff	Export	Import	
										Private	Public							
Activity	Intermediate		28*28				28*20	28*1	28*1	28*1	28*1					28*1		
Production factors	Labor		3*28							3*1	3*1							
	Capital		1*28							1*1	1*1							
	Knowledge		1*28															
Institution	Household			20*3	20*1	20*1												
	Government						1*20					1*1	1*1	1*1	1*1			
Investment	Physical capital						1*20	1*1										
	Knowledge capital	Private					1*20	1*1										
		Public					1*20	1*1										
Tax	Indirect																	
	Corporation		1*28															
	Income		1*28															
	tariff		1*28															
Row	Export																1*1	
	Import		1*28						1*1									
Total																		

3.2 Fixed Capital Stock and Knowledge Capital Stock

3.2.1 Fixed Capital Stock

Gross fixed capital stock refers to the cost assessed to be required to repurchase all assets that a producer holds at a certain point. It includes both capital stock owned by a producer and leased capital stock, and also includes idle capital stock that is not input in the production process. On the other hand, net capital stock refers to gross fixed capital stock at a point from which gross fixed capital consumption cumulated up to the point; in turn, net capital stock can be said to be the market value of fixed assets of the entire economy at a given point (Pyo, Jung, & Cho, 2007). This study used net capital stock projections annually made by the Korea Productivity Center. Capital stock is measured using "National Wealth Statistics" by the Korea National Statistical Office, and the statistics include data on capital stock by industry and asset for all industries. However, because the National Wealth Survey has not been conducted since 1997, projections are made using the perpetual inventory method. Specifically, net capital stock was projected using the perpetual inventory method in which the gross national wealth for each of 72 industries in 1997 was converted to 2000 constant prices using the gross fixed capital formation (GFCF) deflator; then, GFCF's were added up with depreciations applied starting from 1998. The projection results showed that the gross capital stock of South Korea is approximately 3,485 trillion KRW as of 2010.

3.2.2 Knowledge Stock

Knowledge stock refers to the amount of produced knowledge that continuously accumulates over time. However, as it is difficult to quantify knowledge, it was assumed in this study that R&D stock is identical to knowledge stock. Accordingly, if new knowledge is formed as a result of R&D, newly supplied knowledge is incorporated into knowledge stock, and cumulated knowledge becomes obsolete at a certain rate, then knowledge stock can be expressed by Eq. (3.1) (Shin, 2004).

$$RDS_t = (1-\delta)RDS_{t-1} + RDI_{t-i} \qquad \text{Eq. (3.1)}$$

RDS in the equation denotes knowledge stock, and RDI denotes R&D investment. δ denotes rate of obsolescence, and i denotes R&D time lag. On the other hand, estimation of knowledge stock requires the information of knowledge stock in the base year. When it is assumed that new knowledge had been accumulated every year previously, knowledge stock of the base year can be expressed by Eq. (3.2).

$$RDS_{t_0} = \sum_{i=0}^{\infty} RDI_{t_0-i}(1-\delta)^i \qquad \text{Eq. (3.2)}$$

When it is assumed that the knowledge growth rate prior to the base year is the same as the average knowledge growth rate after the base year, Eq. (3.2) can be converted into

Eq. (3.3).

$$RDS_{t_0} = RDI_{t_0}\left[\frac{1+g}{g+\delta}\right] \qquad \text{Eq. (3.3)}$$

In this study, knowledge stock was estimated with the assumption that R&D time lag was one year, and that the rate of knowledge obsolescence was 0.15. In addition, knowledge stock was estimated separately for private and government/public sectors, and private knowledge stock was estimated for each industry. Knowledge stock of government/public sector was projected using the "Scientific and Technical Research Activities Survey Report" published annually by the Korea Institute of Science and Technology Evaluation and Planning (KISTEP), with 1991 as the base year. The results showed that knowledge stock of government/public sector was projected to be approximately 43 trillion KRW as of 2010. On the other hand, for industry-specific knowledge stock of the private sector, KISTEP data were not used because industry classification of KISTEP differs from industry classification on the I–O table. Instead, projections were generated by creating a knowledge-based social accounting matrix from 2005 to 2010 using 2005 as the base year. Regarding knowledge data for each industry, values of the "knowledge" row of the knowledge-based social accounting matrix were used. The results showed that the total knowledge stock of the private sector in 2010 was approximately 134 trillion KRW. Knowledge stock for each industry in 2010 is shown in Table 12.

Table 12. Knowledge stock in 2010

Private knowledge stock by industries (unit: million won)		
S1	Agriculture, forestry, and fisheries	73,559
S2	Mining and quarrying	10,518
S3	Food, beverages and tobacco prod.	681,705
S4	Textile and apparel	285,242
S5	Wood and paper products	222,539
S6	Printing and publishing	166,431
S7	Petroleum and coal products	759,748
S8	Chemicals, drugs and medicines	11,250,398
S9	Non-metallic mineral products	912,378
S10	Basic metal products	5,775,429
S11	Fabricated metal products	1,195,676
S12	General machinery and equipment	8,125,178
S13	Electronic and electrical equip.	51,818,493
S14	Precision instruments	4,478,035
S15	Transportation equipment	17,486,992
S16	Furniture and other manufactured prod.	421,018
S17	Electric, gas, steam and water supply	4,108,598
S18	Construction	5,120,662
S19	Wholesale and retail trade	742,149
S20	Accommodation and food services	33,272
S21	Transportation and warehousing	832,497
S22	Communications and broadcasting services	6,541,028
S23	Finance and insurance	821,031
S24	Real estate and business services	7,429,727
S25	Public administration and defense	3,634,805
S26	Educational, health and social work	1,017,634
S27	Social, personal and other services	176,849
Total private knowledge stock		134,121,593
Total public knowledge stock		42,908,306

3.3 Construction of Knowledge-Based CGE Model

3.3.1 Structure of Knowledge-Based CGE

CGE models are analysis models whose core of analysis is the procedure to make all goods and service markets in the economy achieve general equilibrium by incorporating economic actors consisting of the real economy into a model (Kim & Kim, 2010). Such CGE models consist of equations with various variables. In the present study, the knowledge-based CGE model was built to examine the effect of economic activities. As discussed earlier in Section 3.1 on knowledge-based social accounting matrix, the difference between the knowledge-based CGE model and conventional CGE model is that factors of production include knowledge, and investment includes R&D investment. Another difference is that industry-specific knowledge stock accumulated by R&D investment influences productivity of other industries through spillover effect. These differences result in changes in model structure and equation system. First, the structure of the knowledge-based CGE model is shown in Figure 8.

The model can mainly be divided into aspects of demand and supply. Regarding the supply aspect, value added and intermediates are input to produce domestic goods. Value added consists of labor, capital, and knowledge. On the other hand, regarding the demand aspect, produced domestic good are exported or consumed domestically along with imported goods. Domestic consumption includes consumption of investment goods and intermediates in addition to final consumption by households and government.

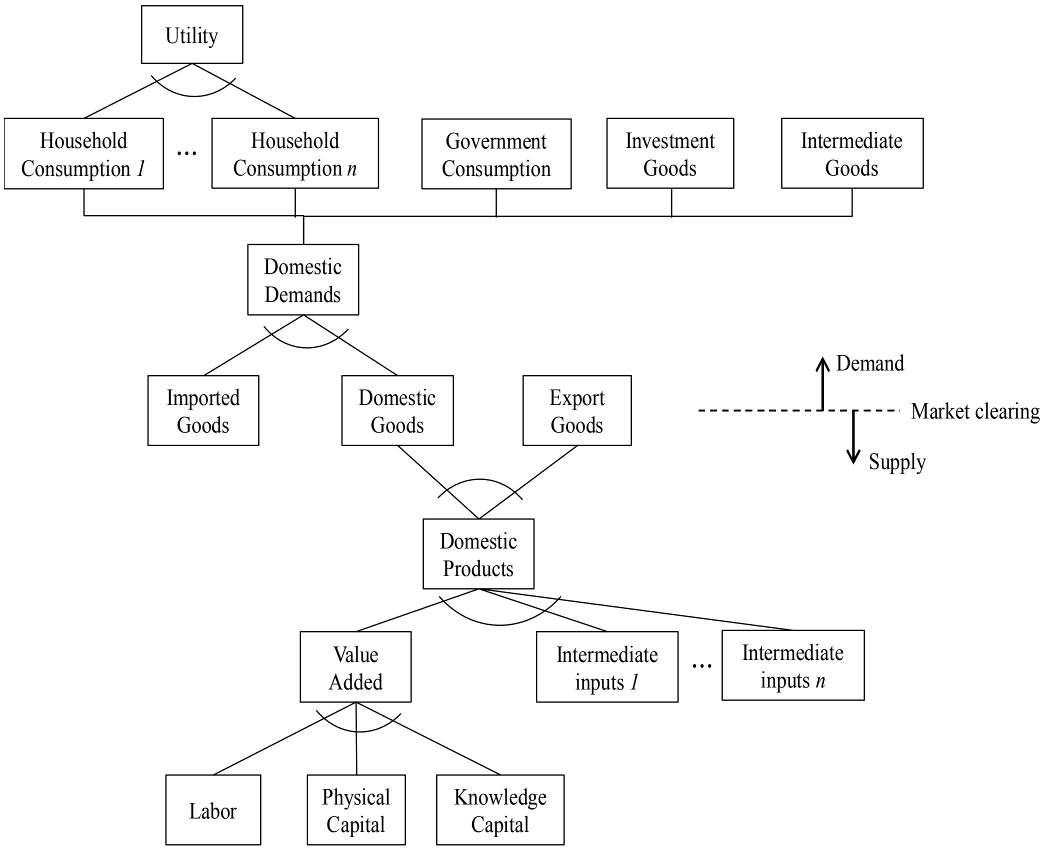


Figure 8. Structure of knowledge based CGE

Source: Hong(2015)

On the other hand, CGE is subject to influences among various components. This is reflected in economic structure; the economic structure of the knowledge-based CGE model is shown in Figure 9. The structure mainly consists of the following components: production, input factor, household, government, capital investment, R&D investment, tax, and overseas. The next subsection presents variables and equations for each component.

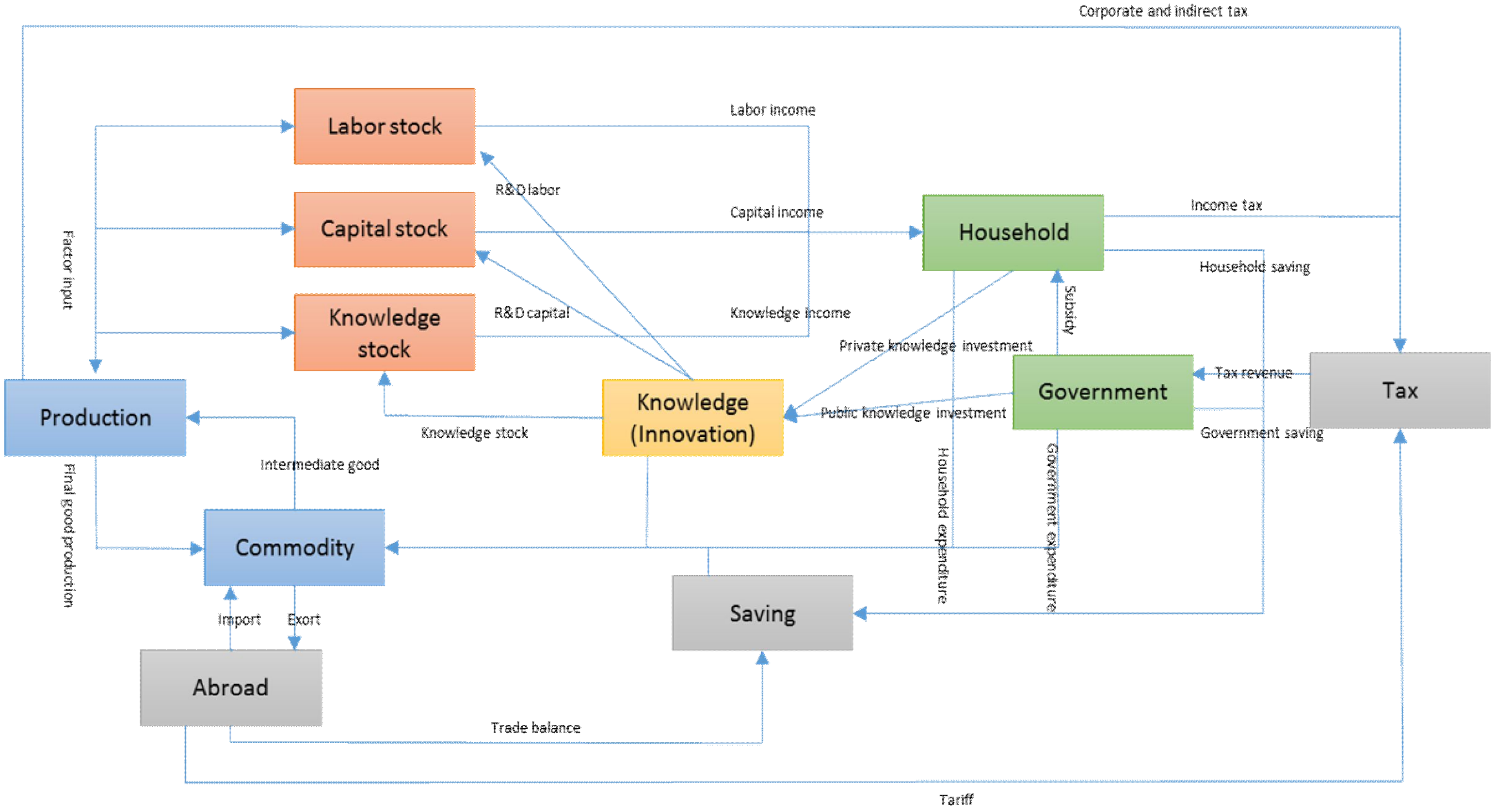


Figure 9. Economic structure of knowledge based CGE

3.3.2 Equation of Knowledge-Based CGE Model

3.3.2.1 Variable description

As mentioned earlier, CGE consists of the system of numerous equations. To define the equations, first, variables must be declared. The variables and parameters used in the present model are shown in Table 13.

Table 13. Symbols of variables and parameters

Sets and indices	
i, j	Sectors and goods
rdt	Type of R&D
hh	Type of household
n	Type of production factor
t	Time(year)
Activity variables	
L1(i)	Unskilled labor of sector i
L2(i)	Skilled labor of sector i
L3(i)	High skilled labor of sector i
K(i)	Physical capital of sector i
H(i)	Knowledge capital of sector i
X(i,j)	Intermediate goods of sector j produced in sector i
VA(j)	Value-added composite of sector j
AVA(j)	Value-added requirement coefficient of sector j
HLK(j)	Composite factor from L3, K and H in sector j

TOTSAV	Total saving
Z(j)	Final output of sector j
D(i)	Domestic goods of sector i
E(i)	Export of sector i
M(i)	Import of sector i
Q(i)	Armington composite goods of sector i
XP(i,hh)	Household consumption of sector i
XG(i)	Government consumption of sector i
XV(i)	Investment demand of sector i
RLS1(rdt)	Unskilled labor in R&D investment of sector rdt
RLS2(rdt)	Skilled labor in R&D investment of sector rdt
RLS3(rdt)	High skilled labor in R&D investment of sector rdt
RKS(rdt)	Physical capital in R&D investment of sector rdt
RVA(rdt)	Composite factor from RHK, RLS1, and RLS2 in sector rdt
RHK(rdt)	Composite factor from RLS3 and RKS in sector rdt
XVRD(rdt,i)	Intermediate input in R&D investment in sector rdt
RDZ(rdt)	R&D investment in sector rdt
SPCOEFF(i)	Spillover coefficient in sector i
INTINDST(i)	Interindustry spillover in sector i
INVPRD(i)	Private R&D investment in sector i
INVGRD	Public R&D investment
INVK	Demand for capital investment
INVRES	Investment resource
SP(hh)	Household saving
SG	Government saving
HG	Public knowledge stock
TG(hh)	Government transfer to household

SF	International trade balance
LS(t)	Labor stock in time t
KS(t)	Capital stock in time t

Price variables	
PL1	Factor price of unskilled labor
PL2	Factor price of skilled labor
PL3	Factor price of high skilled labor
PK	Factor price of physical capital
PRD(i)	Factor price of knowledge capital
PVA(i)	Price of value-added composite in sector i
PHLK(i)	Price of composite factor from L3, K and H in sector j
PZ(i)	Price of final output in sector i
PD(i)	Price of domestic goods in sector i
PE(i))	Price of export in sector i
PM(i)	Price of import in sector i
PQ(i)	Price of Armington composite goods in sector i
PWE(i)	World price of export in sector i
PWM(i)	World price of import in sector i
PINVK	Price of capital investment
PRDZ(rdt)	Price of R&D composite
PRVA(rdt)	Price of composite from RLS3 and RKS in sector rdt
PRHK(rdt)	Price of composite from RHK, RLS1, and RLS2 in sector rdt
Tax and income variables	
TZ(i)	Production tax
TL(i)	Tax for labor
TK(i)	Tax for physical capital

TH(i)	Tax for knowledge capital
TM(i)	Import tariff
HINC(hh)	Household income of hh
HLINC1	Household income from unskilled labor
HLINC2	Household income from skilled labor
HLINC3	Household income from high skilledlabor
HKINC	Household income from physical capital
HRINC	Household income from knowledge capital
GINC	Government income
FHL1(hh)	Household hh's income from unskilled labor
FHL2(hh)	Household hh's income from skilled labor
FHL3(hh)	Household hh's income from high skilledlabor
FHK(hh)	Household hh's income from physical capital
FHR(hh)	Household hh's income from knowledge capital
Parameter	
ax0(i,j)	Intermediate input requirement coefficient
ava0(i)	Composite factor input requirement coefficient
$\beta 10(i)$	Share parameter in CES production function for L3
$\beta 20(i)$	Share parameter in CES production function for K
$\beta 30(i)$	Share parameter in CES production function for L1
$\beta 40(i)$	Share parameter in CES production function for L2
$\theta 10(i)$	Scale parameter in CES production function for L3, K, and H
$\theta 20(i)$	Scale parameter in CES production function for L1, L2, and HLK
$\rho 1$	CES exponent for L3, K, and H
$\rho 2$	CES exponent for L1, L2, and HLK
ffhh0(hh,n)	Income share parameter of household in each production factor
$\alpha 0(i, hh)$	Household hh's consumption share parameter by industry

$\tau 0_i^n$	Income Tax rate of production factor in sector i
$\tau 0_i^z$	Value-added tax rate in sector i
$\tau 0_i^M$	Rate of Tariff in sector i
$\mu 0_i$	Government consumption share parameter by industry
Other0(j,i)	Interindustry spillover stock weight
spc0(i)	Scale parameter in interindustry spillover function
rdelas(i)	Interindustry R&D stock elasticity
grdelas(i)	Public R&D stock elasticity
$\varphi 10$	Scale parameter in CES production function for RLS3 and RKS
$\varphi 20$	Scale parameter in CES production function for RLS1, RLS2, and RHK
$\psi 10$	Share parameter in CES production function for RLS3
$\psi 20$	Share parameter in CES production function for RLS1
$\psi 30$	Share parameter in CES production function for RLS2
ayrd0(rdt)	Composite factor input requirement coefficient in R&D
axrd0(rdt,i)	Intermediate input requirement coefficient in R&D
ε	Exchange rate
g(t)	Population growth rate
rkdep	Capital depreciation rate
rhdep	Knowledge depreciation rate

3.3.2.2 Domestic production

Production of goods requires intermediates as parts of the goods, as well as the machinery, equipment, and space for assembly of the intermediates. That is, capital is required. In addition, labor to produce the goods using machinery and equipment is required, and knowledge to develop and improve the goods is required. Here, capital, labor, and knowledge are value added as well as factors of production to produce the goods. Therefore, outputs (Z_j) of each industry become production by factors of production, intermediates ($X_{i,j}$), and value-added composites (VA_j). If the intermediates and value-added composites required to produce a unit of output in industry j are $ax0_{i,j}$[2] and $ava0_j$, respectively, and the factors of production of industry j exist as much as $[X_{1,j}, X_{2,j}, \cdots, X_{n,j}, VA_j]$, output is expressed by Eq. (3.4). In addition, to incorporate it into the equation system, Eq. (3.5) and Eq. (3.6) were generated. The reason for using AVA rather than ava0 is to incorporate spillover effect of knowledge stock. This will be explained in Section 3.3.2.5.

$$Z(j) = \min[\frac{X(1,j)}{ax0(1,j)}, \ldots\ldots, \frac{X(n,j)}{ax0(n,j)}, \frac{VA(j)}{ava0(j)}] \qquad \text{Eq. (3.4)}$$

---

[2] Symbols with 0 in this chapter indicate the parameters obtained by variable values of knowledge-based social accounting matrix of base year.

$$X_{i,j} = ax0_{i,j} \cdot Z_j \qquad \text{Eq. (3.5)}$$

$$VA_j = AVA_j \cdot Z_j \qquad \text{Eq. (3.6)}$$

Eq. (3.4) is a type of Leontief production function used when substitution between factors of production is not possible. Accordingly, it was assumed that intermediates and value-added composites of each industry could not be substituted.

On the other hand, value-added composites were assumed to be generated by labor, capital, and knowledge. In this study, knowledge was included as one of the factors of production to determine the effect of innovative activities. In addition, to incorporate elasticities of substitution between factor inputs, the constant elasticity of substitution (CES) function was introduced. The CES production function is frequently used in innovation studies because it allows cases where elasticity of substitution is not 1 (Shin, 2005). Although CES production function is used to combine two types of factors of production, more than two types of factors of production can be used if elasticities of substitution among various types of factors of production are identical (Sato, 1967). For example, as previously discussed, Bor et al. (2010) included four factors of production including land, labor, non-R&D capital, and R&D capital in the CES function for production.

In this study, it was assumed that high-skilled labor, capital, and knowledge are complementary to one another, and have the same elasticity of substitution to one another.

In addition, it was assumed that a substitutive relationship exists between high-skilled labor and capital, and also among composites of knowledge, non-skilled labor, and skilled labor, and that they have the same elasticity of substitution. Accordingly, the structure of production function applied in this model has the form as shown in Figure 10, which can be expressed by Eq. (3.7) and Eq. (3.8).

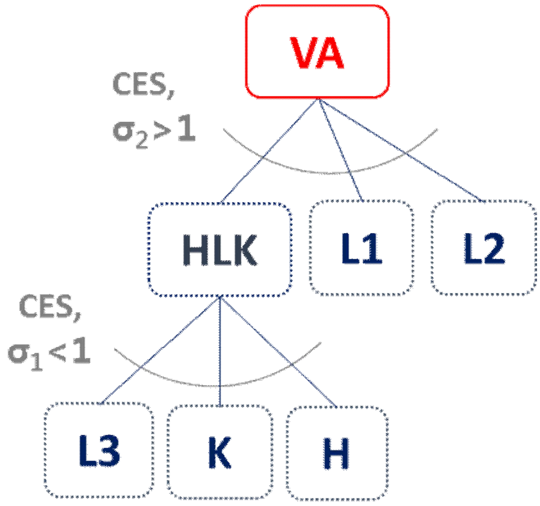


Figure 10. Structure of production function

$$HLK_i = \theta 10_i \cdot (\beta 10_i \cdot L3_i^{-\rho 1} + \beta 20_i \cdot K_i^{-\rho 1} + (1 - \beta 10_i - \beta 20_i) \cdot H_i^{-\rho 1})^{-1/\rho 1} \qquad \text{Eq. (3.7)}$$

$$VA_i = \theta 20_i \cdot (\beta 30_i \cdot L1_i^{-\rho 2} + \beta 40_i \cdot L2_i^{-\rho 2} + (1 - \beta 30_i - \beta 40_i) \cdot HLK_i^{-\rho 2})^{-1/\rho 2}$$

Eq. (3.8)

3.3.2.3 Household

In this model, households were classified into 20 quantiles based on income. Each income quantile of households gain income through wage income, capital income, and knowledge income. This can be expressed in the following equations. First, Eq. (3.9) indicates wage income for unskilled labor, Eq. (3.10) indicates wage income for skilled labor, and Eq. (3.11) indicates wage income for high-skilled labor. Wage income for each skill level is earned as the sum of the payment for labor invested into production activities and the payment for labor investment into R&D activities. Eq. (3.12) and Eq. (3.13) indicate capital income and knowledge income, respectively. Capital income is gained as the return for capital invested into production activities and the return for the capital invested into R&D activities, and knowledge income is gained as the payment for the knowledge invested into production activities.

$$HLINC1 = \sum_{i}(L1_i \cdot PL1) + \sum_{rdt}(RLS1_{rdt} \cdot PL1) \qquad \text{Eq. (3.9)}$$

$$HLINC2 = \sum_{i}(L2_i \cdot PL2) + \sum_{rdt}(RLS2_{rdt} \cdot PL2) \qquad \text{Eq. (3.10)}$$

$$HLINC3 = \sum_{i}(L3_i \cdot PL3) + \sum_{rdt}(RLS3_{rdt} \cdot PL3) \qquad \text{Eq. (3.11)}$$

$$HKINC = \sum_{i}(K_i \cdot PK) + \sum_{rdt}(RKS_{rdt} \cdot PK) \qquad \text{Eq. (3.12)}$$

$$HRINC = \sum_{i}(H_i \cdot PRD_i) \qquad \text{Eq. (3.13)}$$

On the other hand, household income for each factor of production is split into each household quantile in accordance with proportions of household income quantiles ($ffhh_{hh,n}$). This is expressed by Eqs. (3.14–3.18). In this way, each household splits the payments for labor, capital, and knowledge inputs, and the sum of them is the total income of each household as shown in Eq. (3.19).

$$FHL1_{hh} = ffhh0_{hh,L1} \cdot HLINC1 \quad \text{Eq. (3.14)}$$

$$FHL2_{hh} = ffhh0_{hh,L2} \cdot HLINC2 \quad \text{Eq. (3.15)}$$

$$FHL3_{hh} = ffhh0_{hh,L3} \cdot HLINC3 \quad \text{Eq. (3.16)}$$

$$FHK_{hh} = ffhh0_{hh,k} \cdot HKINC \quad \text{Eq. (3.17)}$$

$$FHR_{hh} = ffhh0_{hh,R} \cdot HRINC \quad \text{Eq. (3.18)}$$

$$HINC_{hh} = FHL1_{hh} + FHL2_{hh} + FHL3_{hh} + FHK_{hh} + FHR_{hh} \quad \text{Eq. (3.19)}$$

$$XP_{i,hh} = \alpha 0_{i,hh} \cdot (HINC_{hh} - SP_{hh} - TG_{hh}) / PQ_i \quad \text{Eq. (3.20)}$$

The incomes gained by each household in this way are saved (SP) or paid to government as transfer payment (TG). The remaining income is spent for consumption (XP). This can be expressed by Eq. (3.20). Household consumption expenditure for each industry is determined by the proportion ($\alpha 0_{i,hh}$) of consumption expenditure for each industry within each household quantile.

3.3.2.4 Government

Government gains income through tax. In the present model, tax is collected in the form of indirect tax, direct tax, and customs. Indirect tax is the value added tax imposed on the output a company produces, and direct tax is the income tax imposed on the income gained as payments for labor, capital, and knowledge inputs. Customs are the tax imposed on the goods imported from overseas. These are expressed by the following equations: Eq. (3.21) indicates indirect tax; Eq. (3.22), Eq. (3.23), and Eq. (3.24) indicate income tax; and Eq. (3.25) indicates customs. On the other hand, each tax rate was estimated based on the 2010 Statistical Yearbook of National Tax, and the value was assumed to stay constant using 2010 as the reference year.

$$TZ_i = \tau 0_i^z \cdot Z_i \cdot PZ_i \qquad \text{Eq. (3.21)}$$

$$TL_i = \tau 0_i^{L1} \cdot L1_i \cdot PL1_i + \tau 0_i^{L2} \cdot L2_i \cdot PL2_i + \tau 0_i^{L3} \cdot L3_i \cdot PL3_i \qquad \text{Eq. (3.22)}$$

$$TK_i = \tau 0_i^K \cdot K_i \cdot PK_i \qquad \text{Eq. (3.23)}$$

$$TH_i = \tau 0_i^H \cdot H_i \cdot PRD_i \qquad \text{Eq. (3.24)}$$

$$TM_i = \tau 0_i^M \cdot M_i \cdot PWM_i \qquad \text{Eq. (3.25)}$$

On the other hand, as Eq. (3.26) shows, government gets income through tax and household transfer payments, and the rest of the government income collected excluding government savings is taken as government's consumption expenditure (Eq. (3.27)). Here, government's consumption expenditure for each industry is determined by the proportion of consumption expenditure for each industry ($\mu 0$).

$$GINC = (\sum_{i}(TZ_i + TL_i + TK_i + TH_i + TM_i)) + \sum_{hh} TG_{hh} \quad \text{Eq. (3.26)}$$

$$XG_i = \mu 0_i \cdot (GINC - SG) / PQ_i \quad \text{Eq. (3.27)}$$

3.3.2.5 Knowledge

In this study, it was conceptualized that knowledge stock of each industry is applied in other industries at no cost, and influences productivity. In other words, spillover effect of knowledge stock was incorporated. To this end, the model incorporated the consideration that knowledge spillover effect of each industry is influenced by knowledge stock of other industries. In this mode, the spillover effect from other industries was set to be in proportion to the volume of intermediates' transactions on the I–O table using the method of Terleckyj (1980). This can be expressed by Eq. (3.28). In the equation, INTINDST denotes knowledge stock spilled over from other industries. This value was calculated by adding up the knowledge stock of other industries multiplied by the proportion ($other0$) of the volume of intermediates transactions between the given industry and other industries. On the other hand, public knowledge stock is used as public goods that can be used by all industries simultaneously, and thus influences industry-specific productivity in the private sector (Guellec and Potterie, 2001). Accordingly, public knowledge stock was set to have a spillover effect on all industries. Accordingly, industry-specific knowledge spillover effect was set to be generated by the spillover effect of knowledge stock of other industries and spillover effect of public knowledge stock at the end (Eq. (3.29)), based on Hong et al. (2014). The spillover effect of knowledge stock of other industries (rdelas) employed the value of elasticity by which external R&D capital influenced value added in Cho (2004); the spillover effect of public knowledge stock employed the value of elasticity by which government R&D influenced the total factor productivity in Hwang et al. (2008). The knowledge spillover effect formed this way influences productivity. Accordingly, increase in knowledge stock as a result of R&D leads to increased productivity and, consequently, more final products can be produced even though the same amount of factors of production is used (Eq. (3.30)).

$$INTINDST_i = \sum_{j,j \neq i} other0_{j,i} \cdot H_j \qquad \text{Eq. (3.28)}$$

$$SPCOEFF_i = spc0_i \cdot INTINDST_i^{rdelas_i} \cdot HG^{grdelas_i} \qquad \text{Eq. (3.29)}$$

$$AVA_i = ava0_i \, / \, SPCOEFF_i \qquad \text{Eq. (3.30)}$$

On the other hand, R&D activities are conducted with intermediates for R&D, R&D workforce, and the capital for R&D. In addition, R&D activities were divided into private and public R&Ds. Labor and capital for R&D produces knowledge value added, which is generated by CES function, as shown in Eq. (3.31) and Eq. (3.32). Moreover, it was assumed that, as in production, knowledge value added and industry-specific intermediates for R&D were also combined based on the Leontief function in R&D. Accordingly, they are expressed by Eq. (3.33) and Eq. (3.34).

$$RHK_{rdt} = \varphi 10_{rdt} \cdot ((1-\psi 10_{rdt}) \cdot RKS_{rdt}{}^{-\rho 1} + \psi 10_{rdt} \cdot RLS3_{rdt}{}^{-\rho 1})^{-1/\rho 1} \qquad \text{Eq. (3.31)}$$

$$\begin{aligned} RVA_{rdt} = \varphi 20_{rdt} \cdot (&\psi 20_{rdt} \cdot RLS1_{rdt}{}^{-\rho 2} + \psi 30_{rdt} \cdot RLS2_{rdt}{}^{-\rho 2} \\ &+ (1-\psi 20_{rdt} - \psi 30_{rdt}) \cdot RHK_{rdt}{}^{-\rho 2})^{-1/\rho 2} \end{aligned} \qquad \text{Eq. (3.32)}$$

$$RVA_{rdt} = ayrd0_{rdt} \cdot RDZ_{rdt} \qquad \text{Eq. (3.33)}$$

$$XVRD_{rdt,i} = axrd0_{rdt,i} \cdot RDZ_{rdt} \qquad \text{Eq. (3.34)}$$

3.3.2.6 Investment and Savings

Investment is classified into physical capital investment and R&D, as shown in Figure 11, and R&D is classified into public and private R&D, as discussed earlier. Therefore, the total investment consists of the sum of industry-specific physical capital investment, private R&D, and public R&D, as shown in Eq. (3.35).

On the other hand, savings consists of household and government savings (Eq. (3.36)). The sum of the savings and foreign trade balance is the total investment (Eq. (3.37)). The trade balance indicates the value of the total exports subtracted by the total imports, and expressed by Eq. (3.38).

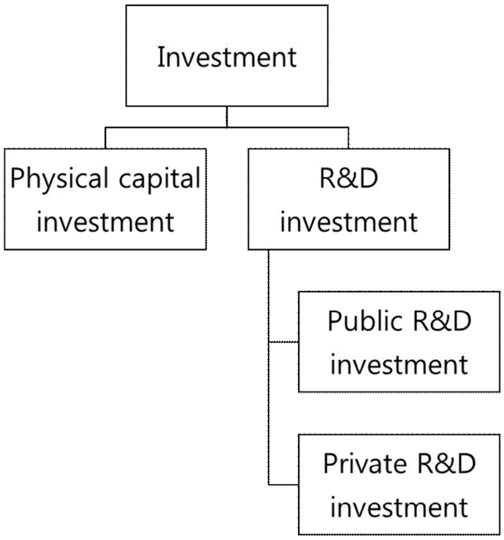


Figure 11. Types of investment

$$INVRES = \sum_{i}(XV_i \cdot PQ_i) + \sum_{rdt}(RDZ_{rdt} \cdot PRDZ_{rdt}) \quad \text{Eq. (3.35)}$$

$$TOTSAV = \sum_{hh} SP_{hh} + SG \quad \text{Eq. (3.36)}$$

$$INVRES = TOTSAV + SF \quad \text{Eq. (3.37)}$$

$$SF = \sum_{i}(PE_i \cdot E_i) - \sum_{i}(PM_i \cdot M_i) \quad \text{Eq. (3.38)}$$

3.3.2.7 Foreign Trade

Foreign trade consists of import and export. In export, price is determined by multiplying foreign price by exchange rate (Eq. (3.38)); in import, price is determined by multiplying foreign price by exchange rate and customs (Eq. (3.39)). As shown in Figure

8, the domestic aggregate demand equals the sum of domestic goods consumed domestically and imported goods (Eq. (3.41)), and the total domestic output equals the sum of domestic goods consumed domestically and export goods (Eq. (3.42)).

$$PE_i = \varepsilon \cdot PWE_i \qquad \text{Eq. (3.39)}$$

$$PM_i = \varepsilon \cdot (1+\tau_i^M) \cdot PWM_i \qquad \text{Eq. (3.40)}$$

$$PQ_i \cdot Q_i = PM_i \cdot M_i + PD_i \cdot D_i \qquad \text{Eq. (3.41)}$$

$$PZ_i \cdot Z_i = PE_i \cdot E_i + PD_i \cdot D_i \qquad \text{Eq. (3.42)}$$

3.3.2.8 Dynamics

This model was designed as a dynamic model to enable examination of the effect of innovative activities on economy over time. To design a dynamic model, labor, capital, and knowledge as factors of production were set to accumulate over time. First, labor stock of the base year is determined as the sum of labor for production activities and labor for R&D activities in the base year (Eq. (3.43)). In addition, labor at each skill level was set to increase over time according to population growth rate (Eq. (3.44)).

$$\sum_i (L1_i + L2_i + L3_i) + \sum_{rdt} (RLS1_{rdt} + RLS2_{rdt} + RLS3_{rdt}) = LS \qquad \text{Eq. (3.43)}$$

$$LS_{t+1} = (1+g_t) \cdot LS_t \qquad \text{Eq. (3.44)}$$

For capital stock, perpetual inventory method of applying depreciation to capital stock of the base year that was projected in Section 3.2.1 and adding additionally invested capital was applied (Eq. (3.45)).

$$KS_{t+1} = (1 - rkdep) \cdot KS_t + INVK_t \qquad \text{Eq. (3.45)}$$

In addition, for knowledge stock, the perpetual inventory method of making deduction as much as the rate of knowledge obsolescence from private knowledge stock and public knowledge stock of base year projected in Section 3.2.2 and adding additionally invested R&D investment was also applied. Industry-specific private knowledge stock was calculated by making a deduction applying the rate of obsolescence from industry-specific knowledge stock in the previous period, and adding newly invested industry-specific R&D investment for this period, as shown in Eq. (3.26). Public knowledge stock was calculated by making a deduction applying the rate of obsolescence from public knowledge stock of the previous period and adding newly invested public R&D investment this period, as shown in Eq. (3.47).

$$H_{i,t+1} = (1 - rhdep) \cdot H_{i,t} + INVPRD_{i,t} \qquad \text{Eq. (3.46)}$$

$$HG_{t+1} = (1 - rhdep) \cdot HG_t + INVGRD_t \qquad \text{Eq. (3.47)}$$

Chapter 4. The effect of innovation on employment structure and economic growth

4.1 Background and Purpose of Study

Recently, a growing number of people have argued that technological advance would have an adverse effect on employment. In particular, some offer bleak future prospects, contending that such phenomenon will worsen in the future due to the progress in information and communication technology and the emergence of robot technology. As discussed earlier, Brynjolfsson and McAfee (2014) viewed that the speed of jobs disappearing is faster than the speed of jobs being created due to exponentially rapid progress in technology, and this is a cause of stagnant income and increasing inequality observed recently in the U.S. and elsewhere. On the other hand, Cowen (2013) argued that, as robot and computer technology advances rapidly, the U.S. population will be divided into the top 10% and the other 90%, stating that the 10% that can keep up with the speed of technological advance enjoy a life of abundance, while the remaining 90% may face a situation of decreased or stagnant wages relative to inflation. Frey and Osborne (2013) argued that a half of U.S. jobs will be replaced by robots and artificial intelligence within 20 years. Moreover, arguing that robots intensify inequality, Autor (2010) claimed that wage growth stagnated and the gap between rich and poor increased in the last 15 years in the U.S. due to robots and automation.

However, opposing views have also been raised. Goldin and Katz (2008) argued that, from a long-term perspective, employment rate has been stable, and human beings have always created new jobs and that it just takes time to catch up with technological advance and consequent social change. In addition, Bessen (2015) argued that technological innovation does not replace jobs, and it simply displaces workforce to the places requiring new skills. Using the typesetting industry as an example, he argued that advances in computer technology reduced jobs in the typesetting industry, but that many new jobs were created due to the advent of computer. He accepted that benefits of new technology, however, are not distributed among majority of workers until new technological innovation takes place and become widespread, and go to high-skilled labor that can use skills for the new technology in the interim. He argued that once new technology becomes stabilized and standardized, however, ordinary workers can access the technology, and eventually jobs increase. In other words, he suggested that technological innovation displaces jobs to new industry and new jobs with a time lag, rather than taking away jobs. Nevertheless, he also contended that job displacement requires good education and training, and, accordingly, sufficient time and effort. In addition, according to his argument, SBTC takes place because a lot of skilled workforce is required at the initial period of new technology, and capital-biased technological change also takes place because a lot of machinery and equipment for introduction of technology is required in the initial period of new technology. However, as new technology begins to become widespread, the knowledge on the particular technology is widely shared, ordinary workers can then use the technology, and the premium for high-skilled labor disappears. As a result, the problem of SBTC also disappears. Moreover, because once technology becomes stabilized, experience-based knowhow becomes an important factor, human capital investment rather than physical capital investment is focused on and, consequently, the value of human labor becomes larger than capital, also solving the problem of capital-biased technological change.

As these considerations show, optimists generally view that technological advance would not take away jobs as much as concerns expressed by others for the following five reasons. First, historically, technology has been a job creator rather than job destroyer. Second, technological advance created more jobs and industries than the existing jobs and industries it took away. Third, many areas of production activity that only humans can do still exist. Fourth, the technological advance that will take place over the next 10 years is not sufficient to substantially impact the labor market. Fifth, social and legal actions will minimize the impact of robots on employment.

Amidst these conflicting arguments, the issue of the effect of innovation on employment is also attracting a great deal of attention in Korea. However, it remains difficult to find quantitative evaluation on the effect of innovation on employment in the digital age. Thus, this study aims to quantitatively evaluate the effect of innovation on employment structure and economic growth.

4.2 Analytical framework

The paths through which various technologies influence the economy will be examined using a few examples, prior to analysis. Mainly, three types of technologies are examined.

The first is an industrial automation robot. As robot technology has advanced in recent years, it has influenced our life and economy significantly. The advent of industrial automation robots may facilitate the growth of the robot industry directly, and the growth of other related industries indirectly. Therefore, employment may increase through the growth of related industries. In addition, the advent of automation robots can increase productivity of the manufacturing industry, and reduce product price as a result of cost savings, reducing the burden on consumers. However, the advent of automation robots reduces unskilled labor jobs in the manufacturing industry. Such changes in employment structure impact household income, which influences consumption, eventually impacting economic growth. Incidentally, competitiveness of domestic manufacturing may increase, as it is no longer necessary to relocate factories overseas in search for cheap labor, thanks to automation robots. In addition, social costs associated with industrial accidents may decrease as the latter decreases. These considerations are illustrated in Figure 12.

The second technology is a domestic robot. When the domestic robot industry grows, as in the case of industrial automation robots, related robot industries will grow, and as a result, employment in related industries will increase. However, the jobs for domestic helpers will decrease. On the other hand, the advent of domestic robots decreases housework, facilitating women's activities in society, and increasing working age population, ultimately leading to increased productivity. The advent of domestic robots influences employment and productivity through these paths, which impacts economic growth. This is summarized in Figure 13.

The third technology is an autonomous car. Although it is yet to be commercialized, when it is, the technology will have a significant impact. First, the advent of autonomous cars will increase the growth and employment in related industries. However, a considerable number of workers in the current transportation industry may lose their jobs. Furthermore, a wide range of effects generated by autonomous cars can be imagined, for example, those working in the insurance industry can be affected due to decreased traffic accidents, and the needs for road patrols will decline due to decreased accidents. In addition, growth of the autonomous car industry will influence employment and production in various ways, ultimately affecting economic growth. These considerations are illustrated in Figure 14.

The examination of the three representative innovative technologies so far indicates that these can influence the economy in various complex ways. Accordingly, it is not easy to generalize the impact of technologies or new products developed by technological innovation. However, if the effect of technological innovation on employment can be generalized and expressed, it can mainly be expressed in the following two forms. The first is the direct employment effect as a result of capital-biased technological change and

SBTC, as discussed earlier. The second is the indirect employment effect occurring due to spillover effect of innovation. This can be observed in Figure 15.

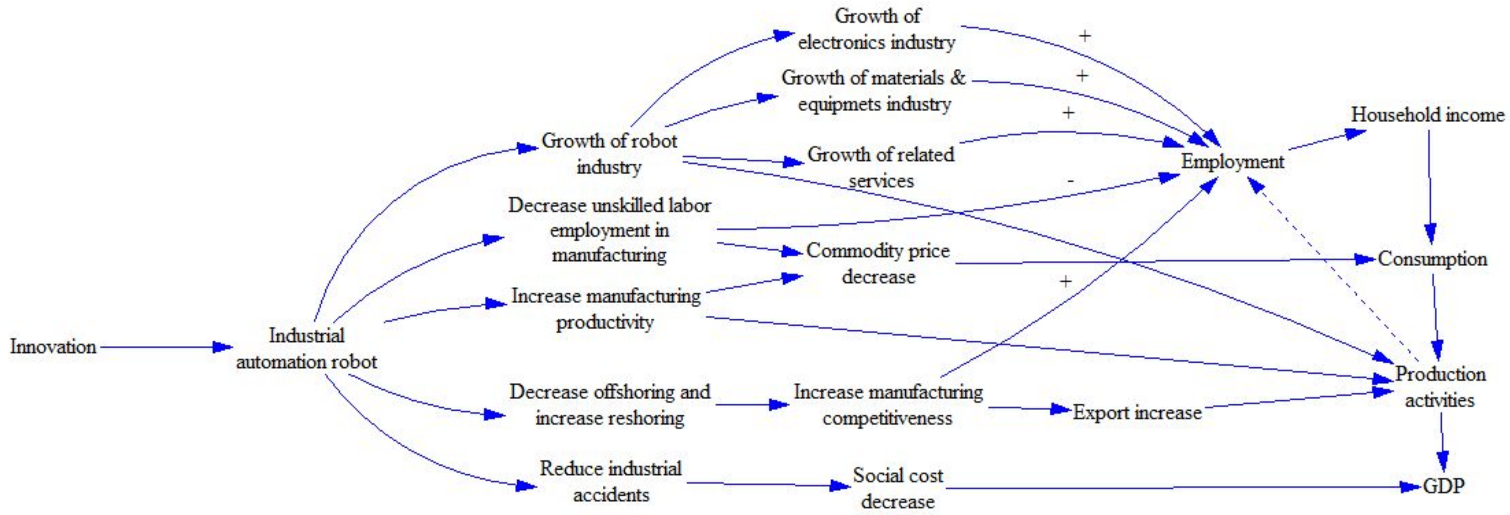


Figure 12. Impact of Industrial automation robot on the economy

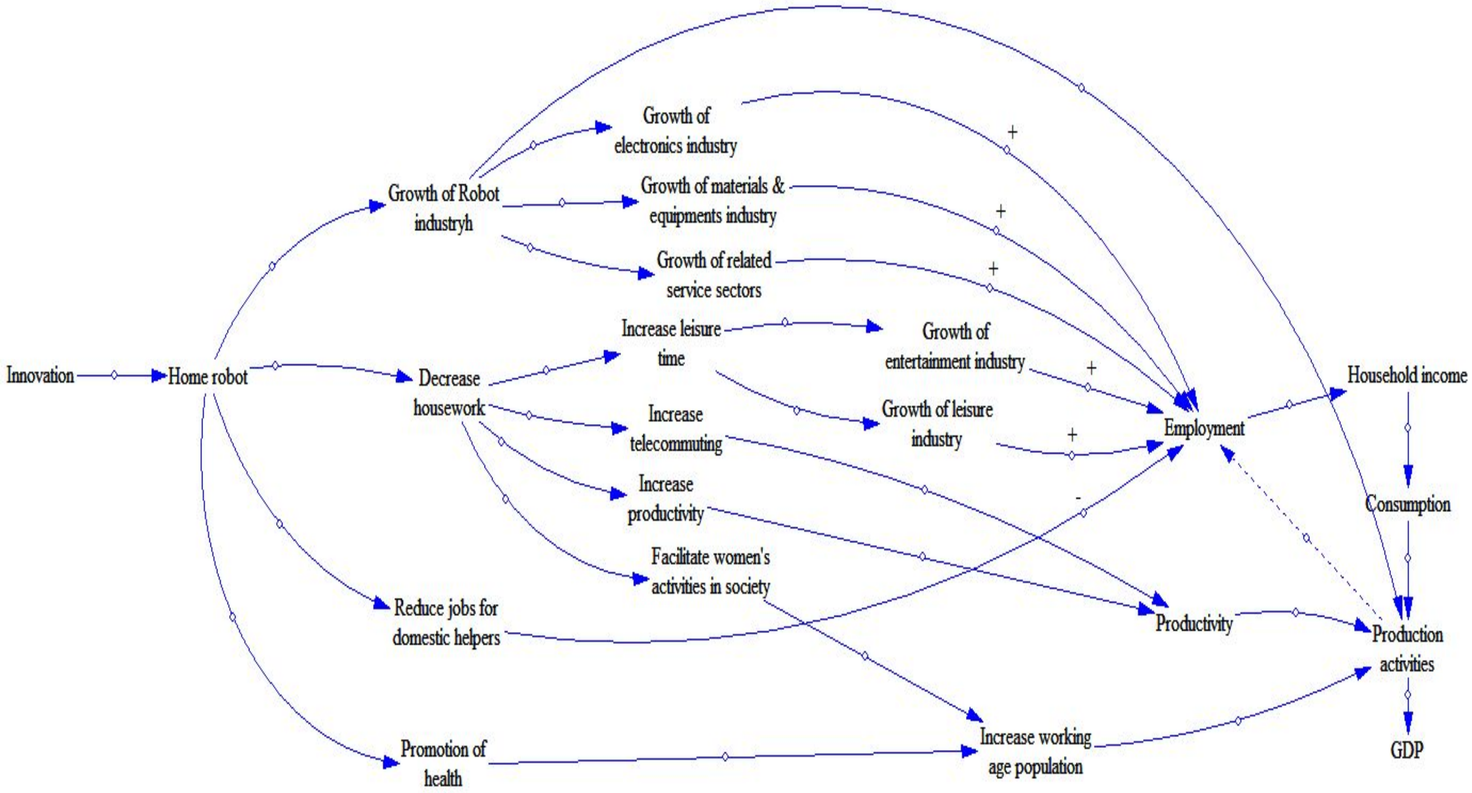


Figure 13. Impact of home robot on the economy

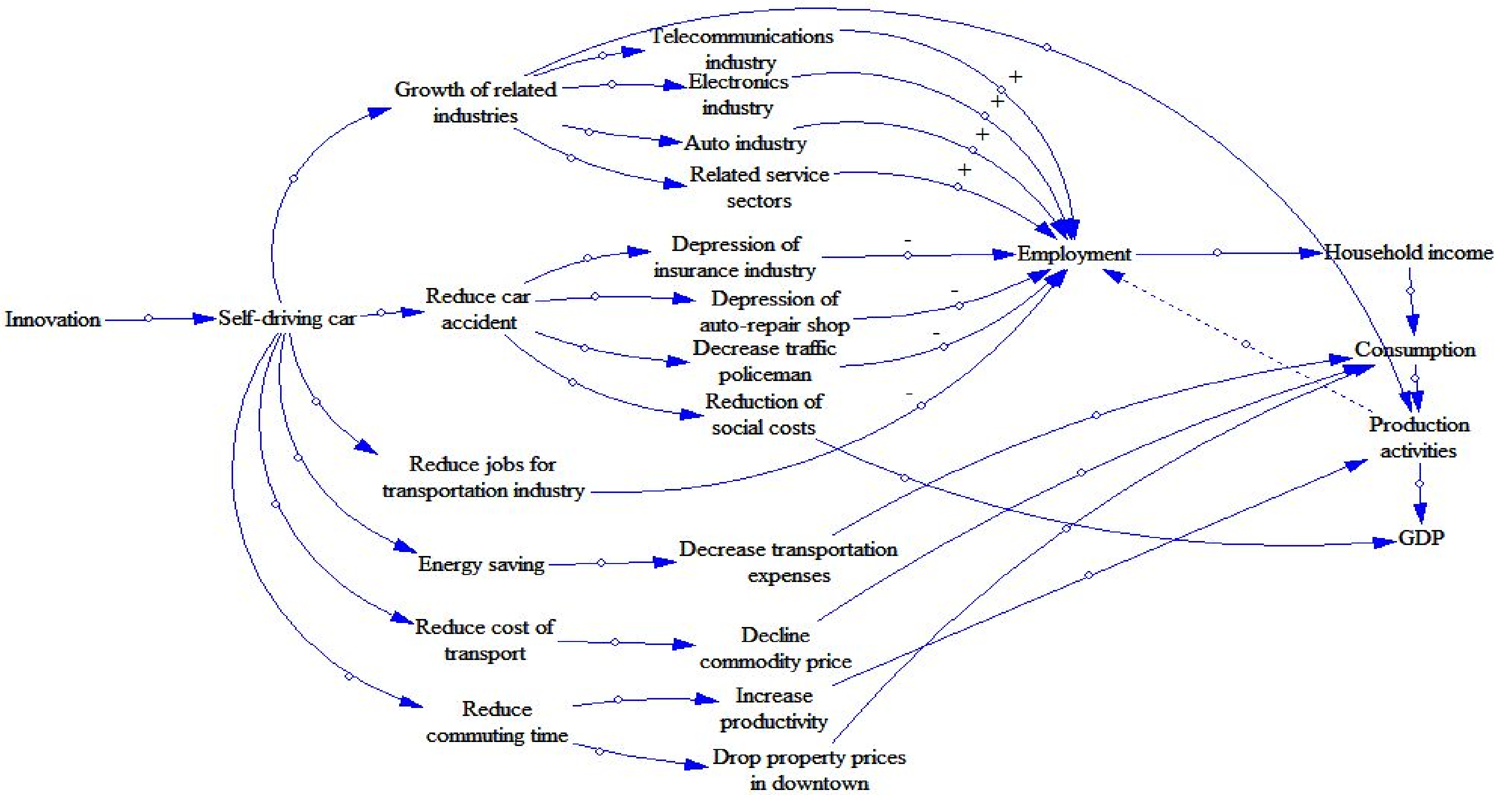


Figure 14. Impact of self-driving car on the economy

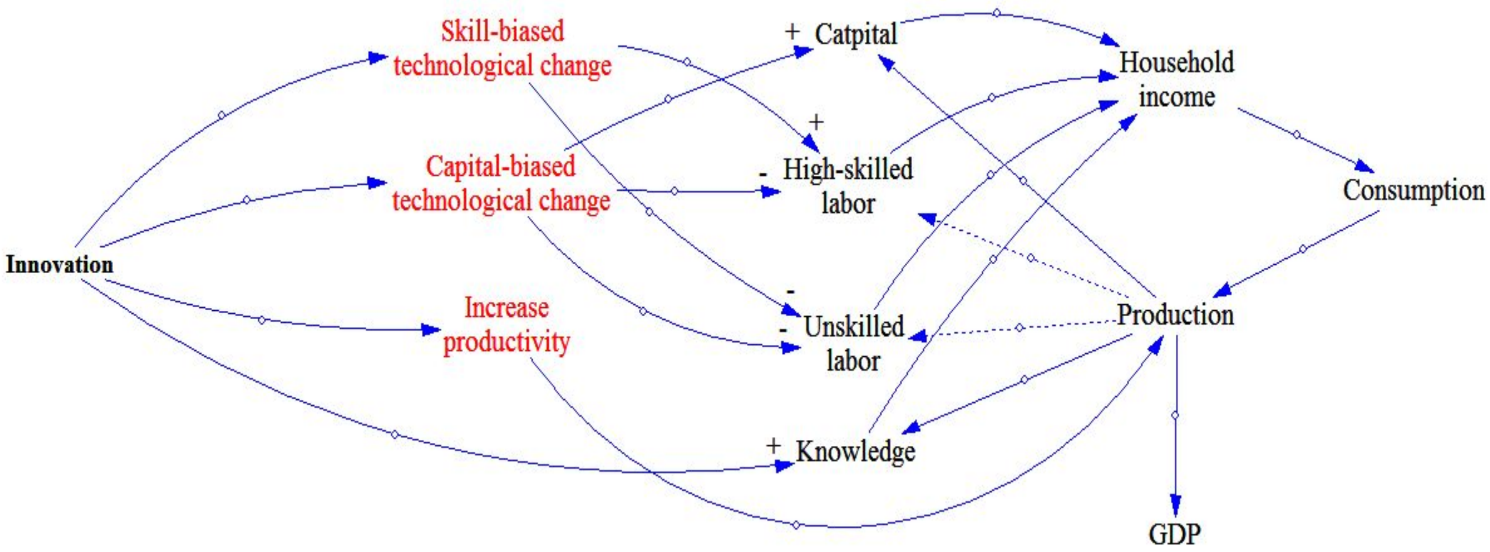


Figure 15. Impact of technical innovation on the economy

In this chapter, analysis was performed incorporating these characteristics using Korean data. First, SBTC and capital-biased technical change were incorporated into the model based on the argument of Brynjolfsson and McAfee (2014). Their argument can be summarized as follows. When technological innovation occurs as a result of increased knowledge stock, productivity increases. However, recent technological innovation is accompanied by SBTC and capital-biased technical change as a result of increased productivity. Accordingly, employment structure changes – specifically, wages of high-skilled labor increases, whereas unskilled workers either have decreased wages or lose their jobs. In addition, because those with a lot of capital benefit more, income inequality and polarization intensifies. This change in income structure leads to a change in aggregate demand, and, generally, higher income class tends to have low marginal propensity to consume for increased income, and high marginal propensity to save, whereas the reverse is true for the middle- and low-income classes, causing deeper polarization and decreased market aggregate demand. As aggregate demand decreases, output decreases, and employment also declines, and finally recession occurs.

To investigate whether this scenario also occurs in Korea, SBTC and capital-biased technical change were incorporated in this model, for which CES production function was introduced. The conventional model used the Cobb–Douglas production function, and C–D function struggles to incorporate realistic substitutive relationships among factors of production because elasticities of substitution among labor (L), capital (K), and knowledge (H) are each fixed as 1. On the other hand, although the CES production function has fixed elasticity of substitution, but has the advantage that the value can be freely determined (Shin, 2005). Accordingly, in the present model, production function was set with the CES function, as shown in Figure 16.

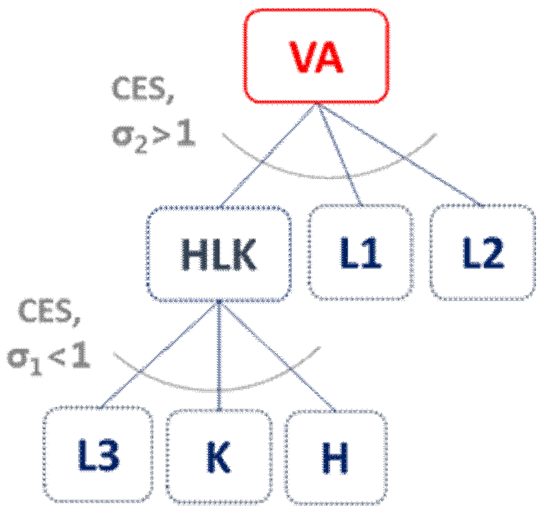


Figure 16. Structure of CES production function

Regarding the production function, to incorporate capital-biased technical change and SBTC, the values for elasticities of substitution among L3 (high-skilled labor), K (capital), and H (knowledge) were set at <1, and the values for elasticities of substitution among HLK (composites of high-skilled labor, capital and knowledge), L2 (skilled labor), and L1 (unskilled labor) were set at >1. The values for elasticity of substitution used the values for elasticities of substitution between skilled labor and capital, and between unskilled labor and capital used in Krusell, Ohanian, Ríos-Rull, and Violante (2000); the values are shown in Table 14.

Table 14. Value of parameter

Elasticity of substitution in production	
σ_1	0.67
σ_2	1.67

On the other hand, to examine the indirect effect of technological innovation on employment, a knowledge-based CGE model was used. The model was set up such that spillover effect of innovation increases productivity, influencing various areas of the economy. Specifically, it was set up such that knowledge spillover effect (SPCOEFF) of each industry was generated by knowledge stock of other industries (INTINSDT) and public knowledge stock (HG), as discussed in Chapter 3. This shows that when knowledge stock increases from R&D investment, industry-specific knowledge stock (H) and SPCOEFF increase. Consequently, the proportions of labor and capital invested when a unit of product is produced in each industry decrease. The decreased proportions are differentially affected depending on elasticity of substitution. However, if spillover effect of R&D investment increases output and demand, and economy grows, input of factors of production increase, affecting employment indirectly. Therefore, the direct and the indirect effect of technological innovation on employment can be examined simultaneously using this model.

4.3 Simulation analysis

4.3.1 Scenario

The effect of innovation on employment structure and economic growth was examined based on the model discussed so far. Analysis was performed for three separate scenarios. In the first scenario, R&D intensity gradually decreases from 4% in the base year of 2010 to 3% in 2020. In the second scenario, R&D intensity is maintained at 4% from the base year of 2010 onward. In the third scenario, R&D intensity gradually increases from 4% in the base of 2010 to 5% in 2020. The scenarios analyzed in this chapter are summarized in Table 15.

Table 15. Scenario description

	R&D intensity in 2010	R&D intensity in 2020
Scenario 1	4%	3%
Scenario 2	4%	4%
Scenario 3	4%	5%

4.3.2 Change of Employment

4.3.2.1 Change of Aggregate Labor Demand

First, change of aggregate labor demand was examined. The results of analysis are shown in Figure 17. In addition, the change rates in the aggregate labor demand between 2030 and the base year of 2010 are shown in Table 16.

(Unit: trillion won)

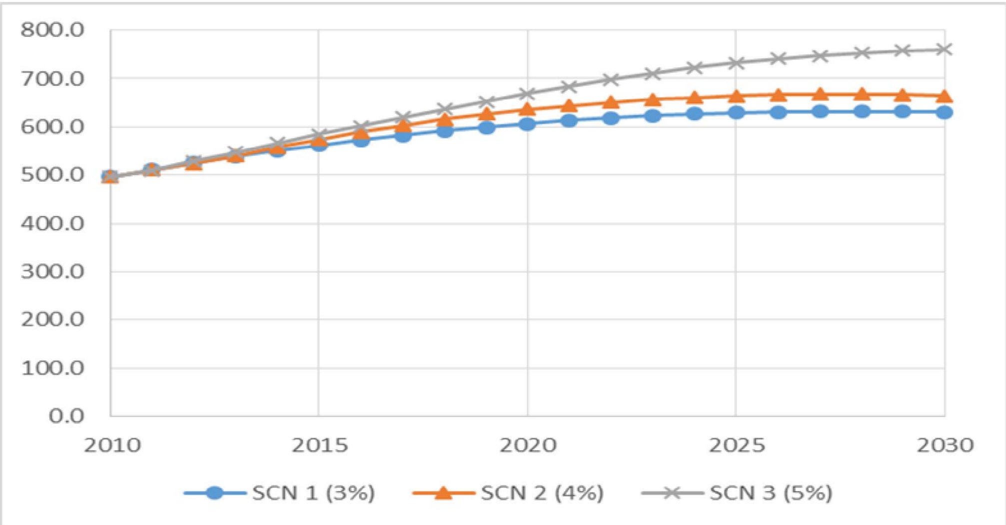


Figure 17. Change of aggregate Labor demand in each scenario

Table 16. The change rate in the aggregate labor demand between 2010 and 2030 (%)

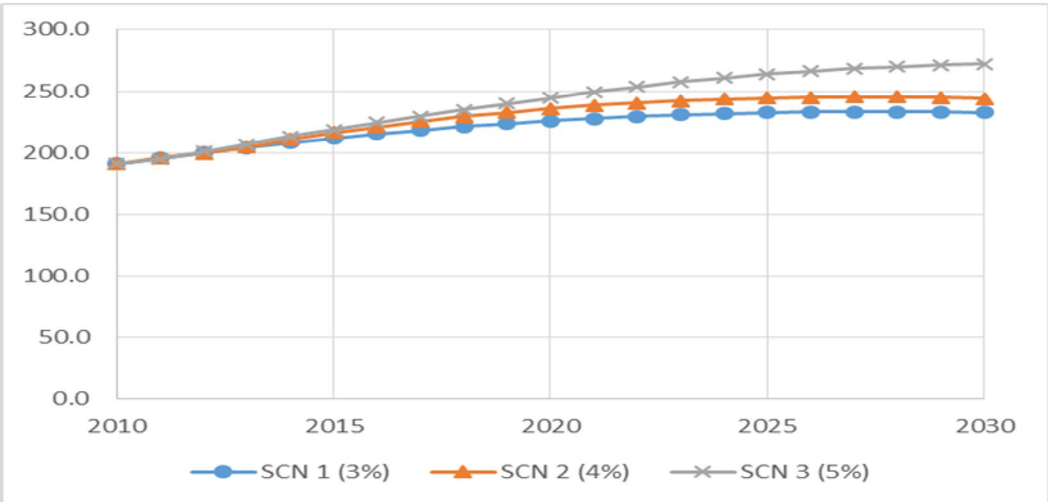
	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
Total labor demand change (%)	26.9	33.9	53.2

The analysis results showed that the aggregate labor demand increased most in Scenario 3, where additional R&D investments were made. Conversely, in the first scenario, in which decreasing R&D intensity showed relatively smaller increase in aggregate labor demand, and in the long term, the aggregate labor demand stagnated. To summarize these results, increase of employment due to increased output was found to have a greater impact than the decrease of employment as a result of capital-biased technical change as a result of innovation. Accordingly, innovation was found to create additional employment. To determine the reason for this result, additional analysis on demand for labor by skill level and demand for labor by industry was performed.

4.3.2.2 Change in Demand for Labor by Skill Level

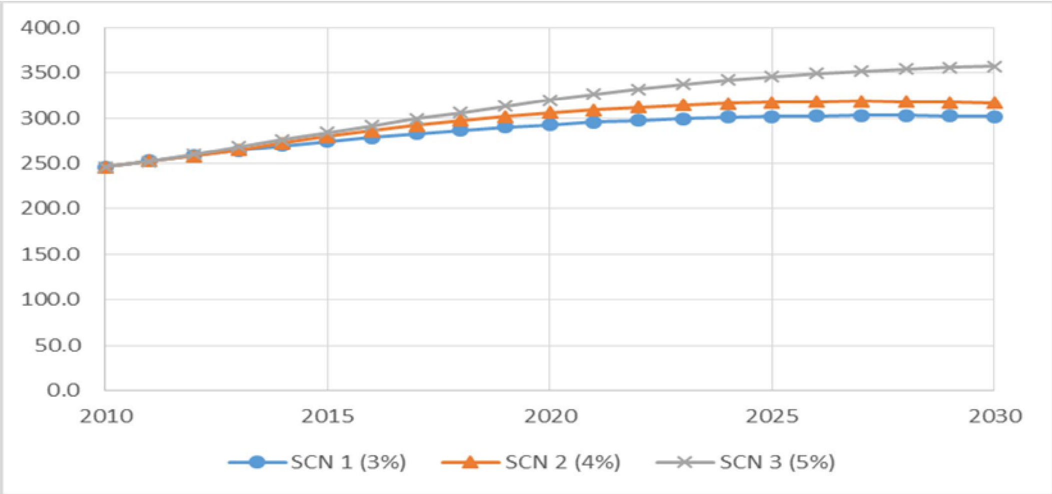
(a) Unskilled labor

(Unit: trillion won)



(b) Skilled labor

(Unit: trillion won)



(c) High-skilled labor

(Unit: trillion won)

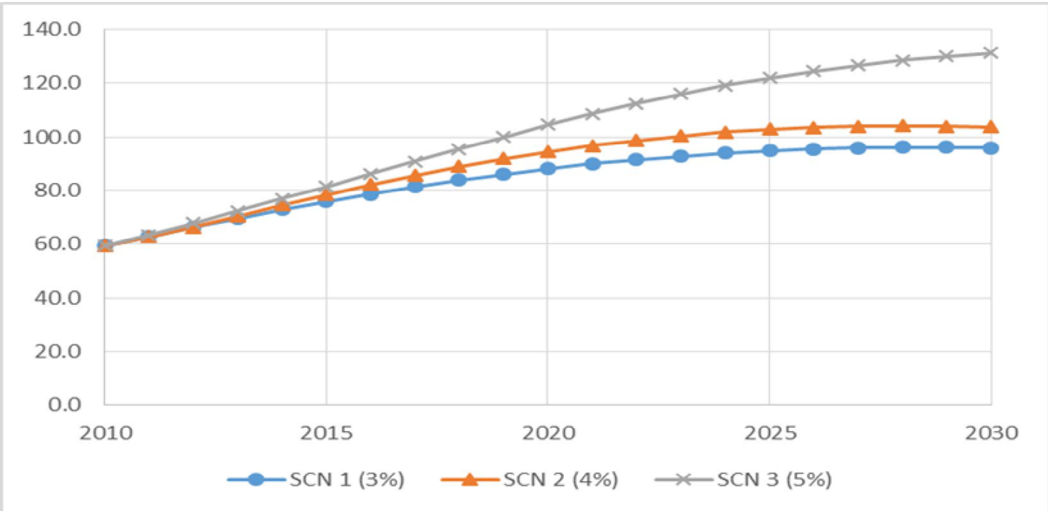


Figure 18. Change in demand for labor by skill level

Table 17. The change rate for demand for labor by skill level between 2010 and 2030 (%)

	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
Unskilled	21.9	28.0	42.6
Skilled	22.5	28.6	44.9
High-skilled	61.7	75.0	121.3

The analysis results on demand for labor by skill level are shown in Figure 18. Additionally, the change rates for demand for labor by skill level between the base year of 2010 and 2030 are shown in Table 17. The analysis results showed the appearance of SBTC, resulting in a larger increase in demand for high-skilled labor than the increase in the demand for unskilled and skilled labor in all three scenarios. Moreover, in Scenario 3, in which additional R&D investments were made, demand for all skill level increased more than in other scenarios. In particular, demand for high-skilled labor in Scenario 3 showed a ~121% increase in 2030 compared to 2010, showing the highest growth rate. To summarize, demand for labor increase due to innovation has a differential effect depending on skill level, and the demand for high-skilled labor was found to have the highest growth rate due to SBTC.

Based on these results, contribution of each skill level was examined for Scenario 3, which showed the greatest increase in aggregate labor demand, and the results are shown in Figure 19. The results showed that the demand for skilled labor increased most in Scenario 3. This result was due to the fact that although demand for high-skilled labor showed the highest growth rate, its proportion in the base year was small.

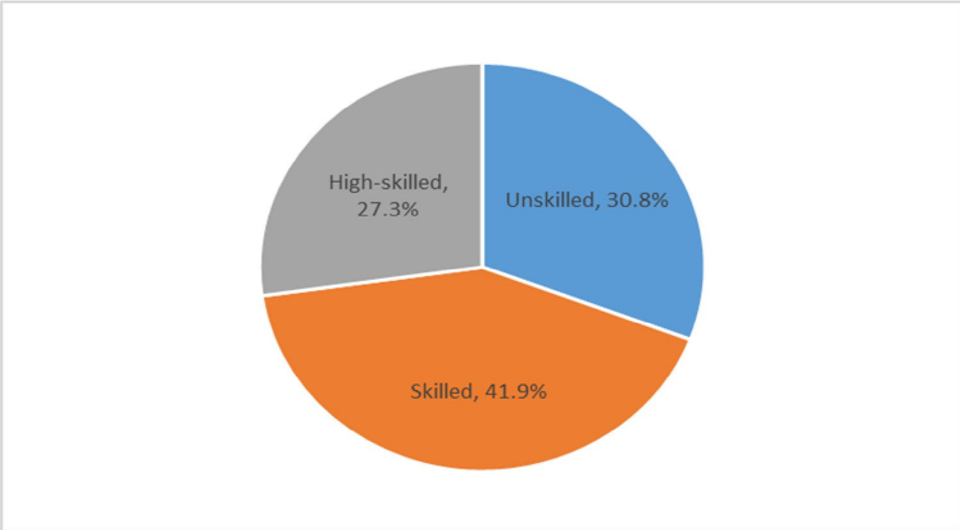
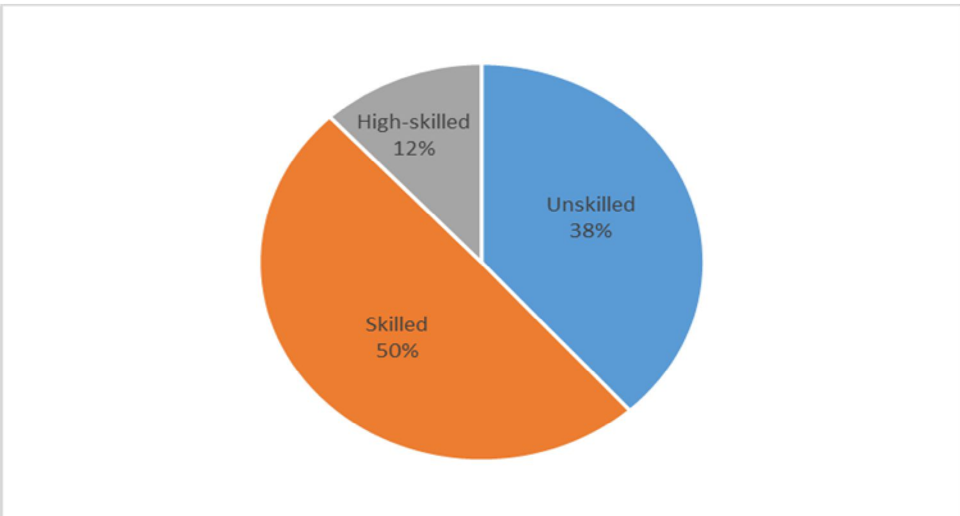


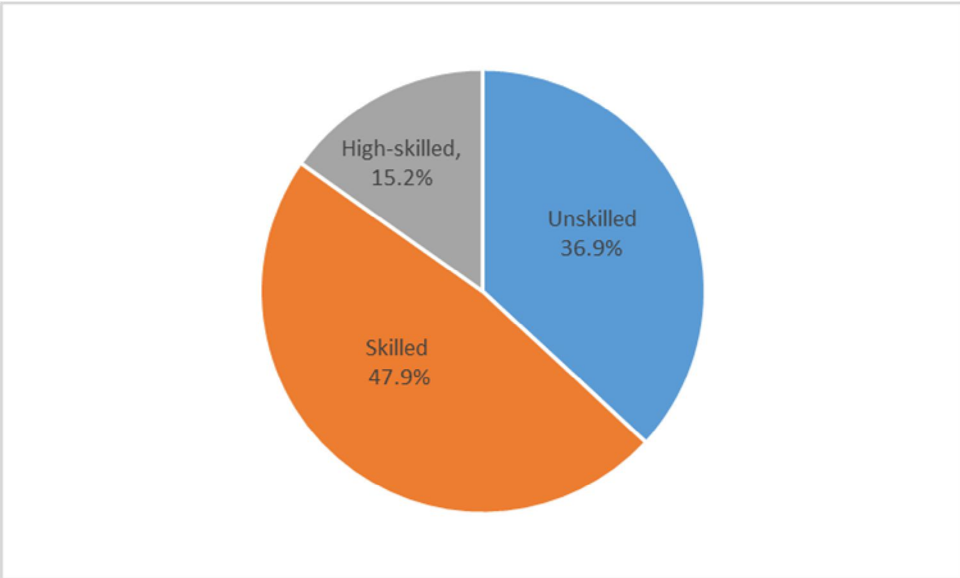
Figure 19. Decomposition of aggregate labor demand with respect to skill level in SCN 3 (5%)

On the other hand, the change in proportion of demand for labor by skill level in each scenario is shown in Figure 20.

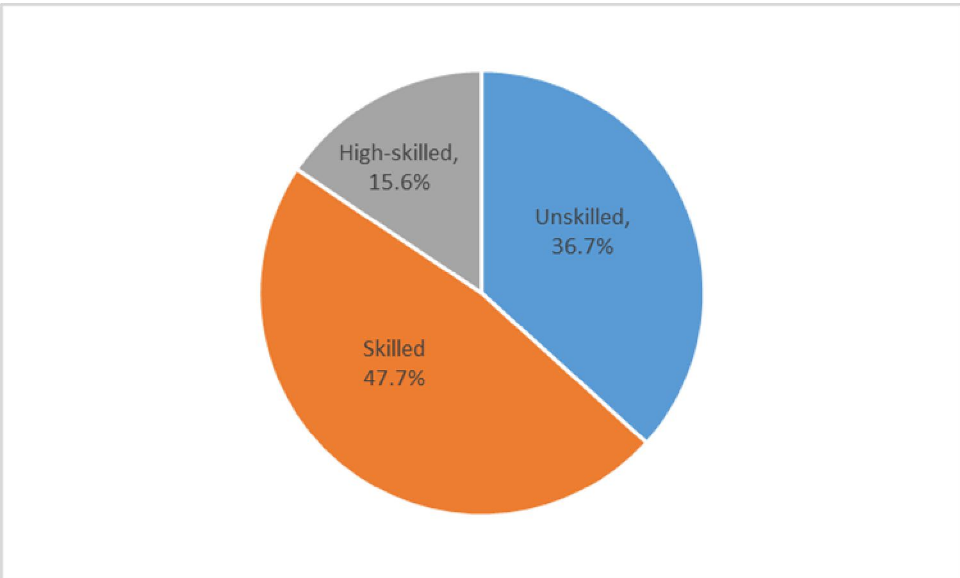
(a) Base year



(b) SCN 1 (3%) in 2030



(c) SCN 2 (4%) in 2030



(d) SCN 3 (5%) in 2030

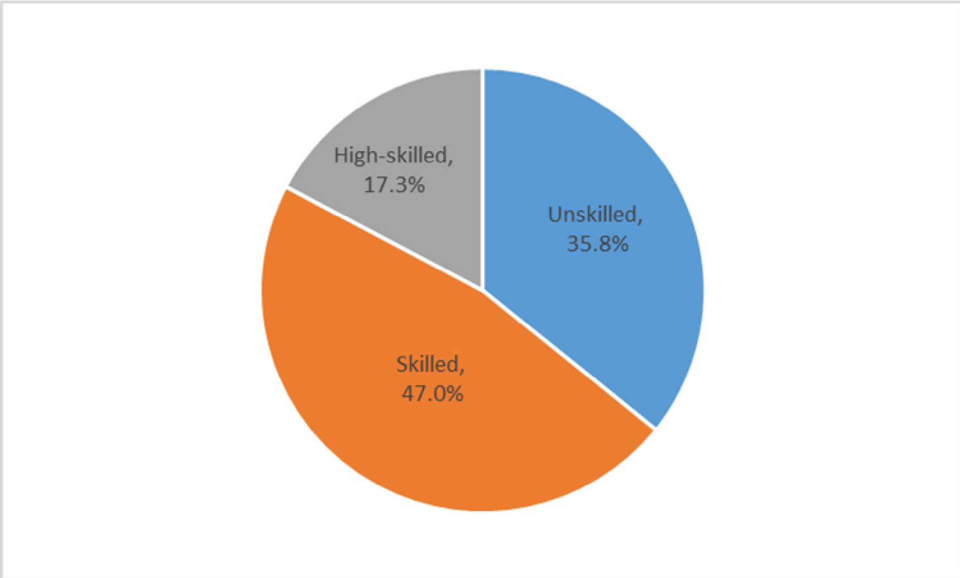
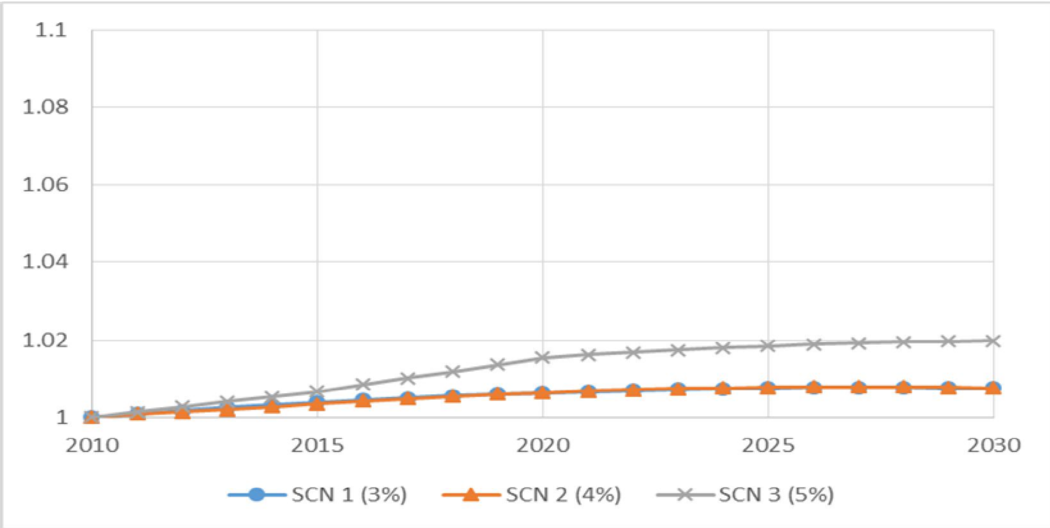


Figure 20. The change in proportion of demand for labor by skill level

In Scenario 3 where additional R&D investments were made, the demand for unskilled labor and skilled labor were found to decrease, whereas demand for high-skilled labor increased. Accordingly, when innovation-driven economic policy is maintained, jobs for high-skilled labor are expected increase more than for other groups.

On the other hand, the increase in demand for labor increases employment or wage, and because the number of workers for each skill level cannot change rapidly, wages generally increase. As a result, wage gap between different skill levels occurs as a result of the change in demand for labor at each skill level. As discussed earlier, innovation further increases demand for high-skilled labor, and skill premium increases; the changes in skill premium are shown in Figure 21.

(a) Skilled labor wage/Unskilled labor wage



(b) High skilled labor wage/Unskilled labor wage

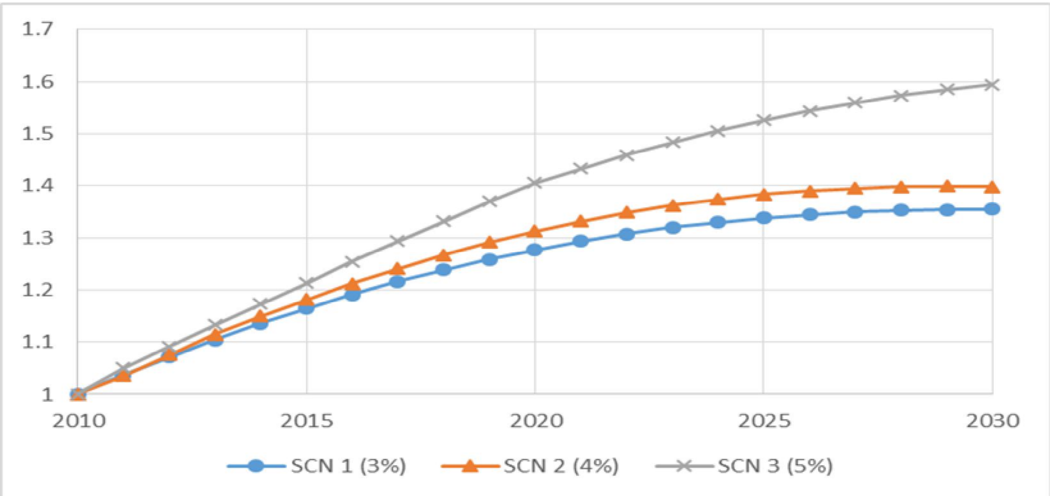


Figure 21. Skill premium change

In this model, it was not applied that unskilled labor becomes skilled labor or skilled labor becomes high-skilled labor through additional education, and it was assumed that the proportion of each skill level of labor is held constant from the base year. Under this condition and assumption, the skill premium for high-skilled labor increased considerably. Thus, because demand for high-skilled labor and skill premium increases when an innovation-driven economic growth is pursued, a lot of high-skilled labor needs to be produced through additional education.

According to the examination of change in demand for labor by skill level so far, innovation was found to increase demand for high-skilled labor more so than other skill levels of labor due to SBTC.

4.3.2.3 Change in Demand for Labor by Industry

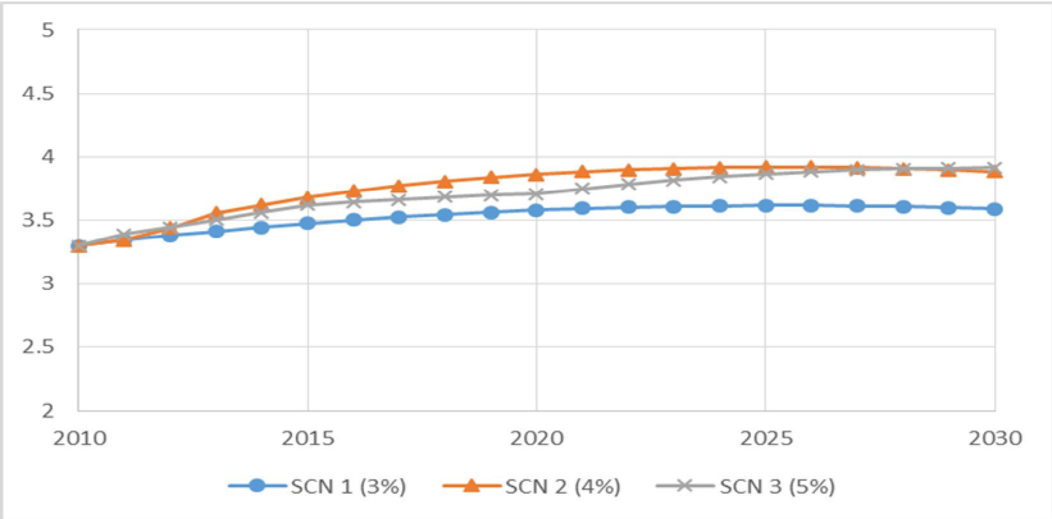
Innovation has differential effects on industry-specific demand for labor. The effects of innovation on demand for labor by industry are shown in Figure 22.

Analysis of change in demand for labor by industry was performed by reclassifying industries into four types. The four types included the primary industries of agriculture, forestry, and fisheries; the secondary industry of manufacturing industry, which were further classified into high-tech and low-tech manufacturing industry; and the tertiary industries of service industries. The classification between high-tech and low-tech manufacturing industries was performed based on whether the proportion of R&D

investment in the total output in each industry is higher than the mean R&D investment of all industries.

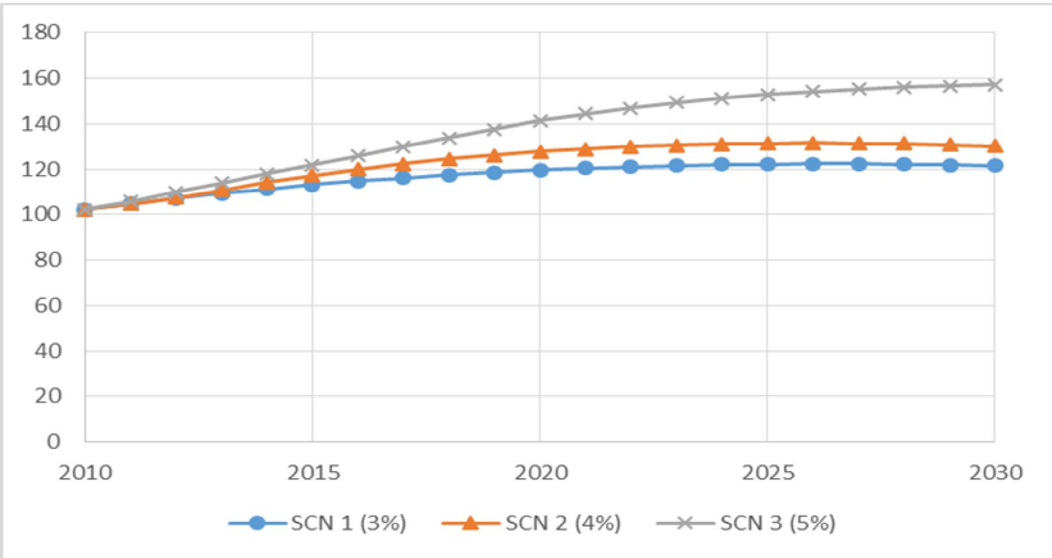
(a) Agriculture, forestry, and fisheries

(Unit: trillion won)



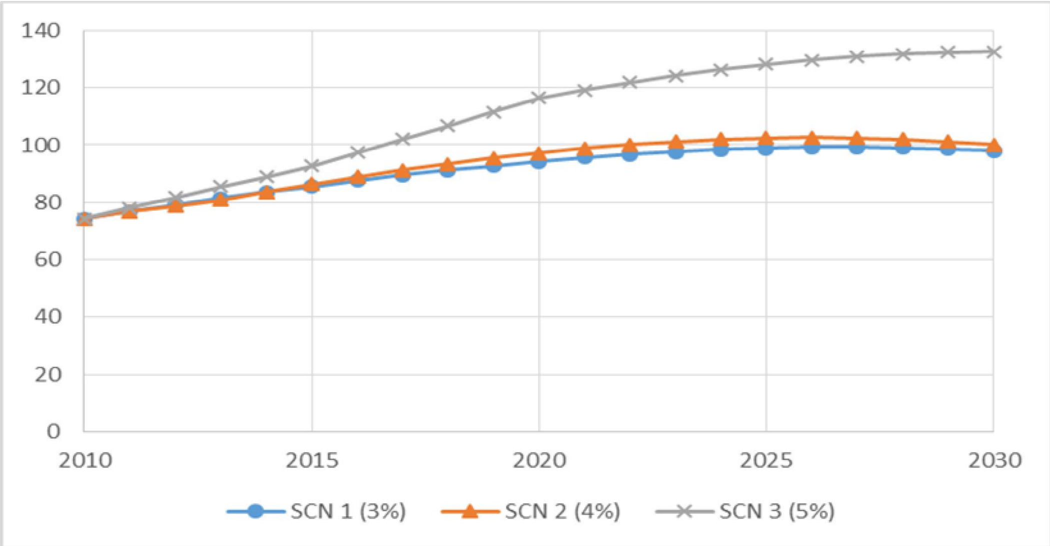
(b) Low-tech manufacturing

(Unit: trillion won)



(c) High-tech manufacturing

(Unit: trillion won)



(d) Service

(Unit: trillion won)

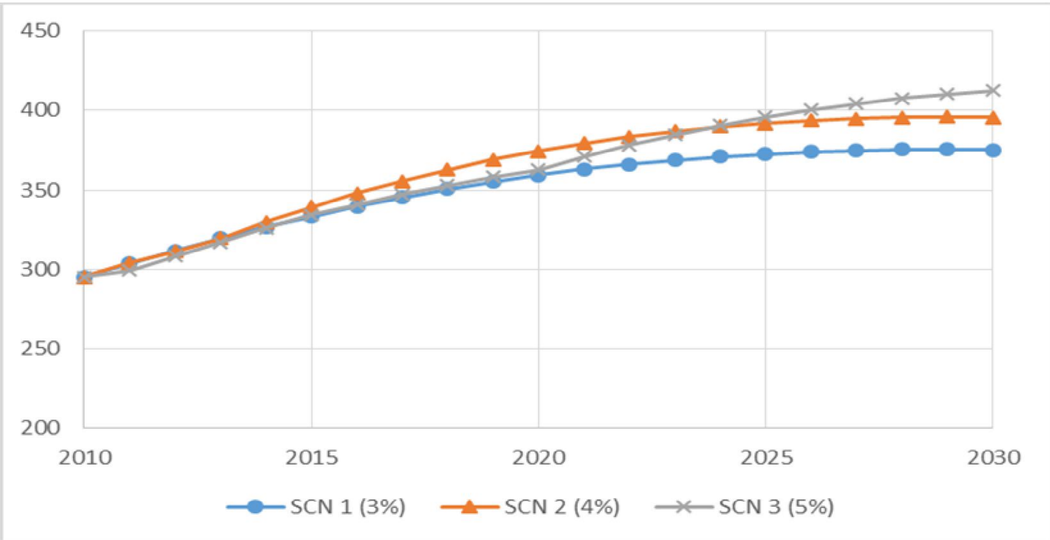


Figure 22. Change in demand for labor by industry

Table 18. Rate of change in demand for labor by industry between 2010 and 2030 (%)

Industry	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
Agriculture, forestry, and fisheries	8.8	17.7	18.7
Low-tech manufacturing	18.9	27.5	53.8
High-tech manufacturing	31.8	34.5	78.4
Service	27.2	34.1	39.9

The results for rate of change in demand for labor by industry type in 2030 in comparison to the base year are shown in Table 18. The results showed that when R&D investment increases, demand for labor in each industry type increases. In particular, in Scenario 3 in which R&D intensity increased up to 5% showed the highest change rate for demand for labor in high-tech manufacturing industry. This suggests that industry with higher levels of innovation showed a larger increase in demand for labor. In addition, it was indicated that additional innovation activities increase employment in all industries through spillover effect on other industries.

This study classified R&D workforce as labor for knowledge production rather than by industry. Accordingly, R&D workforce can be classified as labor in the industry for knowledge production. The change in R&D workforce for each scenario is shown in Figure 23. In addition, the changing rates of demand for labor for R&D workforce between the base year and 2030 are shown in Table 19. The results showed that when

R&D investment increases, demand for labor for R&D workforce increases. In particular, in Scenario 3, demand for labor for R&D workforce in 2030 increases by about 151% compared with 2010.

Table 19. The changing rates of demand for labor for R&D workforce between the base year and 2030 (%)

	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
R&D personnel demand growth (%)	47.4	60.9	150.9

(Unit: trillion won)

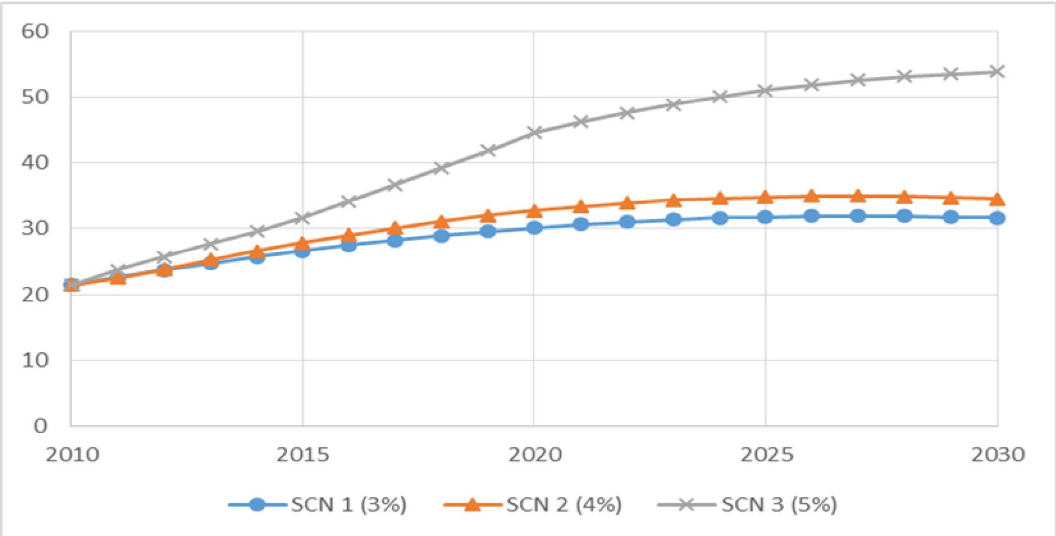


Figure 23. The change of labor demand for R&D workforce in each scenario

Based on these results, the contributions of innovation by industry types in Scenario 3 with the largest increase in aggregate demand for labor were analyzed, and the results are shown in Figure 24. The results showed that demand for labor in the service industry showed the largest increase in Scenario 3. Although the R&D workforce and high-tech manufacturing industry showed higher growth rates in demand for labor, the service industry showed the largest increase in the amount of increase in demand for labor. This is because the proportion of demand for labor for the service industry is higher than for other industries in the base year.

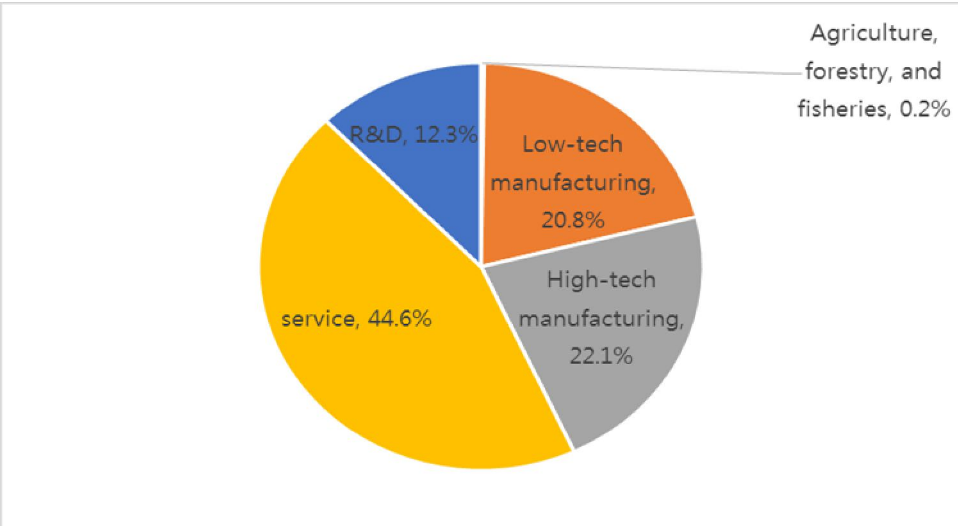
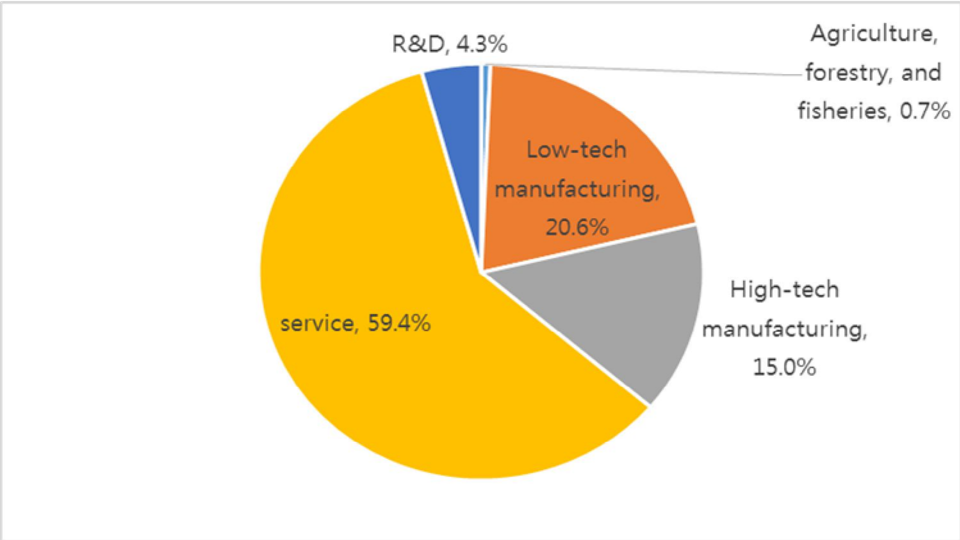


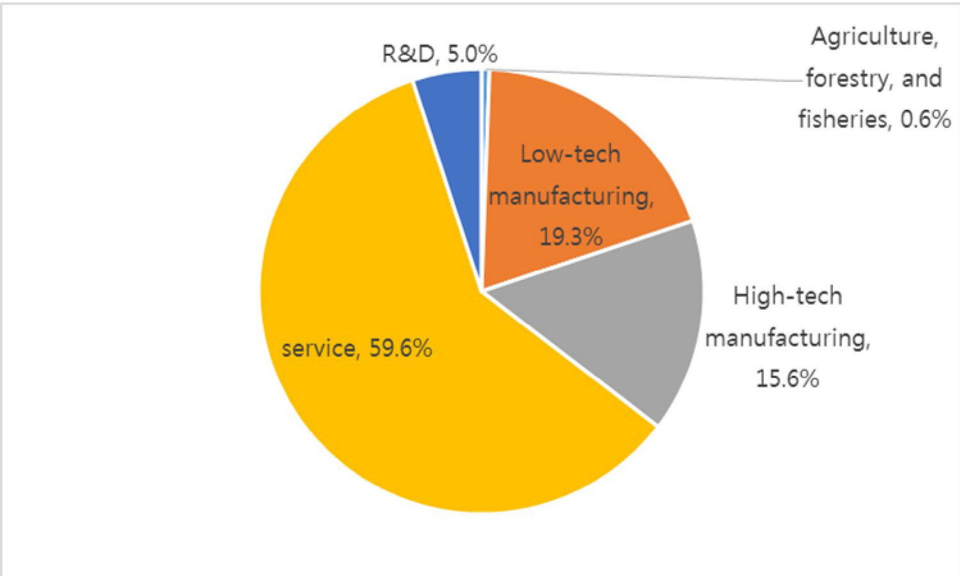
Figure 24. Decomposition of aggregate labor demand with respect to industry in SCN 3 (5%)

On the other hand, the changes in proportions of demand for labor by industry for each scenario are shown in Figure 25.

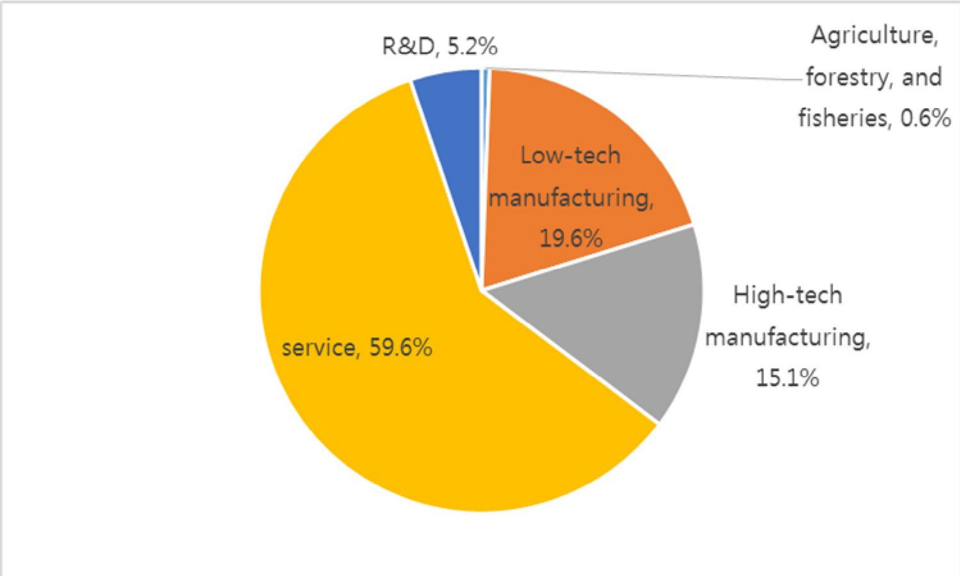
(a) Base year



(b) SCN 1 (3%) in 2030



(c) SCN 2 (4%) in 2030



(d) SCN 3 (5%) in 2030

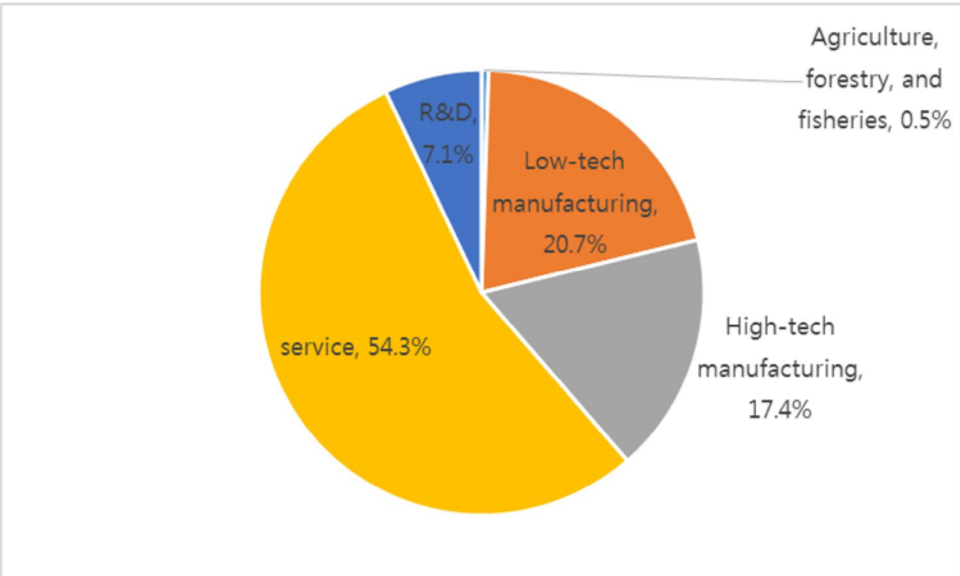


Figure 25. The changes in proportions of demand for labor by industry

The results showed that in Scenario 3, where additional R&D investments were made, the proportions of demand for labor for the R&D industry and high-tech manufacturing industry increase, whereas the proportions of demand for labor for the service industry and the agriculture, forestry, and fisheries industry decrease. Accordingly, when innovation-driven economic growth policies are maintained, jobs in the high-tech manufacturing industry and R&D industry are expected to increase more than others.

4.3.3 Economic Growth

4.3.3.1 GDP

So far, the effect of R&D investment on employment has been examined. From here on, the effect of R&D investment on economic growth will be examined. First of all, how GDP changes in each scenario was examined. The results of the analysis are shown in Figure 26. In addition, GDP growth rates between the base year and 2030 are shown in Table 20, and annual GDP growth rates are shown in Table 21.

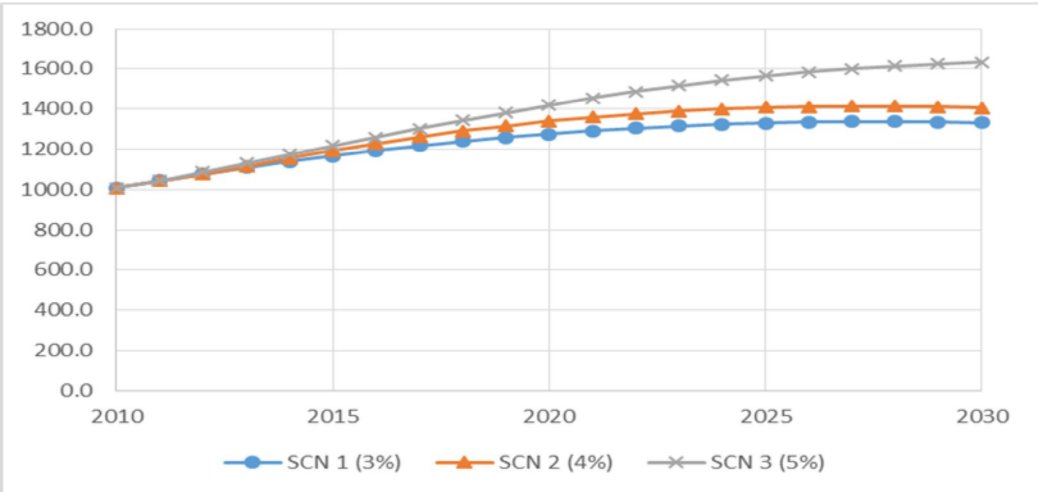


Figure 26. GDP changes in each scenario

Table 20. GDP growth rates between the base year and 2030 (%)

	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
GDP growth (%)	32.1	39.5	62.0

Table 21. Annual GDP growth rate (%)

	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
Annual GDP growth rate	1.40	1.68	2.44

The results showed that, in Scenario 3 in which R&D intensity increased compared with the base year, GDP increased by 62% in 2030, showing the largest increase among scenarios. In other words, it was found that more innovative activities benefited economic growth more. In addition, the annual GDP increase rate by scenario is shown in Table 21. The results showed that when R&D intensity increases by up to 5%, an annual economic growth of 2.44% is achieved until 2030. On the other hand, when R&D intensity maintains 4% and decreases to 4%, the annual economic growth rates are 1.68% and 1.40%, respectively—lower than the scenarios of increasing R&D intensity. In addition, in the long term, the values of economic growth rates were negative in Scenario 1 and Scenario 2 from 2028. To conclude, additional R&D investment is suggested to have a positive impact on economic growth. Accordingly, to achieve innovation-driven economic growth, R&D investment needs to continue to increase.

On the other hand, to determine the reasons for these results, additional analyses on factors of production and output by industry were performed.

4.3.3.2 Value Added

The value added between the base year and 2030 for each scenario is shown in Table 22, and the change rates for value added between the base year and 2030 are shown Table 23. Scenario 3, which achieved the highest economic growth rate among the scenarios, showed the highest value-added increase rate for high-skilled labor and knowledge at 121.3% and 160.0%, respectively. In addition, value added for capital, unskilled labor, and skilled labor also showed higher increase rates than the other scenarios. The reason why the value-added increase rates for high-skilled labor and knowledge were higher than those of other factors of production in Scenario 3 was because of the effect of SBTC due to innovation.

On the other hand, contributions of factors of production to economic growth by scenario are shown in Figure 27. Although the increase rate of capital was lower than those of high-skilled labor and knowledge, the amount of increase was largest among them. In other words, the factor of production that made the largest contribution to economic growth in each scenario was found to be capital. In particular, in the case of Scenario 3 in which additional R&D investments were made, the proportion of contribution to economic growth by capital was higher than in the other scenarios. This is because of the effect of capital-biased technological change due to innovation.

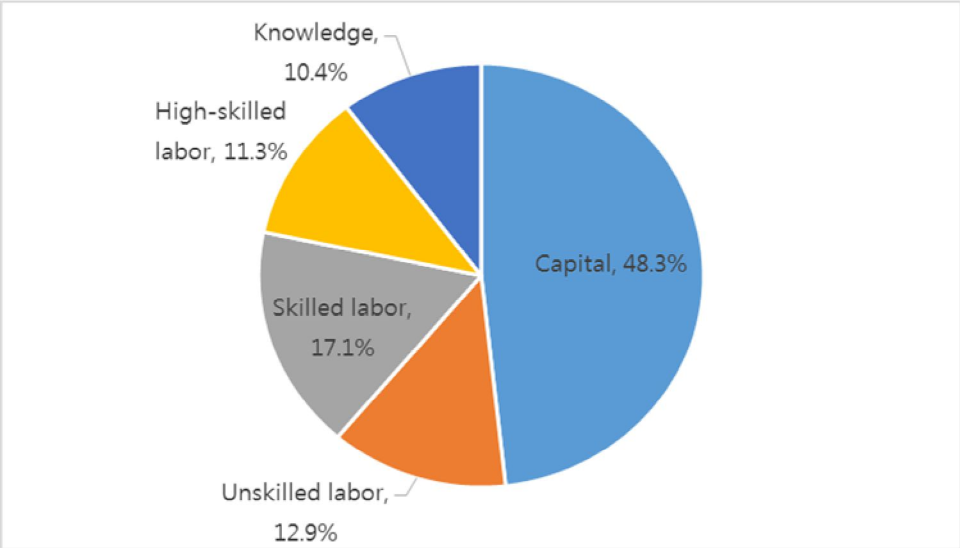
Table 22. Value added and income share in 2010 and 2030 (Unit: trillion won)

	Base year	SCN 1 (3%, Year 2030)	SCN 2 (4%, Year 2030)	SCN 3 (5%, Year 2030)
Capital	474.4 (47.1%)	630.3 (47.4%)	665.0 (47.3%)	776.7 (47.6%)
Unskilled labor	190.7 (18.9%)	232.4 (17.5%)	244.0 (17.4%)	272.0 (16.7%)
Skilled labor	246.4 (24.5%)	301.7 (22.7%)	316.7 (22.5%)	357.1 (21.9%)
High-skilled labor	59.3 (5.9%)	95.9 (7.2%)	103.7 (7.4%)	131.2 (8.0%)
Knowledge	36.8 (3.7%)	70.3 (5.3%)	75.9 (5.4%)	95.6 (5.9%)
GDP	1007.5 (100%)	1330.7 (100%)	1405.3 (100%)	1632.6 (100%)

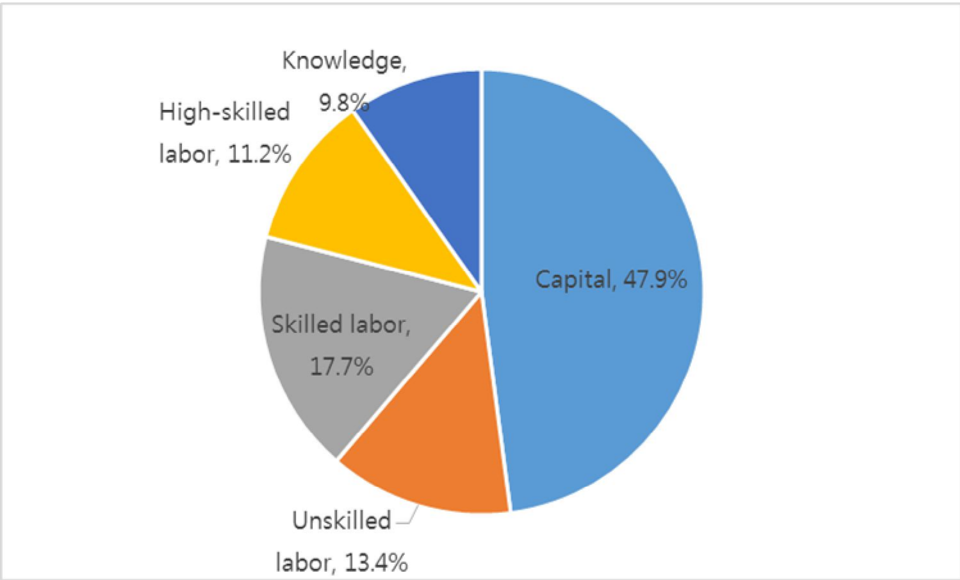
Table 23. The change rates for value added between the base year and 2030 (%)

	SCN 1 (3%, Year 2030)	SCN 2 (4%, Year 2030)	SCN 3 (5%, Year 2030)
Capital	32.9	40.2	63.7
Unskilled labor	21.9	28.0	42.6
Skilled labor	22.5	28.6	44.9
High-skilled labor	61.7	75.0	121.3
Knowledge	91.1	106.3	160.0

(a) SCN 1 (3%)



(b) SCN 2 (4%)



(c) SCN 3 (5%)

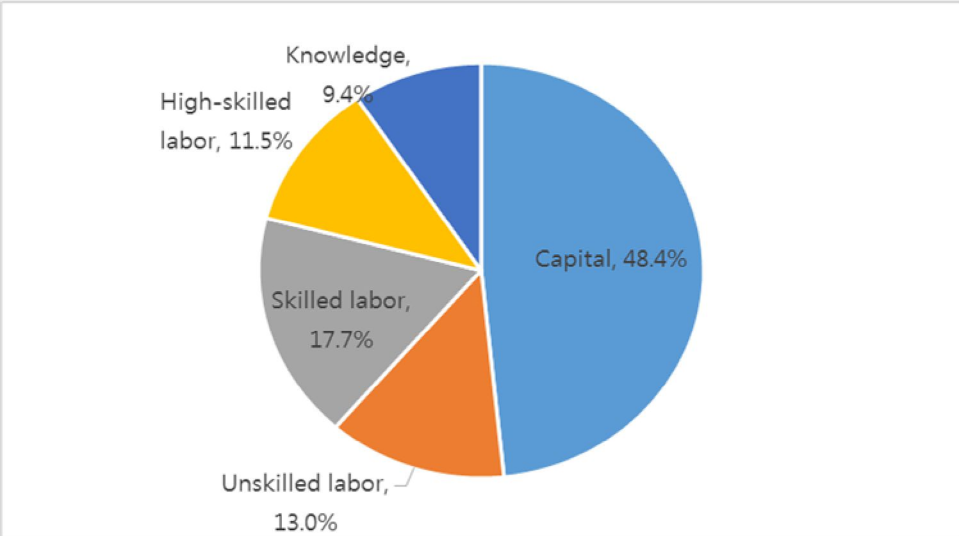
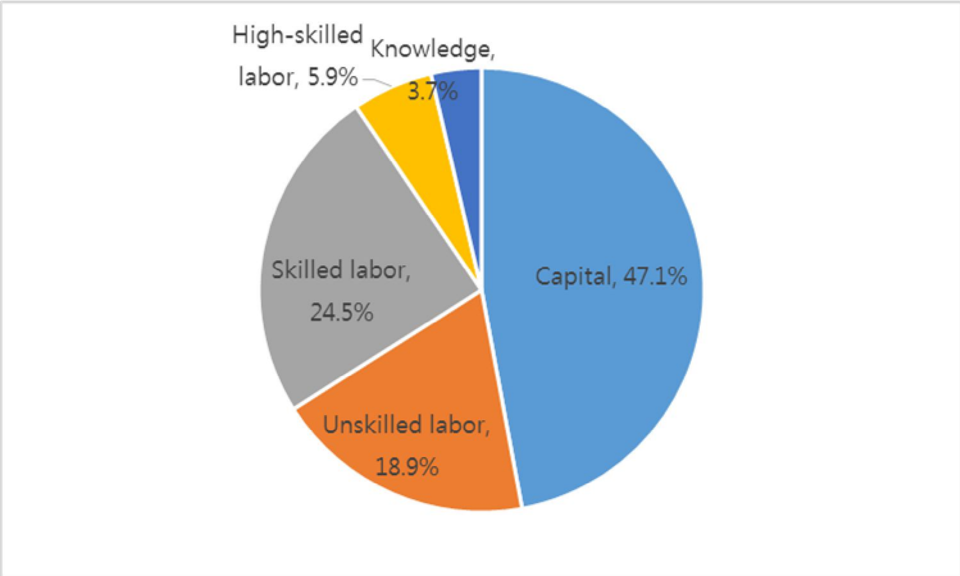


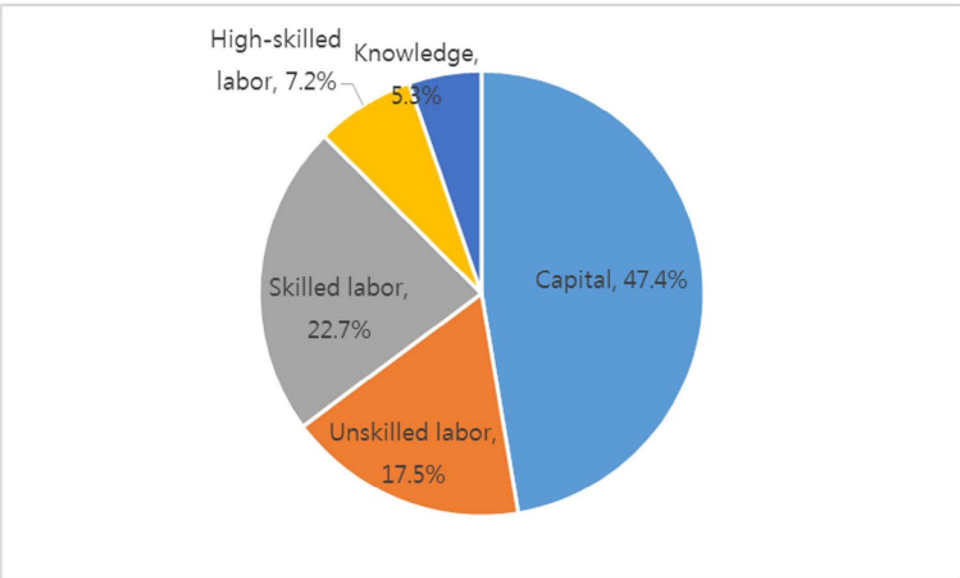
Figure 27. Contribution of factors of production to economic growth by scenario

On the other hand, the changes in the distribution ratio of value added in each scenario are shown in Figure 28. The results show that when R&D intensity increases, the value-added distribution ratios of capital, knowledge, and high-skilled labor increase, whereas the value-added distribution ratio of skilled and unskilled labor decreases. In Scenario 3, the value-added distribution ratio of knowledge increased by 2.2% between the base year and 2030, showing the highest increase rate among the factors of production. Moreover, high-silled labor showed a 2.1% increase, and capital showed a 0.5% increase. On the other hand, skilled labor showed a 2.6% decrease, and unskilled labor showed a 2.2% decrease. The reason for these results is because of the effect of SBTC and capital-biased technological change.

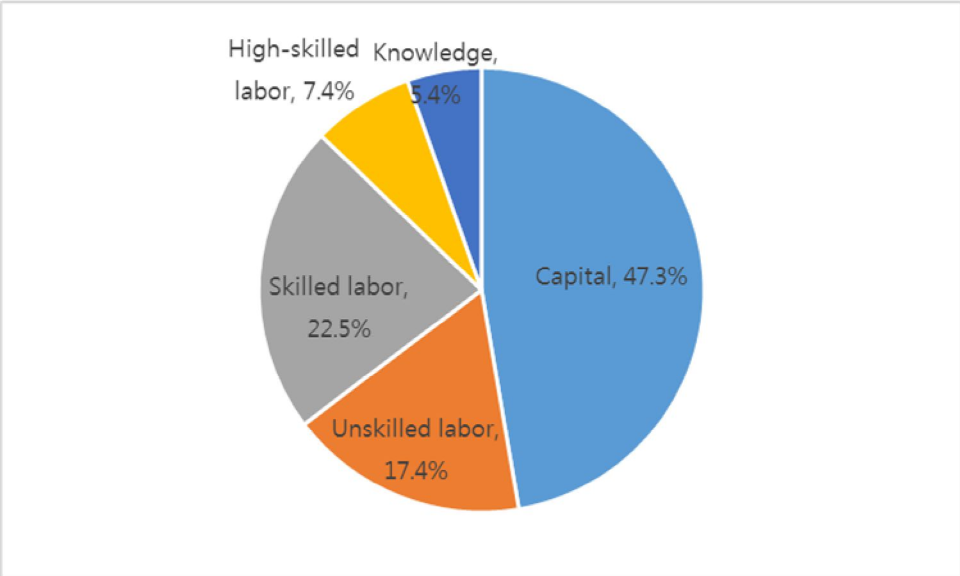
(a) Base year



(b) SCN 1 (3%) in 2030



(c) SCN 2 (4%) in 2030



(d) SCN 3 (5%) in 2030

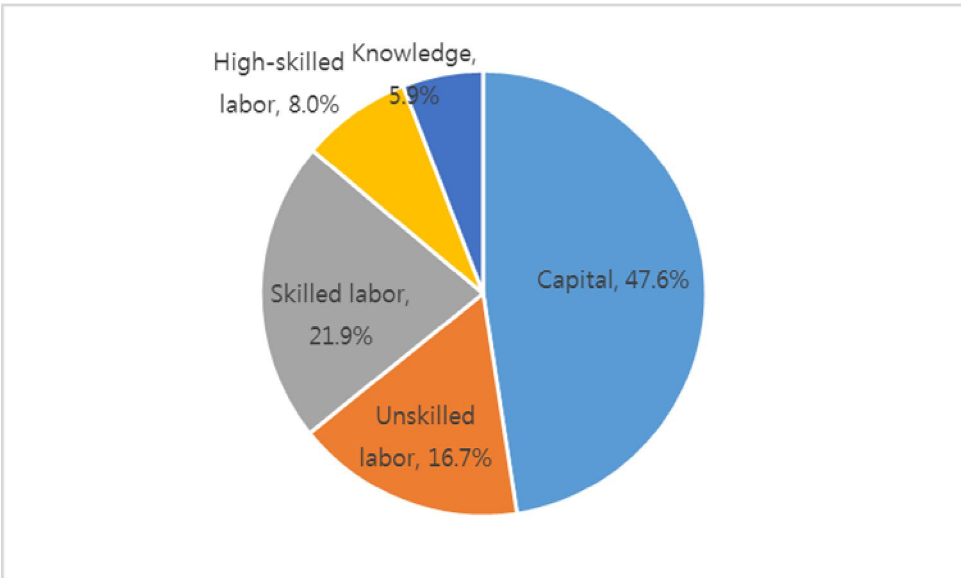


Figure 28. The distribution ratio of value added in each scenario

4.3.3.3 Output by Industry

Table 24. Changes in the output of 27 industries between 2010 and 2030 (%)

	Industry	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
S1	Agriculture, forestry, and fisheries	42.7	58.8	63.0
S2	Mining and quarrying	88.2	110.3	133.1
S3	Food, beverages and tobacco prod.	46.4	63.7	67.0
S4	Textile and apparel	87.7	116.2	123.0
S5	Wood and paper products	43.7	56.0	76.8
S6	Printing and publishing	36.7	47.1	59.4
S7	Petroleum and coal products	63.3	79.8	98.5
S8	Chemicals, drugs and medicines	61.4	71.7	104.9
S9	Non-metallic mineral products	1.6	2.5	40.3
S10	Basic metal products	36.3	39.9	91.0
S11	Fabricated metal products	14.6	18.1	53.6
S12	General machinery and equipment	9.7	11.9	47.5
S13	Electronic and electrical equip.	1.6	5.3	51.4
S14	Precision instruments	-2.6	3.2	29.4
S15	Transportation equipment	40.6	39.4	96.9
S16	Furniture and other manufactured prod.	33.1	42.4	64.1
S17	Electric, gas, steam and water supply	39.8	51.4	66.7
S18	Construction	-13.4	-9.0	17.5
S19	Wholesale and retail trade	30.4	40.6	58.3
S20	Accommodation and food services	38.8	53.1	57.7
S21	Transportation and warehousing	84.1	111.6	113.7
S22	Communications and broadcasting services	39.7	54.1	61.3
S23	Finance and insurance	35.4	47.6	58.4
S24	Real estate and business services	27.8	38.7	53.3
S25	Public administration and defense	24.7	19.5	10.1
S26	Educational, health and social work	30.0	35.0	34.1
S27	Social, personal and other services	33.2	43.8	53.8

Table 25. Changes in the output of 4 industry types between 2010 and 2030 (%)

	SCN 1 (3%)	SCN 2 (4%)	SCN 3 (5%)
Agriculture, forestry, and fisheries	42.7	58.8	63.0
Low-tech manufacturing	37.5	46.9	76.8
High-tech manufacturing	16.4	29.2	64.4
Service	36.5	47.4	55.0

Changes in the output of 27 industries in each scenario are shown in Table 24. In Scenario 3, in which additional R&D investments were made, a larger increase in most industries was shown than Scenario 2 and Scenario 3. The output varied in the degree of change in accordance with the size of knowledge spillover effect and the proportions of factors of production in each industry. Additionally, analysis was performed with industry types, and the results are shown in Table 25. In the Scenario that showed the largest increase in output, the output of the low-tech manufacturing industry showed the largest increase in output. In addition, the low-tech manufacturing industry also showed the largest difference in the increase amount. As illustrated by Figure 29, 40.3% of the total output increase in Scenario 3 was made by the low-tech manufacturing industry. Next, the service industry made 32.7% of the contribution, and the high-tech manufacturing industry made 25.3% of the contribution.

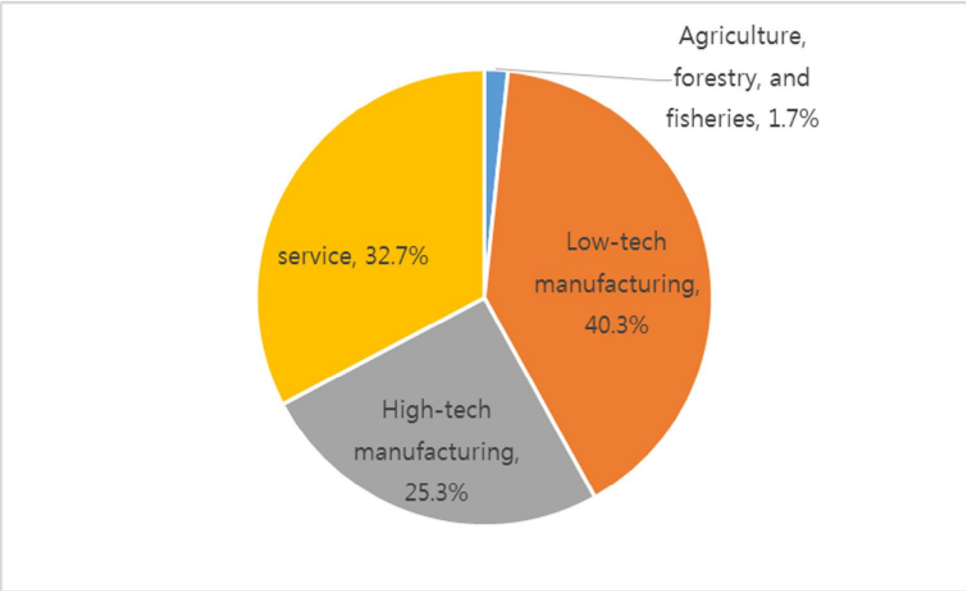
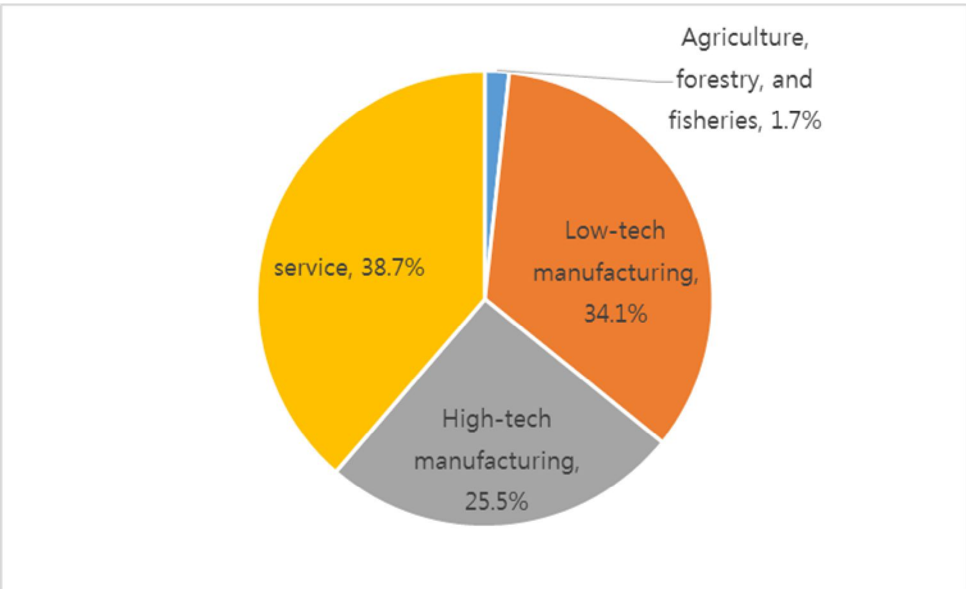
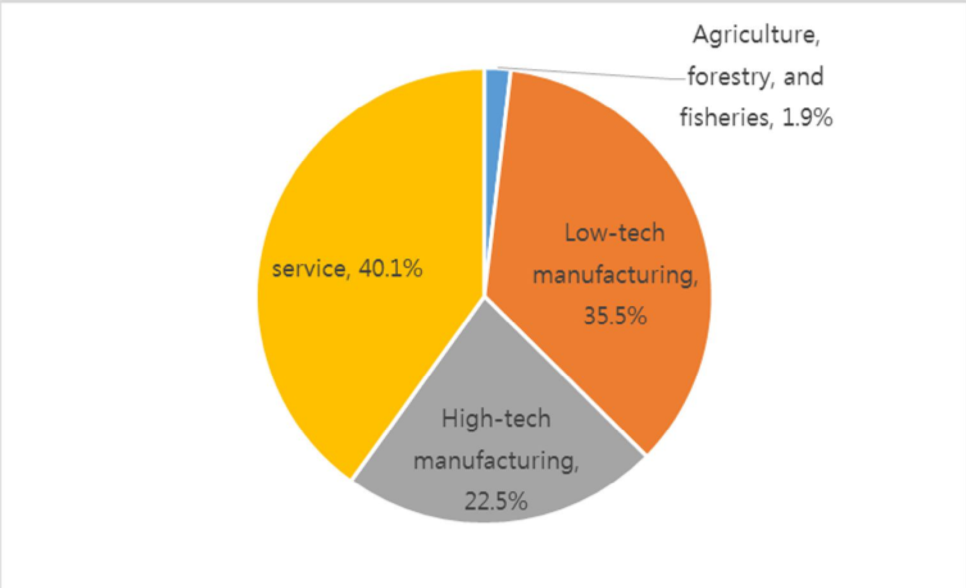


Figure 29. Decomposition of total output growth with respect to industry in SCN 3 (5%)

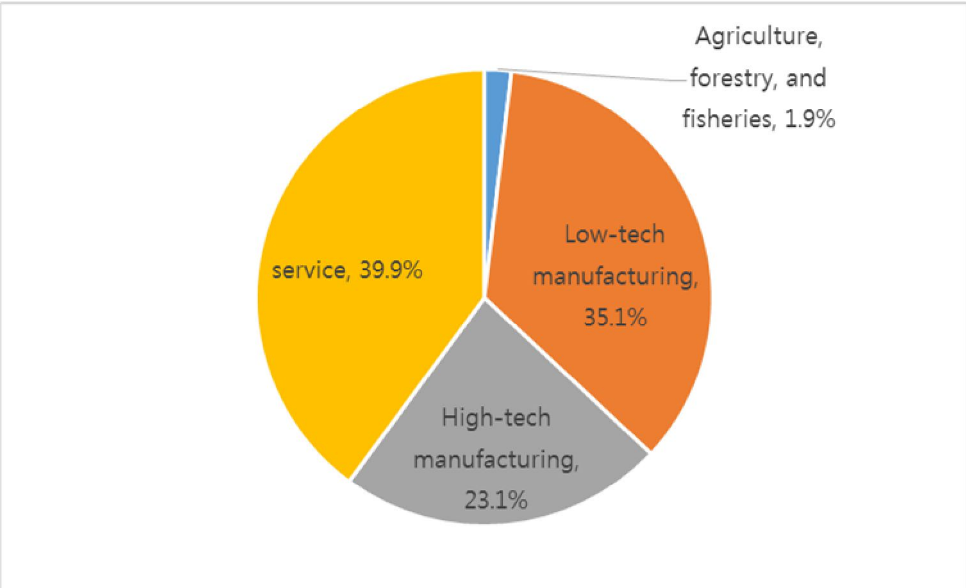
(a) Base year



(b) SCN 1 (3%, Year 2030)



(c) SCN 2 (4%, Year 2030)



(d) SCN 3 (5%, Year 2030)

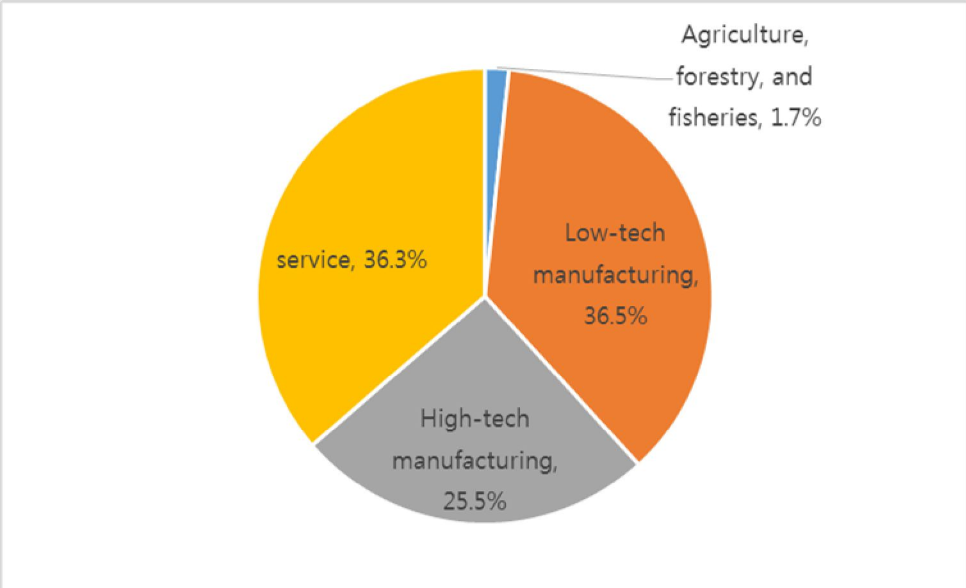


Figure 30. Output proportion by industry

On the other hand, the output proportion by industry in 2030 by scenario is shown in Figure 30. The results showed that in Scenario 3, when R&D intensity increases by up to 5%, the output proportion of the low-tech manufacturing industry increases, the output proportion of the service industry and the agriculture, forestry, and fisheries industry decreased, and the output proportion of the high-tech manufacturing industry maintained a similar level. In other words, when R&D investment proportion increases, the output of the low-tech manufacturing industry increases the most. The reason for these results is because all industries use many products of the low-tech manufacturing industry as intermediates. The proportions of intermediates and use of value added by industry are shown in Table 26.

Table 26. The proportions of intermediates and use of value added by industry (%)

		Agriculture, forestry, and fisheries	Low-tech manufacturing	High-tech manufacturing	Service
Inter-mediate	Agriculture, forestry, and fisheries	6.96	3.49	0.01	0.66
	Low-tech manufacturing	31.07	59.55	24.60	10.48
	High-tech manufacturing	2.32	4.87	41.61	6.34
	Service	10.11	11.26	8.94	31.54
Value added	Capital	42.82	9.71	11.80	24.01
	Labor	6.68	10.37	9.74	26.62
	Knowledge	0.04	0.75	3.30	0.35

4.3.4 Income Distribution

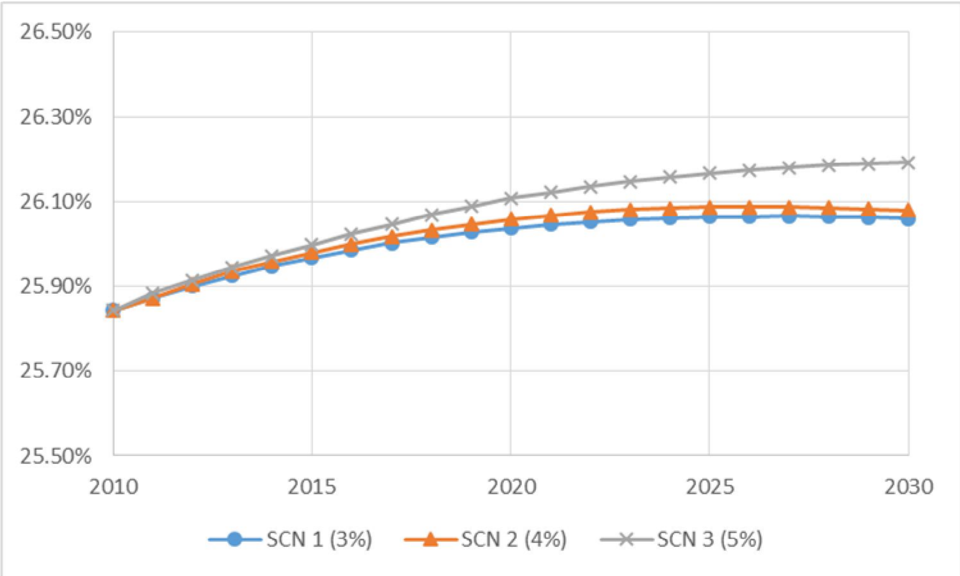


Figure 31. The proportions of income of the top 10% (%)

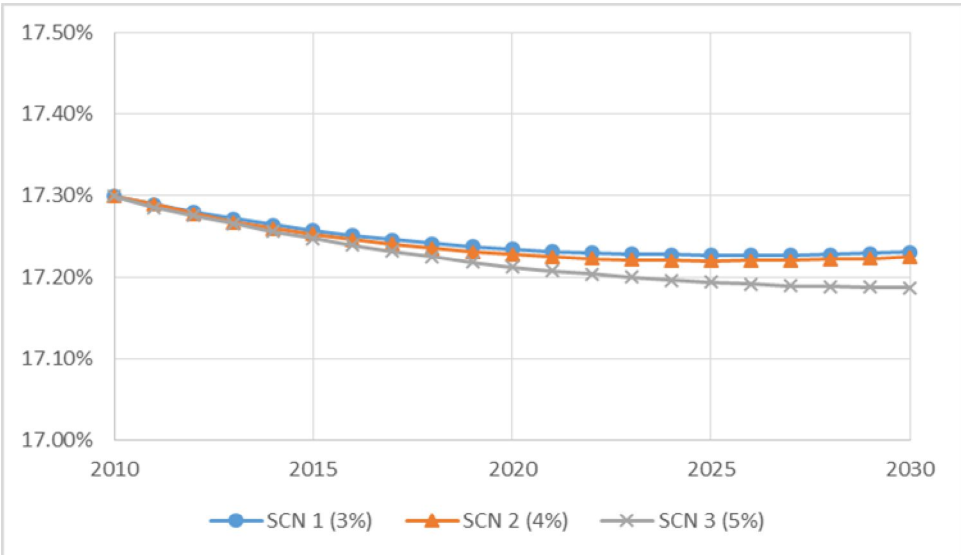


Figure 32. The proportions of income of the middle 40-60% (%)

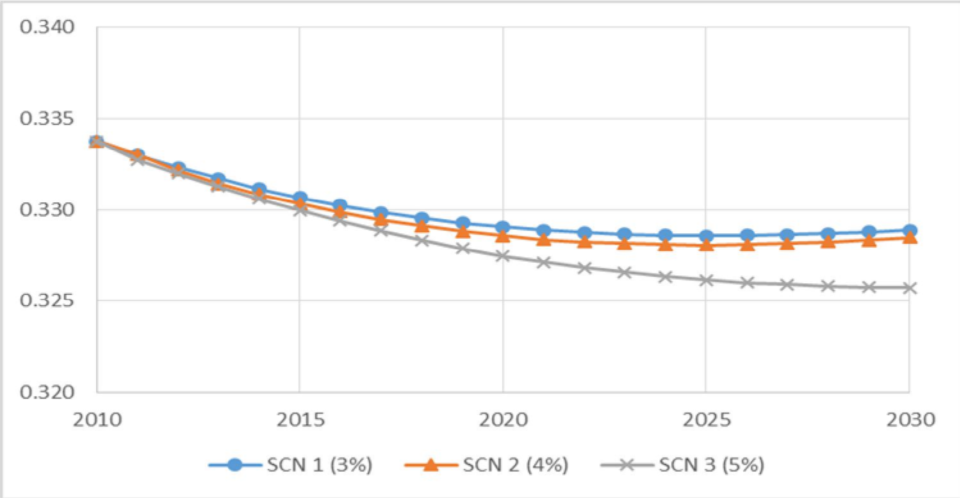


Figure 33. The change in decile distribution ratio

GDP can be obtained from the sum of value added or gross household income. This is because value added as the sum of all factors of production invested in production is transferred to household income. In this study, to examine the income proportions of income quantiles, the changes in the proportions of income of the top 10% and the middle 40–60% were analyzed. The results are shown in Figure 31 and Figure 32, respectively. The results showed that when more innovation activities are conducted, the proportion of income of the top 10% in GDP increases, and in turn, the proportions of income of the middle-income class and the lower-income class decrease. On the other hand, to determine the degree of income inequality, the change in decile distribution ratio (the value obtained by dividing the sum of the bottom 40% of incomes by the sum of the top 20% of incomes) was examined. The results are shown in Figure 33. The results showed that in the Scenario where additional R&D investments were made, the decile distribution ratio was lower than in other scenarios, and the value continued to decrease over time. The reason for this result is because the effects of capital-biased technological change and SBTC increase when more innovation activities are conducted. Accordingly, as the proportions of capital and high-skilled labor with large variations among income quantiles in value added increase, the degree of income inequality increases, and polarization takes place. On the other hand, the results of the analysis of income benefits by household quantile as a result of economic growth in Scenario 3 are shown in Table 27. The benefit from economic growth for the bottom 10% is 0.9%, whereas the top 10% take 26.8% of benefits. Accordingly, when innovation-driven economic growth continues, the income gap between the upper and lower classes will deepen. Therefore, policies to reduce the income gap are needed.

Table 27. Benefits by household quantile as a result of economic growth in SCN 3 (5%)

Decile 1	0.9
Decile 2	2.4
Decile 3	4.4
Decile 4	6.1
Decile 5	7.9
Decile 6	9.1
Decile 7	11.5
Decile 8	13.7
Decile 9	17.2
Decile 10	26.8

4.4 Effect According to Changes in Elasticities of Substitution between Factor Inputs

Although the values of elasticity of substitution should be estimated and used for more accurate research that fits conditions in Korea, in this study, the values of the elasticity of substitution were borrowed from previous studies for analysis. This could be a limitation of the present study. Therefore, this chapter examines the effect of substitution on employment and economic growth according to the change in the values of elasticity.

The form of production function used in this study is reexamined and shown in Figure 34.

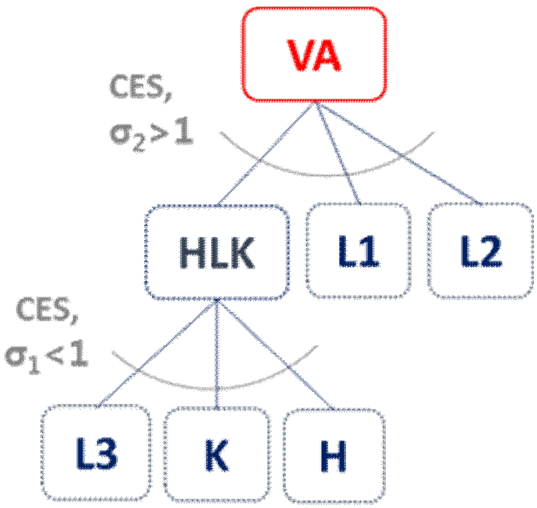


Figure 34. Structure of production function

σ_1 denotes the elasticities of substitution among high-skilled labor (L3), capital (K), and knowledge (H), and it was assumed that a complementary relationship exists among them. Therefore, the elasticity of substitution takes on a value smaller than 1. On the other hand, σ_2 denotes the elasticity of substitution among the composites of high-skilled labor, capital, and knowledge (HLK), unskilled labor (L1), and skilled labor (L2). It was assumed that a substitutive relationship exists among them because of SBTC and capital-biased technological change, and therefore, the elasticity of substitution was set up to take on a value larger than 1. Earlier, the values of elasticity were set at 0.67 and 1.67, respectively, based on previous studies. In the following, the effect of innovation activities on employment and economic growth will be examined according to changes in the elasticities of substitution between factor inputs.

4.4.1 Influence of Changes in Elasticities of Substitution between Factor Inputs on Employment

To examine the influence of changes in elasticities of substitution between factor inputs, using Scenario 3, where R&D intensity increases by up to 5%, the change in demand for labor by skill level as a result of the change in σ_2 was analyzed. Here, the value of σ_1 was constant at 0.67. The results are shown in Figure 35. The results showed that when σ_2 increases, aggregate labor demand in 2030 decreases. The reason for this result is because when σ_2 increases, the influences of capital-biased technological change and SBTC increase. In other words, the composites of capital, knowledge, and high-skilled labor increasingly replace unskilled and skilled labor. Therefore, the demand for unskilled and skilled labor decreases. In addition, as its influence was bigger than the output increase as a result of increased elasticities of substitution between factor inputs, aggregate labor demand decreased. Moreover, this result occurred because despite the increase in demand for high-skilled labor, the demand for unskilled and skilled labor decreased more. However, Table 28 shows aggregate labor demand in 2030 was sufficiently higher compared with the base year of 2010. To summarize, although aggregate labor demand decreases when elasticities of substitution between factor inputs increase, the increase in aggregate labor demand caused by economic growth from innovation offsets the decrease sufficiently.

(Unit: trillion won)

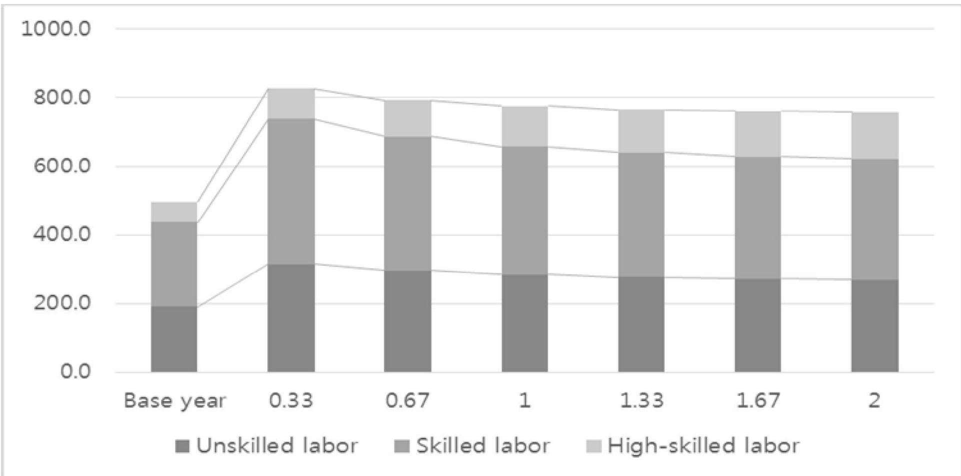


Figure 35. The change in demand for labor as a result of the change in σ_2 in 2030

Table 28. The change in demand for labor by skill level as a result of the change in σ_2 in 2030

(Unit: trillion won)	Base year	0.33	0.67	1	1.33	1.67	2
Unskilled labor	190.7	315.1	296.2	284.1	276.9	272.0	268.8
Skilled labor	246.4	422.6	390.6	373.4	363.7	357.1	352.9
High-skilled labor	59.3	89.6	106.8	118.0	125.4	131.2	135.6
Total labor demand	496.3	827.3	793.6	775.6	766.0	760.2	757.3

4.4.2 Influence of Changes in Elasticities of Substitution between Factor Inputs on Economic Growth

When elasticities of substitution between factor inputs increase, output generally increases, because resources can be more efficiently used. Therefore, when elasticities of substitution between factor inputs increase, economy can grow faster. The present model also showed the following phenomenon; when the value of elasticities of substitution between factor inputs, σ_2 , increases, GDP increases. The results are shown in Figure 36.

Table 29 shows annual economic growth rates according to the changes in elasticities of substitution (σ_2) between compositions of knowledge, capital, and high-skilled labor, skilled labor, and unskilled labor. The results showed that when σ_2 increases, GDP increases; therefore, the economic growth rate also increases.

(Unit: trillion won)

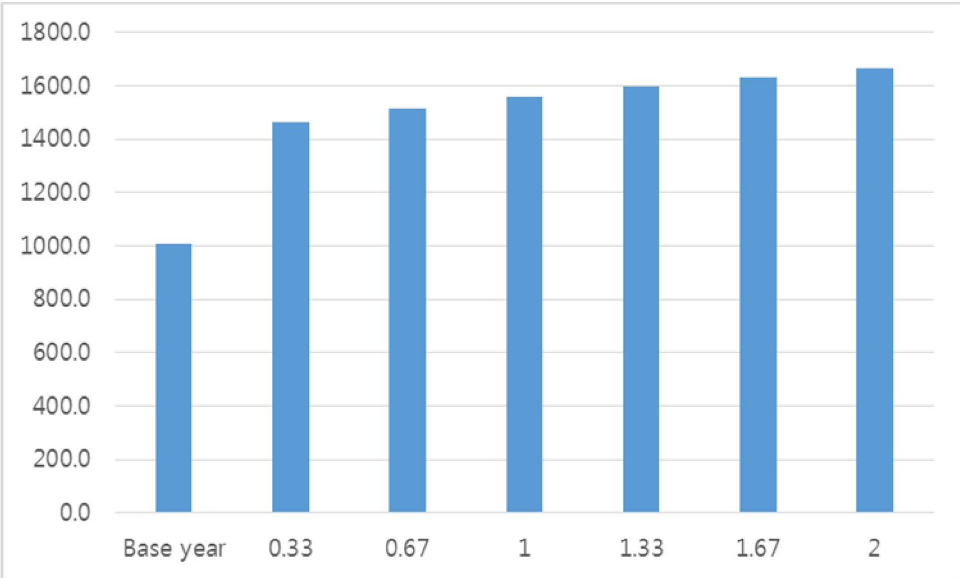


Figure 36. The change of GDP as a result of the change in σ_2 in 2030

Table 29. The annual GDP growth rate as a result of the change in σ_2 (%)

σ_2	0.33	0.67	1	1.33	1.67	2
Annual GDP growth rate	1.89	2.06	2.21	2.33	2.44	2.55

Table 30. Value added and GDP as a result of the change in σ_2 in 2030

(Unit: trillion won)	Base year	0.33	0.67	1	1.33	1.67	2
Capital	474.4	557.9	634.9	692.4	736.4	776.7	811.8
Unskilled labor	190.7	315.1	296.2	284.1	276.9	272.0	268.8
Skilled labor	246.4	422.6	390.6	373.4	363.7	357.1	352.9
High-skilled labor	59.3	89.6	106.8	118.0	125.4	131.2	135.6
Knowledge	36.8	79.9	86.3	90.4	93.3	95.6	97.6
GDP	1007.5	1465.0	1514.8	1558.5	1595.7	1632.6	1666.7

Table 31. Income share as a result of the change in σ_2 in 2030

	Base year	0.33	0.67	1	1.33	1.67	2
Unskilled	18.9%	21.5%	19.6%	18.2%	17.4%	16.7%	16.1%
Skilled	24.5%	28.8%	25.8%	24.0%	22.8%	21.9%	21.2%
High-skilled	5.9%	6.1%	7.1%	7.6%	7.9%	8.0%	8.1%
Total labor	49.3%	56.5%	52.4%	49.8%	48.0%	46.6%	45.4%
Capital	47.1%	38.1%	41.9%	44.4%	46.2%	47.6%	48.7%
Knowledge	3.7%	5.5%	5.7%	5.8%	5.8%	5.9%	5.9%

Table 30 shows value added and GDP in 2030 according to the change in σ_2, and Table 31 shows the income distribution ratio of each factor of production in 2030 according to the change in σ_2. The results showed that as σ_2 increases, value added for unskilled labor and skilled labor decreases, but value added for capital, knowledge, and high-skilled labor increases. Accordingly, it was found that when σ_2 increases, the income distribution ratios of unskilled and skilled labor decrease, and the income distribution ratios of high-skilled labor, capital, and knowledge increase.

In Korea, the working-age population is highly likely to shrink in the future as the birth rate decreases. Therefore, labor shortage could become an issue in the process of economic growth. However, if the elasticities of substitution between factor inputs increase and knowledge and capital can replace labor, this is expected to benefit economic growth.

4.5 Sub-Conclusion

In this chapter, analysis of the effect of innovation on employment structure and economic growth was performed using the knowledge-based CGE model. To incorporate characteristics of innovation, R&D investment and knowledge capital stock were used. It was set up so that knowledge capital stock accumulates through R&D investment. In addition, it was set up so that the knowledge capital stock of each industry were used as the factors of production, having a spillover effect on other industries, and public knowledge capital stock had a spillover effect on all industries. Moreover, to incorporate SBTC and capital-biased technological change taking place recently as a result of innovation, the CES production function was introduced to reflect the elasticities of substitution between factor inputs.

Analyses were performed separately for employment, economic growth, and income distribution. First, the results on employment showed that additional innovation activities have a positive effect on aggregate labor demand. Conversely, when innovation activities at the current level are maintained or decrease, aggregate labor demand was found to stagnate in the long term. Moreover, the results of the analysis on employment by skill level showed that additional R&D investments increase the demand for all unskilled, skilled, and high-skilled labor. In particular, the demand for high-skilled labor showed the highest increase rate. This suggests that despite SBTC and capital-biased technological change, the economy grows rapidly and more jobs are created due to innovation.

Furthermore, it was found that high-skilled labor needs to be obtained through education to meet the rapidly growing demand for high-skilled labor. On the other hand, analysis of the effect of additional R&D investment on the demand for labor in each industry was also performed, and the results showed that the high-tech manufacturing industry with high R&D intensity showed the highest increase rate of demand for labor. This suggests an employment increase in industries with more R&D. Accordingly, if innovation-driven economic growth continues in the future, a large volume of the workforce in the high-tech manufacturing industry and R&D-related industry need to be educated.

Regarding the aspect of economic growth, when R&D intensity increases by up to 5%, it was found that 2.44% annual economic growth is achieved until 2030. Conversely, when R&D intensity maintains the level of the base year or decreases to 3%, economic growth slows down in the long term. The detailed examination of value added showed that more R&D investment results in an increase in the proportion of capital, high-skilled labor, and knowledge in value added, and a decrease in the proportion of unskilled and skilled labor in value added. On the other hand, results on output by industry showed that when innovation activities increase, the output of the manufacturing industry showed a higher increase rate than the output of the service industry.

Finally, regarding the aspect of income distribution, the results showed that additional R&D investment has an adverse effect on income distribution. This is because additional R&D investment increased skill premium due to SBTC, increasing the wage gap between high-skilled and unskilled labor. Furthermore, capital income distribution ratio increases due to capital-biased technological change, resulting in more income gained by the high-income class, who own a lot of capital. Accordingly, economic growth through innovation returns most of the benefits to the high-income class, intensifying polarization. Therefore, to achieve sustainable innovation-driven economic growth, policies to reduce polarization are needed. On the other hand, an additional analysis was performed to examine the effect of innovation on employment and economic growth according to changes in the elasticities of substitution between factor inputs. The results showed that increased elasticities of substitution between factor inputs benefit employment and economic growth. This is because when elasticities of substitution between factor inputs increase, factors of production can be used more efficiently. Accordingly, given the situation in Korea, where the population growth rate is decreasing, increased elasticities of substitution between factor inputs, which allow knowledge and capital to substitute labor, are expected to benefit economic growth.

Rapid change due to the emergence of a new paradigm cause social chaos. However, if we can determine the attributes of the new paradigm and make preparations, the chaos may decrease. Recently, concern has increased over the problems generated from the advent of new technologies as a result of technological innovation. However, these claims consider only the direct effect of technological innovation on employment. Thus, it is necessary to take a balanced look at the direct and indirect effects of technological innovation. Accordingly, understanding the economic effects of technological innovation is crucial, and this is the significance of this study.

Chapter 5. Conclusion

5.1 Summary of findings and policy implications

This study aimed to investigate the effects of innovation on employment structure and economic growth. In particular, the study took the approach of using the knowledge-based CGE model, which goes beyond the limitations of the econometric analysis methodology usually used by existing studies. Moreover, it attempted to generate objective general findings on the direct and indirect effects of innovation by incorporating its characteristics. To this end, analyses were performed by setting up various models, which enabled general conclusions to be drawn on the effects of innovation on employment and economic growth. The study can be summarized as follows.

First, Chapter 2 described previous empirical studies on the relationship between innovation and employment as well as compensation effect theory. In addition, it described the relationship between innovation and employment in the digital age, which has been an issue lately, and discussed SBTC and capital-biased technological change. In addition, studies conducted with knowledge-based CGE models were examined. Based on these studies, the contribution of the present study was delineated.

Chapter 3 described in detail the method of creating a knowledge-based social accounting matrix that serves as data for the knowledge-based CGE model used in this study. In addition, it explained the equations used in the knowledge-based CGE model and the method for projecting physical capital stock and knowledge capital stock. These detailed descriptions of the model provided the framework for future use in innovation policy-related applied research.

Chapter 4 discussed the results of the analysis of the effects of technological innovation on employment and economy based on the model described in Chapter 3. The results showed that increasing investment in innovation had a positive effect on economic growth and also increased aggregate labor demand. These results suggest that increased productivity due to the spillover effect of innovation has a larger effect on the economy than SBTC and capital-biased technological change due to innovation. However, when R&D investment increased, the proportion of unskilled and skilled labor in value added decreased and the proportion of high-skilled labor and capital in value added increased. These results suggest that income polarization increases. This occurs because most of the income from high-skilled labor is gained by the high-income class. On the other hand, the results of the analysis by industry showed that additional R&D investment increases the proportion of demand for labor for the manufacturing industry, whereas it decreased the proportion of demand for labor for the service industry and agriculture, forestry, and fisheries industry. In particular, the increase in rate of demand for labor for the high-tech manufacturing industry was found to be highest. In addition, additional R&D investment was found to increase the proportion of manufacturing output in total output. Moreover, additional analysis showed that when the elasticities of substitution between factor inputs increase, GDP and aggregate labor demand increase. To conclude, technological innovation was found to have a positive effect on employment and economic growth; however, it creates the problem of polarization. The policy implications that can be drawn from these findings are as follows.

First, innovation-driven economic growth needs to be achieved through continuing R&D investment. If innovation slows down, long-term economic growth slows down, resulting in a recession and reducing aggregate labor demand. Therefore, increasing the output of each industry through more active innovation activites is needed.

Second, educating the workforce to fit new jobs generated by innovation is needed. Technological innovation results in SBTC, reducing unskilled labor jobs and increasing high-skilled labor jobs. In addition, jobs in industries with a significant amount of innovation activites increase. Therefore, it is necessary to train the workforce in line with changing job demands due to technological innovation and facilitate retraining for those who lose jobs due to technological innovation to enable them to work in new fields.

Finally, policies are required to solve the polarization problem caused by innovation-driven economic growth. Increasing inequality causes social instability and ultimately results in decreased economic efficiency and productivity. Therefore, for sustainable growth, the problem of polarization needs to be resolved. In innovation-driven economic growth, polarization occurs as the income distribution ratio for high-skilled labor and capital increases due to capital-biased technological change and SBTC; therefore, the problem of polarization needs to be resolved by measures including increasing the tax rate for capital income or applying strong progressive tax for income tax. However, such policies for solving polarization should not work in a direction that may undermine innovative potential. Thus, the solution for the problem of polarization requires a careful approach.

5.2 Significance and limitation of study, and future research

This study, which investigated the effects of innovation on employment and economic growth, is differentiated from existing studies in the following manner.

First, existing studies on the relationship between innovation and employment generally used the econometric analysis methodology for analysis. Accordingly, they could examine only the direct effect of innovation on employment. However, in this study, analysis was performed using the CGE model, which allows a comprehensive examination of direct and indirect effects of policy changes. In particular, this study provided a foundation for studies on innovation policies by creating a knowledge-based social accounting matrix and building the knowledge-based CGE model by applying innovation. It also established a methodology that can generate more accurate results for the analysis of the relationship between innovation and employment.

Second, this study conducted an analysis by subcategorizing household and labor. By subcategorizing household, it created a framework for handling the issue of distribution in innovation policy. In addition, by subcategorizing labor and incorporating elasticities of substitution between factor inputs, the effects of innovation for each skill level could be examined. This is expected to offer new implications to policy makers of innovation policies.

However, this study also has limitations. First, the values of elasticities of substitution between factor inputs were borrowed from previous studies. Elasticities of substitution between factor inputs vary across countries, periods, and industries. Therefore, to perform a more accurate analysis, the study needs to estimate the elasticities of substitution between factor inputs by industry using Korean data. Second, the values of the spillover effects of knowledge stock of other industries and public knowledge stock were borrowed from previous studies. Estimating these values for the study also will result in a more accurate analysis. Third, households were classified into 20 quantiles for the analysis using the micro data of the HIE Survey. Technological innovation leads to a "superstar" economy and provides the top class with the largest benefits. Therefore, the study needs to examine income changes in the top 1% or the top 0.1%. Therefore, a future study needs to examine income changes in the top income classes by applying a microsimulation model to a CGE model. Finally, this study did not incorporate the social cost and the negative effect of income polarization. In the future, studies need to consider the side effects of income polarization and incorporate them into the model for a more accurate analysis.

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Abstract (Korean)

전 세계적으로 많은 나라들에서 1990년대와 2000년대 초반에 걸쳐 경제가 성장하는 가운데서도 고용이 늘지 않는 ‘고용 없는 성장(jobless growth)’을 겪었다. 또한 글로벌 금융위기 이후 많은 나라들에서 경제가 회복하였음에도 불구하고 실업률은 감소하지 않고, 오히려 증가하는 경우도 발생하고 있다. 우리나라의 경우에도 마찬가지로 2000년대 중반부터 ‘고용 없는 성장’을 겪고 있다. 이러한 현상이 발생하는 원인에 대해 경제학계에서는 다양한 주장을 하고 있는데, 그 중 한 가지 주장은 기술혁신 때문이라는 것이다. 즉 기술이 발전하면서 생산성과 산출량은 증가하는 반면 일자리에 대한 수요는 오히려 감소하여 고용에 악영향을 미친다는 것이다. 특히 우리나라의 경우 지속적인 연구개발투자 증가에 따라 세계적으로 가장 높은 수준의 연구개발투자 집약도를 가지고 있는데, 이것이 고용 없는 성장의 원인이라는 지적들이 제기되고 있다.

고용의 양적 측면뿐만 아니라 질적인 측면도 문제가 되고 있는데, 기술 혁신이 숙련노동자에 대한 수요는 증가시키는 반면 비숙련 노동자에 대한 수요는 위축시키는 현상을 발생시킨다는 것이다. 즉 숙련 편향적 기술변화를 야기한다는 것이다. 특히 Brynjolfsson and McAfee (2014)는 ‘*The second machine age*’라는 책에서 정보통신기술이 발전함에 따라 새로운 기술들과 기계들이 우리의 일자리를 더욱 빨리 대체해 나가고 있고, 기술혁신이 숙련편향적 기술변화와 자본편향적 기술변화를 일으켜 소득 양극화를 발생시킨다고 주장하였

다. 하지만 최근에 제기되고 있는 주장들은 혁신이 고용에 미치는 직접적인 영향만을 고려하고 있다. 혁신은 다양한 경로를 통해 고용에 영향을 미치게 된다. 특히 혁신을 통해 제품의 다양성이 증가되면 신 수요가 창출되고 이로 인해 고용이 증가되는 간접적인 영향도 존재한다. 따라서 혁신이 고용과 성장에 미치는 영향은 직접적인 효과와 더불어 간접적인 효과도 같이 살펴보아야 한다. 이에 본 연구에서는 경제의 다양한 측면을 동시에 고려할 수 있는 연산일반균형모형을 이용하여 혁신이 고용구조와 경제성장에 어떠한 영향을 미치는지 살펴보고자 하였다. 이를 위해 지식기반 사회회계행렬과 지식기반 연산일반균형 모형을 구축하였다.

지식기반 연산일반균형 모형을 활용한 연구의 결과를 정리해보면 다음과 같다. 우선 고용측면에서 살펴보면 추가적인 혁신활동은 총 노동수요를 증가시키는 것으로 나타났으며, 이에 비숙련, 숙련, 그리고 고숙련 노동의 수요가 모두 증가하였다. 특히, 고숙련 노동의 수요가 가장 높은 증가율을 보였다. 그리고 산업별로 살펴보면 연구개발투자를 많이 하는 high-tech 제조업에서 고용증가율이 가장 크게 나타났다. 다음으로 경제성장측면에서 살펴보면 추가적인 혁신활동은 경제성장에 긍정적인 영향을 미치는 것으로 나타났다. 이에 모든 생산요소의 부가가치가 증가하는 것으로 나타났다. 하지만 자본과 고숙련 노동, 그리고 지식의 경우 부가가치에서 차지하는 비중이 증가하는 반면, 비숙련 노동과 숙련 노동은 자본편향적 기술변화와 숙련편향적 기술변화에 의해 부가가치에서 차지하는 비중이 감소하는 것으로 나타났다. 이에 따라 소득분배에 악영향을 미치며, 소득 양극화 현상이 심화되는 것으로 나타났다. 한편, 산업

별로 살펴보면 추가적인 혁신활동으로 인해 제조업의 산출량이 서비스업의 산출량보다 높은 증가율을 보이는 것으로 나타났다.

주요어: 혁신, 고용구조, 경제성장, 숙련편향적 기술변화, 자본편향적 기술변화, 연산일반균형모형

학번: 2009-23211