# STUDY ON THE EFFECTS OF INNOVATION ON EMPLOYMENT STRUCTURE AND ECONOMIC GROWTH: A COMPUTABLE GENERAL EQUILIBRIUM APPROACH

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Technological innovations are deeply involved in the issue of growth and distribution, which are like two sides of a coin. Although the technological innovations promote the economic growth with productivity increases, it can replace existing jobs with new technologies and machines. Skill-biased technological change and capital-biased technological change can lead to income polarization. This study aims to quantitatively examine the influence of innovation on the economic system with aspects of growth and distribution, using the computable general equilibrium model. Simulation results imply that additional innovative activities increase the total demand of labor, leading to positive effects on economic growth. However, results show that technological innovation further increases demand for high-skilled labor more than other types of labor due to skill-biased technological change, which deepen income polarization.

*Keywords:* Innovation; Employment structure; Economic growth; computable general equilibrium; South Korea

## 1. Introduction

South Korea has accomplished tremendous economic growth over the past half century. 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, ranking the sixth worldwide as of 2013, and Korea has maintained the R&D intensity at the highest level in the world. 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 proposed as a critical issue 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. 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 (Bessen, 2015; Katz and Margo, 2013). 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. Under this background, debates on innovation and employment has been sparked again.

This paper 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. This research focuses on the employment and income distribution effects from the research and development (R&D) and technological innovations in South Korea. For this objective, 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 skill biased technological change, and capital biased technological change, which are important issues for the model.

The rest of the paper is structured as follows: Section 2 provides a brief review of the relevant literature, focusing on the relationship between the innovation and employment. Section 3 contains general descriptions of the CGE model used for the analyses. Section 4 explains the scenario settings. The main results are presented in Section 5. Lastly, the summary and concluding remarks are provided in Section 6.

## 2. Literature review

Research on the relationship between innovation and employment has been conducted since the early Industrial Revolution, and an active discussion about this issue is in progress with the emergence of robots and automated devices in recent years. To understand debates around the innovation and employment, it is essential to investigate key concepts as follows: compensation effect, skill biased technological change (SBTC), and capital biased technological change. A brief review of these concepts is presented in following subsections including relevant literature.

### *2.1 Compensation effect*

By definition, technological change allows to produce the same amount of goods with a lower amount of production factors, namely capital and labor. Technological unemployment occurs as a direct effect of innovation. This nature of technological innovation had made skilled labor working in handicraft lost jobs, which led to destruction of machinery in protest in the 19$^{th}$ century (Luddite Movement). Despite such concerns, economists argued that new jobs are typically created by the 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).

Vivarelli (2012) claimed that it is essential to examine not only direct effects of innovation, but also indirect effects on the employment, and introduced different mechanisms of compensation effect which are triggered by technological change itself. According to Vivarelli (2012), the initial labor saving impact of process innovation can be counterbalanced by compensation mechanisms via new machines, decrease in commodity prices, new investments, decrease in wages, and increase in households' incomes. This compensation theory highlight that technological changes induces market forces which can potentially counterbalance the initial labor saving effect of process innovation, leading to positive effect on employment trends.

### *2.2 Skill biased technological change*

Technological advance accompany increases of skilled workers, leading to advancement of employment structure, as experienced by developed countries. Skill biased technological change (SBTC) is referred to as a shift in the production technology that favors skilled over unskilled labor by increasing its productivity and, therefore, its relative demand. 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).

Empirical research that supports this claim has been actively conducted. For example, 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. 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) claimed that use of information and communication technology is the factor that causes SBTC. Traditionally, technological change is regarded as factor-neutral, however the observed rapid rise in the relative demand and wages of skilled workers implies that recent technological changes has been skill biased. Furthermore, various empirical studies support the complementarity between recent technological innovations and skilled labor.

### *2.3 Capital biased technological change*

Brynjolfsson and McAfee (2014) argued that technology causes not only SBTC but also capital biased technology change. This means that the influence of capital becomes even greater as automated machines (such as, robots) which is capital intensive goods intrude on the domain of human labor. Consequently, the proportion of labor wages in Gross Domestic Products (GDP) decreases. In the past, the proportion of labor in GDP has remained relatively constant. However, in recent decades, labor share is in decline.

Several studies have tried to examine a link between capital biased technological change and labor share in the economy (Bentolila and Saint-Paul, 2003; Guerriero and Sen, 2012; Karabarbounis and Neiman, 2013). They suggest that the extent of capital biased technological progress can influence the labor share in the production system. Karabarbounis and Neiman (2013) argued that labor share has declined in many countries since the early 1980s. They indicated 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. Therefore, it can be inferred that technological innovation results in recent technological change is biased towards a capital, leading to increased share of capital income for products and services derived or refined from technological innovation.

### *2.4 The relationship between the innovation and employment*

Empirical results on the relationship between innovation and employment are still debated. 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.

Several studies suggest positive employment impact of innovation (Piva and Vivarelli, 2005; Hall, Lotti, and Mairesse, 2008; Harrison, Jaumandreu, Mairesse, and Peters, 2008;

Lachenmaier and Rottmann, 2011; Coad and Rao, 2011; Zuniga and Crepsi, 2013). Most of these studies have examined the direct effect of innovation on employment, based on the firm level analysis using firms' in-house data on innovation and employment. They commonly conclude that employment growth rate is positively correlated with firms' R&D levels and patents, suggesting employment expansion triggered by technological innovations.

On the other hand, several empirical studies report different results, highlighting the possibility of technological unemployment. Brouwer, Kleinknecht, and Reijnen (1993) studied the relationship between employment growth rate and R&D intensity in 859 German manufacturers from 1983 to 1988. They 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 firm level quantitative analysis can consider only direct effect because it utilizes each firm's innovation data and employment data. Therefore, the positive effects of companies' innovation activities are likely to be overestimated (Pianta, 2005). As mentioned above, technological innovation is accompanied by labor saving process innovation leading to technological unemployment. This is understood as the direct effect of technological innovation on employment trends. However, to fully understand the relationship between the technological change and employment, both direct effects and indirect effects should be incorporated, including the compensation effects, and other macroeconomic conditions.

Furthermore, recent technological change is in progress being biased towards specific factors as shown above. Therefore, the bias of technological changes should be taken into considerations when analyzing the employment impacts of innovation. As Vivarelli (2012) mentioned, it is difficult to distinguish the final impact of innovation on employment, since the latter is influenced by many other factors. In this context, this study aims to empirically examine the relationship between the technological innovation and employment trends, based on these key concepts and aggregate macroeconomic settings, which is referred as computable general equilibrium (CGE) model.

## 3. CGE Modelling

In this paper, we use a CGE model to generate ex ante simulations to induce in changes of employment structure and income distributions from technological innovations. It is important to incorporate innovation-related activities (e.g., research and development (R&D)) and characteristics of knowledge (e.g., knowledge accumulation and knowledge spillover effects) into CGE model in order to understand the relationship between technological innovations and employment. In this context, we construct the knowledge-based CGE model by adding R&D

descriptions and characteristics of knowledge with a set of equations based on knowledge-based the Social Accounting Matrix (SAM).

It is also essential to classify the labor into occupational categories based on the skill level to examine the change of employment structure arising from the technological innovation. From this perspective, labor for production of final goods and knowledge production is split into three types within the CGE model, including high skilled labor, skilled labor, and unskilled labor based on the education level. Furthermore, household is classified into 20-quantiels based on total income, using micro data of household level survey datasets to investigate the income distribution impacts of innovation-related activities. The following subsections show approaches for constructing datasets, including SAM and modeling equations that reflect those considerations.

### *3.1 The construction of a Social Accounting Matrix (SAM)*

In this study, the SAM is constructed 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. This SAM is used in the knowledge-based CGE model. The SAM is based on the 2010 Input-Output (I-O) table from the Bank of Korea (the central bank of South Korea) as its key source data, and tax-related data in the 2010 Statistical Yearbook of National Tax. In addition, we use the data on household and government savings in the national accounts.

Key differences between the SAM used in this study and other standard SAM are consideration of R&D activities and detailed description of labor and household types. We explicitly represent the knowledge as a factor of production and knowledge capital formation in an investment account. The SAM used in this study accepts the recommendation of the 2008 SNA in order to incorporate additional accounts for knowledge capital.[1] This study also adopts a knowledge-based SAM made by the method of Yang et al. (2012) and Hong et al. (2014). Within the SAM used for this study, current expenditure on research and development (R&D) which was initially included in intermediate goods transactions, has been moved to the production factor account. In addition, capital expenditure on R&D which was initially included in physical capital formation, has been moved to knowledge capital formation in order to prevent double counting. The transferred value is then subtracted from the original account. Furthermore, the knowledge capital formation account has been subdivide into private and public accounts according to who spent it. The value added from knowledge increases

[1] According to the 1993 System of National Accounts (SNA), R&D spending is treated as intermediate consumption which is used up in the production process. However, the new 2008 SNA expands the range of fixed assets and clarifies how to handle R&D spending for fixed capital formation.

household income, which is a source of additional consumption and savings that benefit industrial activities.

In the SAM used for this study, labor is 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, including high-skilled, skilled, and unskilled labor. 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. We use the 2010 Household Income and Expenditure Survey (HIE Survey) micro data by Korea National Statistical Office, and 2010 Wage Structure Statistics by the Ministry of Employment and Labor. From these datasets, we extract both labor inputs and wage levels by labor types for final goods production, public and private knowledge production activities.

In addition, the household is also classified into 20-quantiles based on total income, using micro data of 2010 HIE Survey to extract the each household's consumption expenditure, physical capital investment, and R&D investment level. Classification of households by income levels enables us to examine the income distribution effects from the technological innovation. Table 1 shows the final form of the integrated SAM used in the knowledge-based CGE model which incorporate those considerations: explicit representation of knowledge, classification of labor by education levels, and household by income levels. The SAM is constructed by classifying households into 20 quantiles and labor into three sectors in the knowledge-based SAM. The numbers in Table 1 indicates the size of matrix of each account.

**Table 1. Structure of integrated 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 The structure of knowledge-based CGE model: Production of final goods*

As discussed earlier in the previous section on knowledge-based SAM, 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 1.

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.

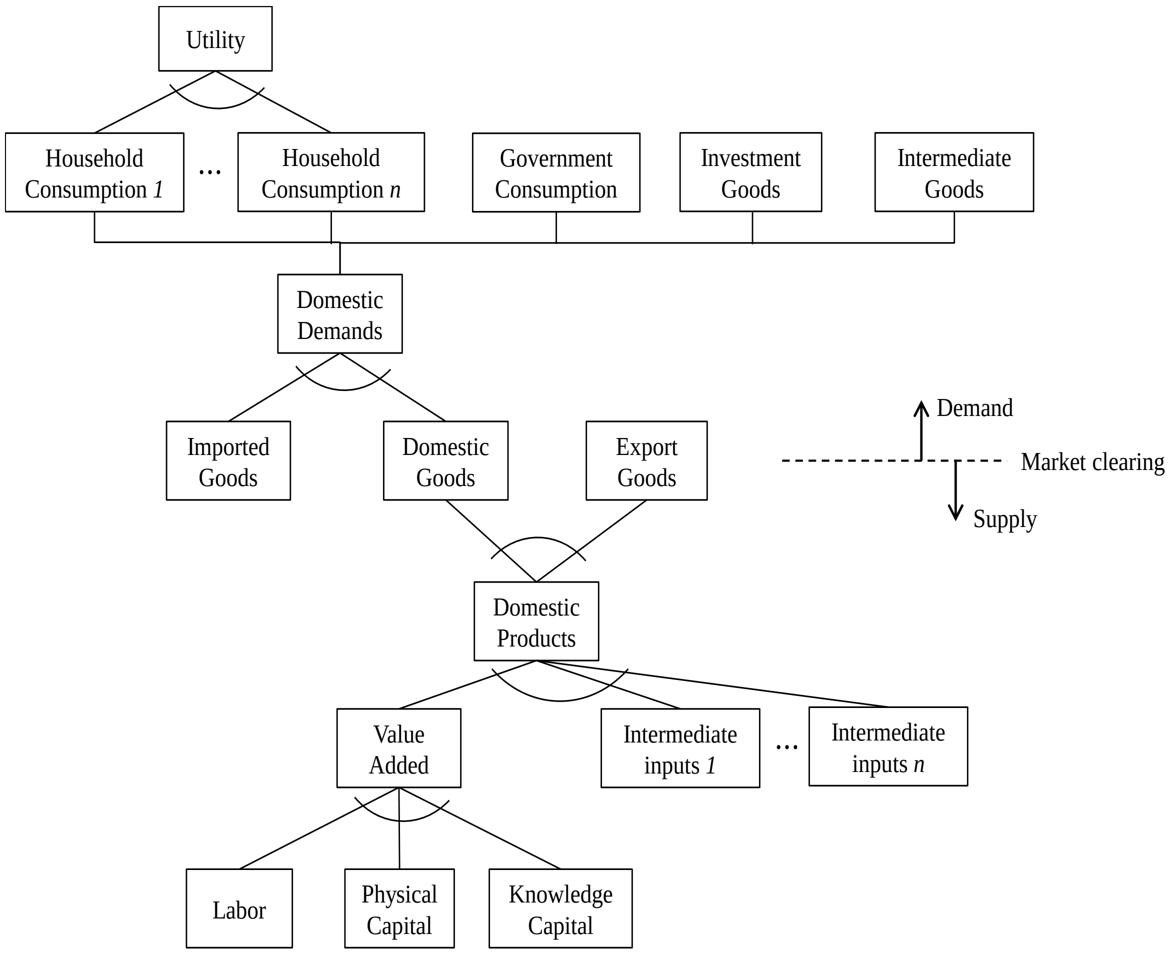



**Figure 1. Structure of Knowledge-based CGE model**

The final goods ($Z_i$) of each industry become production by factors of production, intermediates ($X_{j,i}$), and value-added composites ($VA_i$). If the intermediates and value-added composites required to produce a unit of output in industry j are $ax0_{j,i}$ [2] and $ava0_i$,

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

respectively, and the factors of production of industry i are as much as $[X_{1,i}, X_{2,i}, \ldots, X_{n,i}, VA_i]$, output is expressed by Equation (1). It follows Leontief production function, and production sectors are classified into 27 kinds according to the industrial classification standard in South Korean I-O table.

$$\mathrm{Z(i)} = \min[X(1,i)/ax0(1,i), \ldots\ X(n,i)/ax0(n,i),\ VA(i)/ava0(i)] \qquad \text{Eq. (1)}$$

where i = 1,2, … 27

On the other hand, value-added composite ($VA_i$) is assumed to be generated by labor ($L3_i$: high-skilled labor, $L2_i$: skilled labor, $L1_i$: unskilled labor), capital ($K_i$), and knowledge ($H_i$). In this study, knowledge is regarded 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 is introduced. It is also assumed that high-skilled labor ($L3_i$), capital ($K_i$), and knowledge ($H_i$) are complementary to one another, and have the same elasticity of substitution to one another. In addition, it is assumed that the composite of knowledge, high skilled labor, and capital ($HLK_i$) has a substitutive relationship with skilled and unskilled labor. Accordingly, the structure of production function applied in this model has the form as shown in Figure 2, which can be expressed by Equation. (2) and (3).

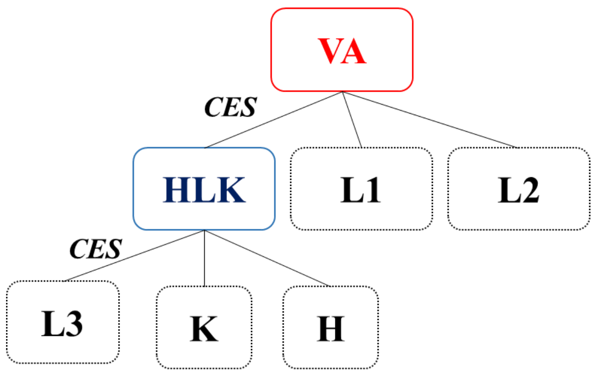



**Figure 2. Structure of value-added composite function**

$$\mathrm{HLK}_i = \theta10_i \cdot (\beta10_i \cdot L3_i^{-\rho1} + \beta20_i \cdot K_i^{-\rho1} + (1 - \beta10_i - \beta20_i) \cdot H_i^{-\rho1})^{-1/\rho1} \qquad \text{Eq. (2)}$$

$$\mathrm{VA}_i = \theta20_i \cdot (\beta30_i \cdot L1_i^{-\rho2} + \beta40_i \cdot L2_i^{-\rho2} + (1 - \beta30_i - \beta40_i) \cdot HLK_i^{-\rho2})^{-1/\rho2} \qquad \text{Eq. (3)}$$

where $\beta10_i$, $\beta20_i, \beta30_i, \beta40_i$: Share parameter for L3, K, L1, L2 in CES function, and $\theta10_i, \theta20_i$: Scale parameter in each CES function

### *3.3 The structure of knowledge-based CGE model: R&D investments and spillover effects*

The CGE model used for this study has a detailed description for R&D investment. R&D investment goods are generated through a separate process as followed by Hong et al. (2014), Křístková (2013), and Visser (2007). It is assumed that both the private and public sectors generate R&D investment goods ($RDZ_{rdt}$, $where\ rdt{:}private\ or\ public$) by combining value added ($RVA_{rdt}$) and intermediate goods ($XVRD_{rdt}$) for R&D, while $RVA_{rdt}$ is produced with labor ($\mathrm{RL}S3_{rdt}$: High skilled labor, $\mathrm{RL}S2_{rdt}$: skilled labor, $\mathrm{RL}S1_{rdt}$: unskilled labor in R&D investment) and physical capital ($RK_{rdt}$) for R&D. This is because expenditure on R&D mainly consists of three items: wage for researchers, physical capital for research like buildings or equipment, and other costs for supplies (Hong et al., 2014). The production structure of R&D investment goods is similar with production of final goods as shown in the Figure 2, which can be expressed by Equation (4), and (5).

$$\mathrm{RDZ}_{rdt} = \min[XVRD_{rdt}/axrd_{rdt},\ RVA_{rdt}/arva_{rdt}] \qquad \text{Eq. (4)}$$

$$\mathrm{RVA}_{rdt} = \varphi 20_{rdt} \cdot (\Psi 20_{rdt} \cdot RLS1_{rdt}^{-\rho 2} + \Psi 30_{rdt} \cdot RLS2_{rdt}^{-\rho 2} + (1 - \Psi 20_{rdt} - \Psi 30_{rdt}) \cdot RHK_{rdt}^{-\rho 2})^{-1/\rho 2}$$
$$\mathrm{RHK}_{rdt} = \varphi 10_{rdt} \cdot ((1 - \Psi 10_{rdt}) \cdot RKS_{rdt}^{-\rho 1} + \Psi 10_{rdt} \cdot RLS3_{rdt}^{-\rho 1})^{-1/\rho 1} \qquad \text{Eq. (5)}$$

where $axrd_{rdt}$: Intermediate input requirement coefficients in R&D;

$arva_{rdt}$: Value-added composite input requirement coefficients in R&D;

$\Psi 10_{rdt}$, $\Psi 20_{rdt}$, $\Psi 30_{rdt}$: Share parameter for RLS3, RLS1, and RLS2 in CES function, and

$\theta 10_{rdt}$, $\theta 20_{rdt}$: Scale parameter in each CES function

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. Accordingly, the knowledge stock can be expressed by Equation.(6) (Shin, 2004). $\mathrm{RDS}_t$ in the equation denotes knowledge stock at time *t*, and RDZ denotes R&D investment. $\delta$ 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 ($RDS_{t0}$)can be expressed by Equation. (7).

$$\mathrm{RDS}_t = (1 - \delta) \cdot RDS_{t-1} + RDZ_{t-i} \qquad \text{Eq. (6)}$$
$$RDS_{t0} = \sum_{t=0}^{\infty} RDZ_{t0-i} \cdot (1 - \delta)^i \qquad \text{Eq. (7)}$$

When it is assumed that the knowledge growth rate prior to the base year is the same as the average knowledge growth rate ($g$) after the base year, Equation. (7) can be converted into Equation. (8). 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 sectors, and private knowledge stock was estimated for each industry.

$$RDS_{t0} = RDI_{t0} \cdot [(1 + g)/(g + \delta)] \qquad \text{Eq.(8)}$$

Furthermore, this model incorporates the characteristic of knowledge, which is referred to as spillover effects. The spillover effect from other industries is 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 Equation. (9). In this 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.

$$\mathrm{INTINDST}_i = \sum_{j,j\neq i} other0_{j,i} \cdot H_j \qquad \text{Eq. (9)}$$

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 (Guellec and Potterie, 2001). Accordingly, public knowledge stock is set to have spillover effects on all industries. In contrast, private R&D, and the outcomes are sector-specific and appropriable (Hong et al., 2014). Therefore, industry-specific knowledge spillover effect is set to be come from other industry's knowledge stock. Those two types of knowledge spillover effects result in total factor productivity (TFP) changes in each sector's production function (Hong et al.,2014; Hwang et al., 2008). The spillover coefficient ($SPCOEFF_i$) can be expressed as a function of government's knowledge stock ($RDS_{GOV}$) and other industry sector's knowledge stock ($INTINDST_i$), as shown in the Equation. (10).

$$\mathrm{SPCOEFF}_i = spc0_i \cdot INTINDST_i^{rdelas_i} \cdot RDS_{GOV}^{grdelas_i} \qquad \text{Eq. (10)}$$

where $spc0_i$: Calibrated coefficient for equation;

rdelas: Elasticity of private knowledge stocks;

$grdelas_i$: Elasticity of government knowledge stocks

The relationship between the spillover effects and TFP changes in the production function for each sector can be represented as shown in the Equation. (11) and (12). In the equation (11), $ava0_i$ represents the share of value added composite in the production structure of the final good. 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 (Equation. (12)).

$$AVA_i = ava0_i / SPCOEFF_i \qquad \text{Eq. (11)}$$

$$VA_i = AVA_i \cdot Z_i \qquad \text{Eq. (12)}$$

### *3.3 The structure of knowledge-based CGE model: Households*

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, Equation. (13) indicates wage income for labor inputs by skill type (unskilled, skilled, and high-skilled labor). Wage income for each skill level is represented as the sum of the payment for labor invested into production activities and the payment for labor investment into R&D activities. Equation. (14) and Eq. (15) 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.

$$HLINC_{type} = \sum_i \left(L_{i,type} \cdot PL_{type}\right) + \sum_{rdt}\left(RLS_{rdt,type} \cdot PL_{type}\right) \qquad \text{Eq. (13)}$$

where $L_{i,type}$: Labor inputs for sector i by skill type;

$RLS_{rdt,type}$: Labor inputs for R&D investments by skill type;

$PL_{type}$: Factor price of labor by skill type

$$\text{HKINC} = \sum_i (K_i \cdot PK) + \sum_{rdt}(RKS_{rdt} \cdot PK) \qquad \text{Eq. (14)}$$

$$\text{HRINC} = \sum_i (H_i \cdot PRD_i) \qquad \text{Eq. (15)}$$

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. 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. The incomes gained by each household in this way are saved or paid to government as transfer payment. The remaining income is spent for consumption. Household consumption expenditure for each industry is determined by the proportion of consumption expenditure for each industry within each household quantile.

## 4. Scenario Settings

Based on the model settings discussed above, this study examines the effect of innovation on the employment structure and economic growth. The level of R&D investments, or R&D intensity is used for a proxy variable to represent innovative activities. Based on this concept, three scenarios are constructed for the analysis. In the first scenario (SCN1), R&D intensity gradually decreases from 4% in the base year of 2010 to 3% in 2020. In the second scenario (SCN2), R&D intensity is maintained at 4% from the base year of 2010 onward. In the third scenario (SCN3), R&D intensity gradually increases from 4% in the base of 2010 to 5% in 2020. The level of the R&D intensity in 2010 is based on the current status of R&D investments in Korea. The scenarios analyzed in this chapter are summarized in Table 2.

**Table 2. Scenario description**

| | R&D intensity in 2010 | R&D intensity in 2020 |
|---|---|---|

| | | |
|---|---|---|
| **Scenario 1 (SCN1)** | 4% | 3% |
| **Scenario 2 (SCN2)** | 4% | 4% |
| **Scenario 3 (SCN3)** | 4% | 5% |

## 5. Main Results

### *5.1 Effects on the employment structure*

#### 5.1.1 Change of aggregate labor demand

Based on the scenario settings presented in the previous section, we firstly examine the change of aggregate labor demand. The results of analysis are shown in Table 3, which presents the change rates in the aggregate labor demand between 2030 and the base year of 2010. The results show that the aggregate labor demand increases most (53.2% increase from 2010 to 2030) in Scenario 3, where additional R&D investments are made. Conversely, in the first scenario, in which decreasing R&D intensity show relatively smaller increase (26.9%) in aggregate labor demand, and in the long term, the aggregate labor demand stagnated. To summarize these results, it can be inferred that higher levels of innovation create much more jobs by offsetting the effects of capital-biased technical change which lowers the employment level. To determine the reason for these results, additional analysis on demand for labor by skill level and demand for labor by industry has been performed.

**Table 3. The change rate in the aggregate labor demand between 2010 and 2030 (%)**

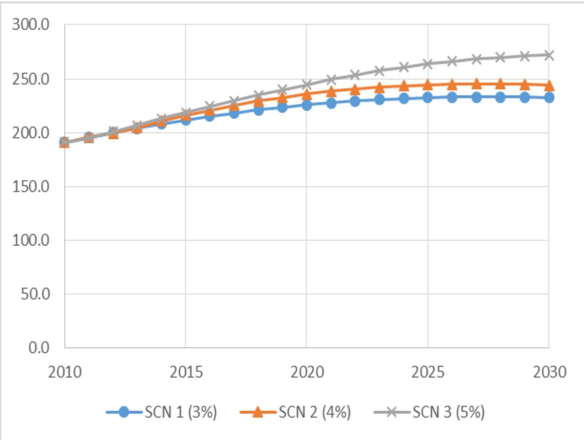
| | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **Total labor demand change (%)** | 26.9 | 33.9 | 53.2 |

#### 5.1.2 Change in demand for labor by skill type

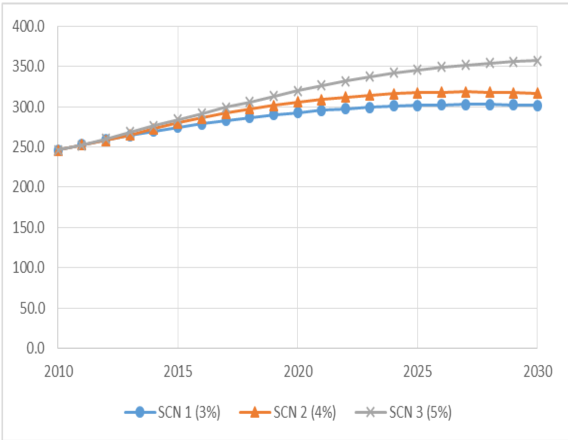
The analysis results on demand for labor by skill type are shown in Figure 3. Additionally, the change rates for demand for labor by skill level between the base year of 2010 and 2030 are shown in Table 4. The analysis results showed the appearance of SBTC, resulting in a larger increase in demand for high-skilled labor than the increase in the demand for unskilled and skilled labor in all three scenarios. Moreover, in Scenario 3 (SCN3), in which additional R&D investments are made, demand for all skill level increased more than in other scenarios. In particular, demand for high-skilled labor in Scenario 3 shows a 121% increase in 2030 compared to 2010, showing the highest growth rate. To summarize these results, we can understand that the impacts of innovation on the demand for labor have differential effects depending on skill level, and the demand for high-skilled labor is found to have the highest growth rate due to SBTC.

**Table 4. The change rate of demand for labor by skill type between 2010 and 2030 (%)**

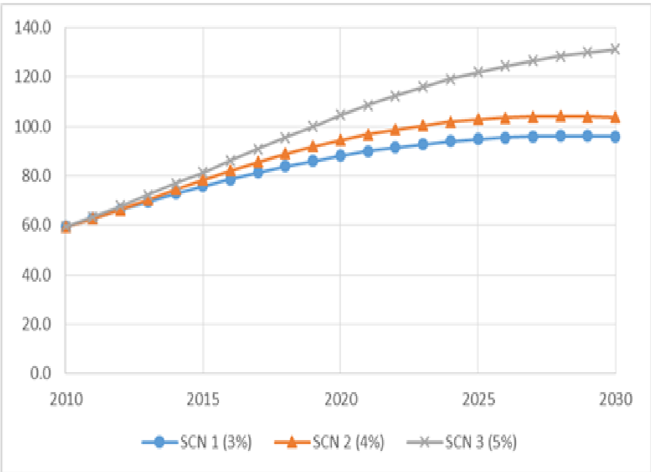
| | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **Unskilled Labor** | 21.9 | 28.0 | 42.6 |
| **Skilled Labor** | 22.5 | 28.6 | 44.9 |
| **High-skilled Labor** | 61.7 | 75.0 | 121.3 |




(a) Unskilled Labor



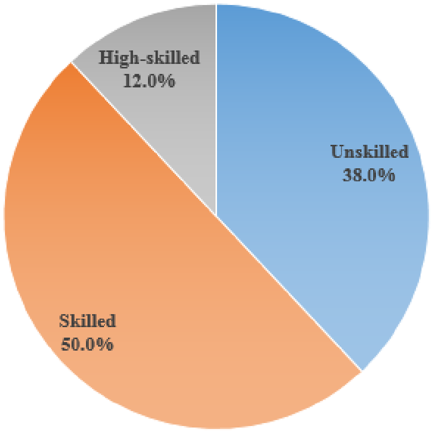

(b) Skilled Labor



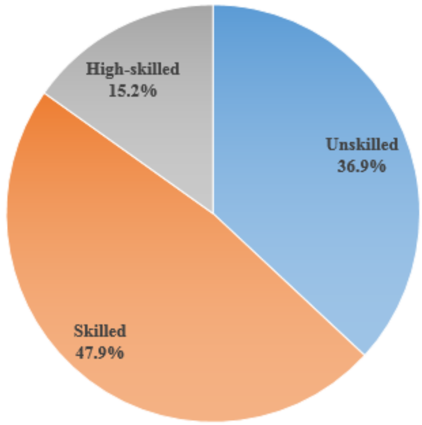

(c) High-skilled Labor

**Figure 3. Change in demand for labor by skill level**

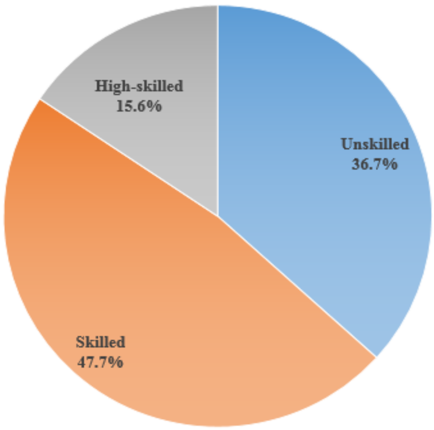
On the other hand, the change in proportion of demand for labor by skill level in each scenario is shown in Figure 4. In Scenario 3 where additional R&D investments are made, the demand for unskilled labor and skilled labor are found to decrease (2.2% decrease for unskilled labor, and 3.0% decrease for skilled labor in the share of employment in SCN3 compared to base year), whereas demand for high-skilled labor increases (5.3% increase for high-skilled labor in the share of employment in SCN3 compared to base year). Accordingly, when innovation-driven economic policy is maintained, jobs for high-skilled labor are expected increase more than for other types of labor.



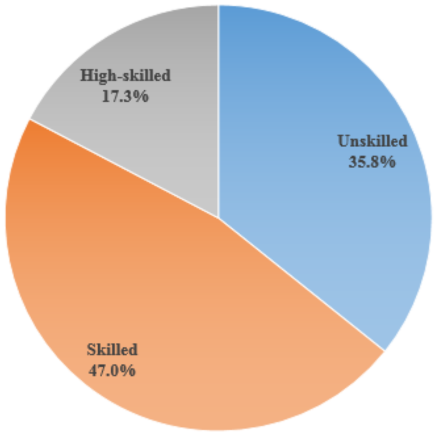

(a) Base year




(b) SCN1 in 2030




(c) SCN2 in 2030



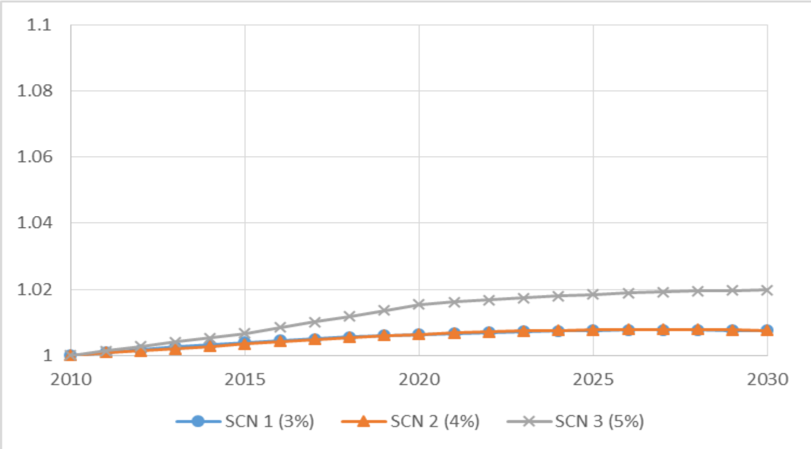

(d) SCN3 in 2030

**Figure 4. The change in proportion of demand for labor by skill type**

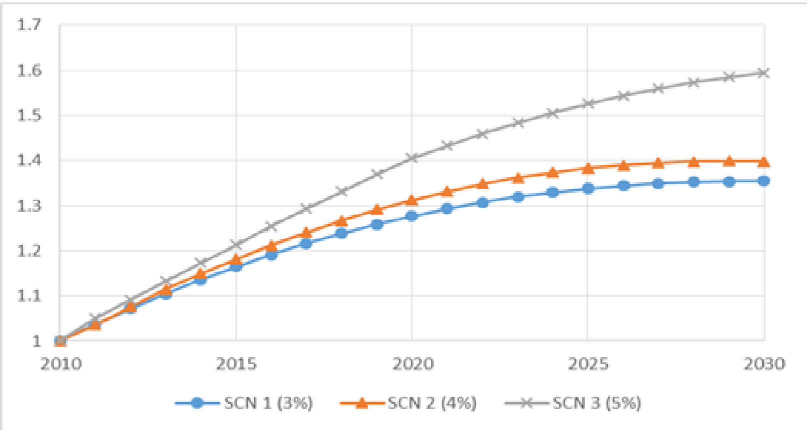
The increase in demand for labor is linked to expansion of employment and wage increases. As a result, wage gap between different skill levels occurs as a result of the change in demand for labor at each skill type. As discussed earlier, innovation further increases demand for high-skilled labor, and skill premium increases; the changes in skill premium are shown in Figure 5. In this model, transition process of labor among different skill types is not reflected,[3] and it is assumed that the proportion of each skill level of labor is held constant from the base year. Under this assumption, it is found that the skill premium for high-skilled labor increases considerably. Thus, we can infer that because demand for high-skilled labor and skill premium increases when an innovation-driven economic growth is pursued, a lot of high-skilled labor

[3] Unskilled labor could become skilled labor, or skilled labor becomes high-skilled labor through additional education. However, this transition process of labor through education is not reflected within the model.

needs to be produced through additional education. According to the examination of change in demand for labor by skill type so far, innovation is found to increase demand for high-skilled labor more so than other skill levels of labor due to SBTC.




(a) Skilled labor wage/Unskilled labor wage




(b) High skilled labor wage/Unskilled labor wage

**Figure 5. Trends of skill premium**

### 5.1.3 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 Table 5. Analysis of change in demand for labor by industry has been performed by reclassifying industries into four types. Four types of industry include primary industry of agriculture, forestry, and fisheries; secondary industry of manufacturing industry, which are further classified into high-tech and low-tech[4] manufacturing industry; and the tertiary industry of service industries.

[4] The classification between high-tech and low-tech manufacturing industries is 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.

**Table 5. Rate of change in demand for labor by industry between 2010 and 2030 (%)**

| Industry | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **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 |
| **R&D** | 47.4 | 60.9 | 150.9 |

As shown in the Table 5, when R&D investment increases, demand for labor in each industry increases. In particular, in Scenario 3 where R&D intensity increases up to 5% it shows the highest increase in the demand for labor in high-tech manufacturing industry (78.4% between 2010 and 2030). This suggests that industry with higher levels of innovation demands more labor than other industries. In addition, this study considers 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. As shown in the Table 5, when R&D investment increases, demand for labor for R&D workforce also increases. In particular, in Scenario 3, demand for labor for R&D workforce in 2030 increases by about 150.9% compared to 2010. 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.

### *5.2 Effects on the economic growth*

#### 5.2.1 Change in GDP growth of the economy

From here on, the effect of R&D investment on economic growth will be examined. First of all, changes in the Gross Domestic Products (GDP) in each scenario are examined. GDP growth rates between the base year and 2030 are shown in Table 6. The Scenario 3 shows the largest GDP growth increased by 62.0% in from 2010 to 2030, compared to other scenarios. The results also indicates that when R&D intensity increases by up to 5%, an annual economic growth of 2.4% is achieved until 2030, which is the highest value among scenarios. In other words, it is understood that 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. Furthermore, to understand the impacts of innovation on the economic growth as mentioned above, additional analyses on factors of production and output by industry have been performed.

Table 6. The effects of innovation on the economic growth

| | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **GDP growth (%)** | 32.1 | 39.5 | 62.0 |
| **Annual GDP growth rate (%)** | 1.4 | 1.7 | 2.4 |

### 5.2.2 Change in composition of value added

To understand key factors of economic growth, we investigate the change of composition of value-added for each scenario. The value-added for factors of production between the base year and 2030 for each scenario is shown in Table 7, and the change rates for value added of that period are shown Table 8. Scenario 3, which achieved the highest economic growth rate among the scenarios, shows 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 show higher increase rates than the other scenarios. The reason why the value-added increase rates for high-skilled labor and knowledge are higher than those of other factors of production in Scenario 3 is because of the effect of SBTC due to innovation.

Table 7. The level of value-added and its share in GDP from 2010 to 2030

| Unit: Trillion Won[a)] | Base year (Year 2010) | SCN 1 (Year 2030) | SCN 2 (Year 2030) | SCN 3 (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%) |

a) 1 U.S. dollar = 1215.0 Korean won (KRW) in March 2016.

Table 8. The change rates for value-added from 2010 and 2030 (%)

| | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **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 |

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 increases by 2.2% between the base year and 2030, showing the highest increase rate among the factors of production. Moreover, high-silled labor shows a 2.1% increase, and capital shows a 0.5% increase. On the other hand, skilled labor shows a 2.6% decrease, and unskilled labor shows a 2.2% decrease. These results support the presence of SBTC and capital-biased technological change, resulting from technological innovations.

### 5.2.3 Change in composition of industrial outputs

Changes in the output by industry type have been analyzed, and main results are shown in the Table 9. As shown in the Table 9, it can be understood that the higher the R&D investments is made, the higher increases in outputs, regardless of industrial type. In addition, when there is additional R&D investments made, the output of the low-tech manufacturing industry shows the largest increase (by 76.8% from 2010 to 2030), followed by the high-tech manufacturing industry whose output increases by 64.4% from 2010 to 2030. The reason for these results is because most of industries use products of the low-tech manufacturing industry as intermediates, and high-tech manufacturing industry has relatively higher R&D intensity. The proportions of intermediates and use of value added by industry for Scenario 3 in 2030 are shown in Table 10.

**Table 9. Changes in the output by industry type between 2010 and 2030 (%)**

| | SCN 1 | SCN 2 | SCN 3 |
|---|---|---|---|
| **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 |

**Table 10. The proportions of intermediates and value added by industry type (%) for SCN3**

| | | 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 |

### *5.3 Effects on the income distribution*

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% are analyzed. The results are shown in Figure 6 and Figure 7, respectively. The results show that when more innovation activities are made, 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.

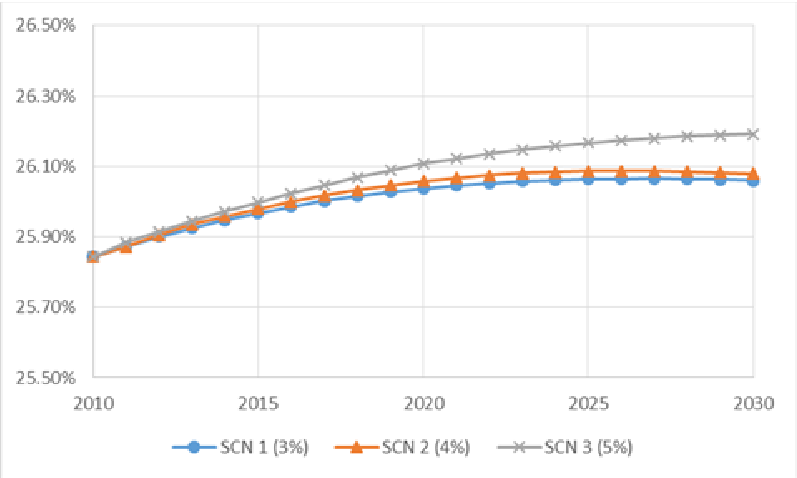



**Figure 6. The proportions of income of the top 10% group (%)**

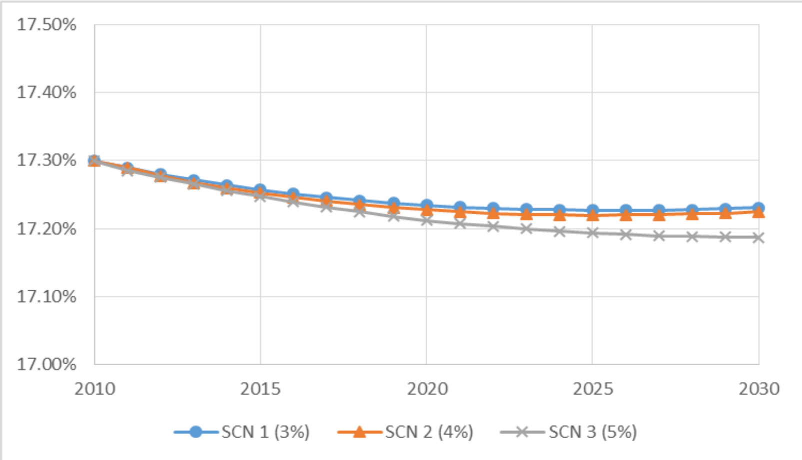



**Figure 7. The proportions of income of the middle 40-60% group (%)**

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) is examined. As shown in Figure 8, in the Scenario where additional R&D investments are made (SCN3), the decile distribution ratio is lower than in other scenarios, and the value continues to decrease over time. This can be explained by the fact that 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.

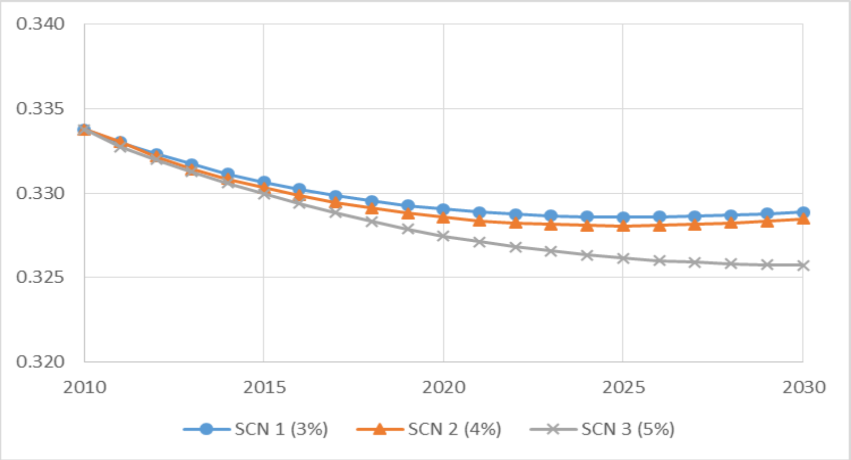



**Figure 8. The change in decile distribution ratio for each scenario**

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 11. 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, implying needs for complementary policies to reduce the income gap.

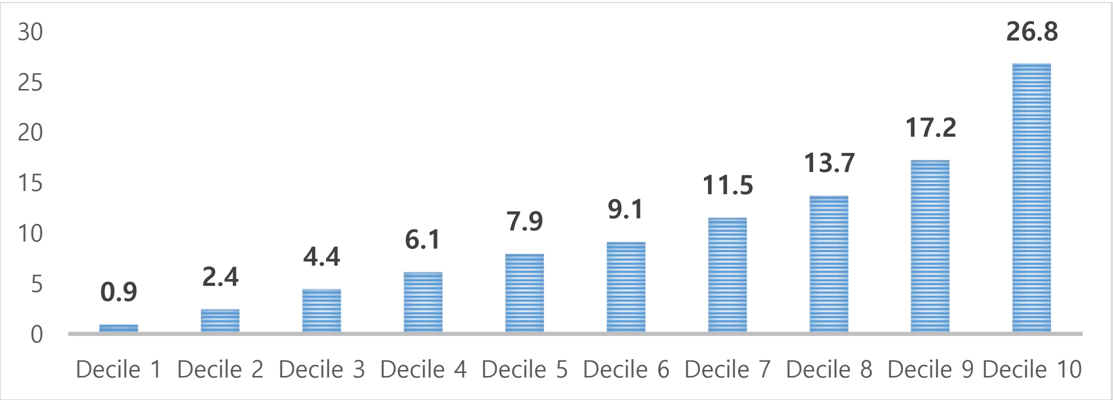



**Figure 9. The share of benefits by household quantile in SCN3 (%)**

## 6. Conclusions

This paper investigated the effects of innovation on employment structure and economic growth using the knowledge-based CGE model. To incorporate characteristics of innovation, R&D investment and knowledge capital stock are reflected in our model. It is set up so that knowledge capital stock is accumulated through R&D investments. In addition, knowledge capital stocks of each industry are used as the factors of production, having a spillover effect on other industries, whereas public knowledge capital stock has spillover effects on all industries. Moreover, to incorporate SBTC and capital-biased technological change taking place recently as a result of innovation, the CES production function is introduced to reflect the elasticities of substitution between factor inputs.

Based on these settings for our CGE model, analyses were performed separately for different aspects including employment structure, economic growth, and income distribution. 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 activities 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 activities 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.

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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