Growth *versus* Equity: A CGE Analysis for Effects of Factor-biased Technical Progress on Economic Growth and Employment

**Abstract:** With factor-biased technical progress described as labor-saving and skill-biased technical changes, there are concerns that technological innovation can lead to unemployment and widen inequality in the economy. This study explores impacts of factor-biased technical changes on the economic system in terms of economic growth, employment, and distribution, using a computable general equilibrium (CGE) model. The results show that technological innovation contributes to higher level of economic growth with productivity improvements. However, our analysis suggests that economic growth accompanied by skill- and capital-biased technical progress disproportionately increases demand for capital and high-skilled labor over skilled and unskilled labor. This shift in the value-added composition is found to deepen income inequality, as more people in higher income groups benefit from skill premium and capital earnings. Our results suggest that policymakers should prepare a wide range of policy measures, such as reforms in educational programs and taxation systems, in order to ensure sustainable growth.

JEL Classification: C68, D58, O30, O40

*Keywords:* Innovation; Economic growth; Employment; Computable General Equilibrium; South Korea

1. Introduction

During the 1990s and the early 2000s, many countries have witnessed “jobless growth,” in which economies experience economic growth while decreasing their employment levels. In other words, increases in economic outputs come predominantly from higher productivities of already employed workers, rather than from the expansion of the labor force. As a result, the unemployment rates show high levels for a prolonged period, despite economic growth (Usanov and Chivot, 2013). There are concerns that jobless growth is not just a cyclical phenomenon, but also a structural problem driven by technological progress.

Brynjolfsson and McAfee (2014) pointed out that firms in the United States (U.S.) did not expand hiring after the Great Recession (from 2007 to 2008), and U.S. economy having shown the highest unemployment rate since the postwar period. They stated that wide deployment of new technologies (i.e., digital technologies) is one of the most important driving forces behind higher structural unemployment rates in recent years. They also argued that newly adopted machines and automation devices with higher productivity replace workers, leading to slower job creation. Furthermore, they describe this situation as being one in which many people are losing the race against the machine (Brynjolfsson and McAfee, 2014; 2012). Stiglitz (2014) also argued that productivity improvements from technological innovations in U.S. manufacturing sectors have been coupled with decreased employment and wages, leading to the current economic slowdown.

Concerns about the role of the technological innovations behind the labor market are not new. The Industrial Revolution during the late 18th and early 19th centuries initially drew attention to the relationship between technology and the labor market, as English workers lost their jobs to newly developed machines during that period (Bessen, 2015; Katz and Margo, 2013). Debates on the impacts of technological innovations on the labor market and employment have been sparked again in recent years, with the advent of emerging technologies, such as robotics and artificial intelligence. However, there are substantial disagreements between studies, in relation to the effects of innovations and technological progress on employment structure.

As described above, there is a growing body of evidence from studies about “technological unemployment” that rapid advances in technologies, and productivity improvements from technological innovations, displace many workers (Marchant et al., 2014). Those studies highlight the fact that technological unemployment in recent years is deeply associated with job polarization and social inequality in the economy. For example, Usanov and Chivot (2013) found that the digital revolution has favored high skilled labor, as technical progress usually replaces tasks traditionally carried out by unskilled labor. Mallick and Sousa (2015) also uncovered a positive relationship between technological progress and the skilled–unskilled labor ratio, which supports “skill-biased” characteristics of technical change. From these findings, they stressed that divergent trends in the wages for skilled and unskilled labor is a main contributor behind income inequality in recent years.

Another strand of the studies emphasized that technological unemployment is the direct effect of technological progress, and that indirect effects or compensating mechanisms should be considered, to fully understand the employment impact of technological change in the economic system (Piva and Vivarelli, 2005). Vivarelli (2014, 2012) highlighted the fact that, from a macroeconomic view, technological progress has several second-order effects on employment, such as income (increase of income) and price mechanisms (decrease of commodities’ prices), which could counterbalance direct employment impacts of technological change (i.e., technological unemployment). Those studies suggest that final impacts of innovations on employment can vary, depending on various economic factors in macroeconomic conditions.

In this regard, from an economy-wide perspective, it is essential to consider both direct effects of technological change and market compensation forces in analyzing final outcomes of technological progress in terms of employment. Despite a growing body of theoretical literature on the employment impact of technological change, there is a lack of quantitative analysis for this issue. In particular, most quantitative studies have focused on direct effects of new technologies on the number of employees and on wages, based on the firm- and industry-level analysis.

This study aims to quantitatively assess the macroeconomic impacts of innovations on employment structure and economic growth, with an economy-wide aspect, using a computable general equilibrium (CGE) model. We focus on the economy in Korea (South Korea), and simulation results for policy scenarios are analyzed in terms of employment structure, economic growth, and social inequality. For the analysis, we reflect innovation-related activities (i.e., endogenously determined R&D investments), characteristics of knowledge (i.e., spillover effects from knowledge accumulation), and factor-biased technological change in the model. The economic intuition behind these methodological approaches is that current labor-saving and skill-biased technological change from innovations shapes the employment structure in the economy by interacting with market mechanisms. Our study is significant, in that it is devoted to a macroeconomic analysis in investigating the link between technological innovations and the labor market, with understanding of both direct and indirect effects of technological change on the economy.

The rest of the paper is structured as follows: Section 2 provides a brief review of the relevant literature, which focuses on the relationship between innovations 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; and, lastly, the summary and concluding remarks are provided in Section 6.

2. Literature review

Technological innovations are deeply involved in the issue of growth and distribution, which are like two sides of a coin. Although technological innovation promotes economic growth via productivity improvements, it may favor skilled labor over unskilled labor, which may gradually worsen the labor market conditions. This “factor-biased” technological change suggests a rise in the skill premium, which implies a growing income gap between workers. Research into the relationship between technological innovation and employment has been conducted since the early stages of the Industrial Revolution (during the late 18th and early 19th century), with the introduction of new technologies that threatened textile workers’ jobs. Debates on the impacts of technological innovations on the labor market and on employment have been sparked again in recent years, with the emergence of robots and automated devices. To understand debates around innovation and employment, it is essential to investigate key concepts, as follows: compensation effect, skill-biased technical change (SBTC), and capital-biased technical change. A brief review of these concepts is presented in the following subsections, along with relevant literature.

**2.1 Compensation effect**

By definition, technological progress allows us to produce the same amount of goods (outputs) with a lower amount of production factors (inputs), such as capital and labor. Technological unemployment occurs as a direct effect of innovation. This aspect of technological innovation led to skilled labor working in handicraft losing jobs, which, in turn, led to the destruction of machinery in protest (Luddite Movement in the 19th century). From that time on, some people have thought that innovation would have harmful effects on employment, and the relationship between innovation and employment drew increasing attention. Despite such concerns, several economists argued that new jobs are typically created by the “compensation effect,” in various ways, even though employment decreases temporarily due to technological innovations. In other words, they argued that employment reduction driven by innovation causes a decrease in wages, and, in turn, promotes labor-intensive technology and industry (Layard et al., 1994, 1991; Venables, 1985).

Vivarelli (2012) claimed that it is essential to examine not only direct but also indirect effects of innovation on employment, and introduced different mechanisms of compensation effects that 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, decreases in commodity prices, new investments, decreases in wages, and increases in households’ incomes. This compensation theory highlights the premise that technological changes induce market forces that can potentially counterbalance the initial labor saving effect of process innovation, thereby having a positive effect on employment trends.

**2.2 Skill-biased technological change**

Technological advance accompanies an increase in skilled workers, leading to advancement of employment structure, as experienced by developed countries. Skill-biased technical 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 (Baccini and Cioni, 2010; Card and DiNardo, 2002; Dunne et al., 1997; Krusell et al., 2000; Machin et al., 1998). This occurs because of complementarity between the capital inherent in new technology and the workforce capability with advanced technology (or higher level of education) (David et al., 1997; Haskel and Heden, 1999). In other words, new technology requires workers with the appropriate skills, and those without such skills lose jobs (Griliches, 1969).

Empirical research supporting this claim has been actively conducted. For example, Berman et al. (1994) investigated the changes in the demand for skilled labor in the manufacturing industry in the U.S., and found that the demand for skilled labor was higher when R&D intensity and the high-tech technology ratio were higher. Falk and Seim (2001) conducted an analysis with companies in the service industry from 1994 to 1996, and showed that the companies using more information and communication technology (ICT) had a higher proportion of employees with higher levels of education. Based on an analysis of company data in the U.S., Bresnahan et al. (2002) claimed that use of information and communication technology is a key determinant that causes SBTC. Moreover, Marouani and Nilsson (2016) analyzed the macro-economic impacts of SBTC, focusing on the Malaysian economy, based on the dynamic general equilibrium model. From the analysis, they showed that SBTC led to structural change, benefiting sectors with a large share of high skilled labor. 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 have been skill-biased (Acemoglu, 2002, 1998; Violante, 2000; Vivarelli, 2013). Furthermore, Autor et al. (2008) and Krusell et al. (2000) claimed that SBTC is often held for the skill premium, which is the ratio between the wages of skilled and unskilled labor, respectively. They suggested that increased wage inequality among workers results from economic growth, driven by new and efficient technologies. In addition, Buera et al. (2015) showed that a shift in the composition of value-added is intensive in high-skilled labor, resulting in the rise of skill premium. They analyzed the U.S. economy from 1977 to 2005, and concluded that a rise in skill premium implies the widened income polarization between high-skilled labor and other types of labor. In this way, various studies have supported the complementarity between recent technological innovations and skilled labor, and the possibility of inequality among works has resulted from SBTC.

Some researchers argue that investments in education for skill accumulation are important to mitigate the factor-biased technological change characterized by the SBTC. For example, He and Liu (2008) built a quantitative model with endogenous skill accumulation and equipment-skill complementarity, and they examined the quantitative effects of some policy shocks on wage inequality and welfare. With the calibrated model, they found that subsidizing skill accumulation can effectively reduce both the skill premium and the equipment-skill ratio. They also found that subsidizing human capital accumulation tends to improve social welfare. In addition, Grossman et al. (2016) investigated how balanced growth could emerge in the economy with endogenous education, and found that balanced growth is possible if schooling is endogenous and capital is more complementary with schooling than with labor. Grossman et al. (2016) also highlighted the fact that balanced growth occurs when capital accumulation raises the returns to education, and this causes schooling to increase at exactly the rate needed to offset the effect of capital-augmenting technical change on capital’s share of national income. Pan (2014) also developed four-sector general equilibrium models to analyze the linkage between the investments in education and wage inequality among workers. From the analysis, it has been found that increased investments in educational programs from the government can reduce skilled–unskilled wage inequality and promote economic development.

**2.3 Capital-biased technological change**

Brynjolfsson and McAfee (2014) argued that technological progress from innovations causes not only SBTC but also a capital-biased technological change. This means that the relative influence of capital within the production process becomes even greater, as automated machines (such as robots), which are capital-intensive goods, intrude on the domain of human labor. Consequently, wages fall relative to the cost of capital, and the proportion of labor wages in Gross Domestic Product (GDP) decreases. In the past, the proportion of labor in GDP has remained relatively constant. However, in recent decades, the labor share is in decline.

Several studies tried to examine a link between capital-biased technical change and the labor share in the economy (Bentolila and Saint-Paul, 2003; Guerriero and Sen, 2012; Karabarbounis and Neiman, 2013). They suggested that the extent of capital-biased technological progress can influence the relative share of labor in the production system. Karabarbounis and Neiman (2013) argued that the labor share has declined in many countries since the early 1980s. Against this background, they tried to demonstrate how the decline of the labor share can be explained by the decline in the relative price of investment goods. They showed that a decrease in the relative price of capital goods with advancements in the ICT induced firms to shift away from labor and move toward capital, which explains half of the observed decline in the labor share. Therefore, it can be inferred that recent technological change from innovations is biased toward capital, leading to an increased share of capital income for products and services.

These findings suggest that technological innovations result in capital-biased technological change, leading to an increased share of capital income for products and services. The problem is that this capital-biased technological change may deepen income polarization. For example, Piketty (2014)’s study supports this argument by showing that capital-related inequality is always larger than is labor-related inequality. Therefore, based on the studies mentioned above, we can infer that SBTC and capital-biased technical change, associated with newly development machines and technological innovations, tend to benefit only a sub-group of workers, which deepens income polarization.

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

Empirical results on the relationship between innovation and employment are still debated. The overall effect of employment due to innovation differs across the scope of analysis, countries, and industries. In addition, a variety of factors are associated with the employment impact of technological change, and it is difficult to determine key mechanisms around this issue in a comprehensive, conclusive manner. For these reasons, the controversy over innovation and employment continues to date, and many empirical studies are still underway.

Several studies suggest a positive employment impact of innovation (Coad and Rao, 2011; Hall et al., 2008; Harrison et al., 2008; Lachenmaier and Rottmann, 2011; Piva and Vivarelli, 2005; Zuniga and Crepsi, 2013). Most of these studies have examined the direct effect of innovation on employment, based on firm-level analysis of 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 that employment expansion is triggered by technological innovations.

On the other hand, several empirical studies report different results, highlighting the possibility of technological unemployment. Brouwer et al. (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 in relation to sales that was more than 1% than it was in companies in which the proportion of R&D to sales was less than 1%. As presented above, numerous empirical studies are based on firm-level analyses, mainly focusing on European countries and the U.S.

As such firm-level quantitative analyses can consider only direct effects of innovation on the employment level, results are likely to be either over- or underestimated (Pianta, 2005). However, to fully understand the relationship between technological change and employment, both direct effects and indirect effects, including compensation effects and other macroeconomic conditions, should be incorporated. Furthermore, the ongoing recent technological change is biased toward specific factors as shown above. Therefore, the bias of technological changes should be taken into consideration 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.

The main mechanisms of the relationship between technological innovations and employment structure can be summarized as follows: direct employment effects, from capital-biased technological change and SBTC; and indirect employment effects, resulting from spillover effects of innovation and compensation. Taking these mechanisms into consideration, this study aims to empirically examine the relationship between technological innovations and employment trends from an economy-wide perspective, based on key concepts drawn from theoretical foundations and macroeconomic settings—referred to as the CGE model.

3. CGE Modeling

In this paper, we use a CGE model to quantitatively assess the macroeconomic impacts of innovations on employment structure and economic growth. It is important to incorporate innovation-related activities (e.g., research and development) and characteristics of knowledge (e.g., knowledge accumulation and knowledge spillover effects) into the CGE model, in order to represent the indirect employment effects resulting from spillover effects of innovation and compensation. In this context, we construct the knowledge-based CGE model by adding R&D descriptions and characteristics of knowledge, with a series of equations based on a knowledge-based Social Accounting Matrix (SAM).

It is also essential to classify the labor into occupational categories by skill level, to examine the changes in employment structure arising from technological innovations via SBTC and capital-biased technical change. From this perspective, the labor input for production of final goods and knowledge production is classified into three types of labor, based on the educational attainment level: high-skilled, skilled, and unskilled labor. Furthermore, households are classified into 20 quantiles, based on income levels, using micro data of household level survey datasets to investigate the income distribution impacts arising from changes in employment structure. The methodological approaches are presented in brief in Figure 1, and the following subsections show approaches for constructing datasets, including SAM, and modeling equations that reflect those considerations.

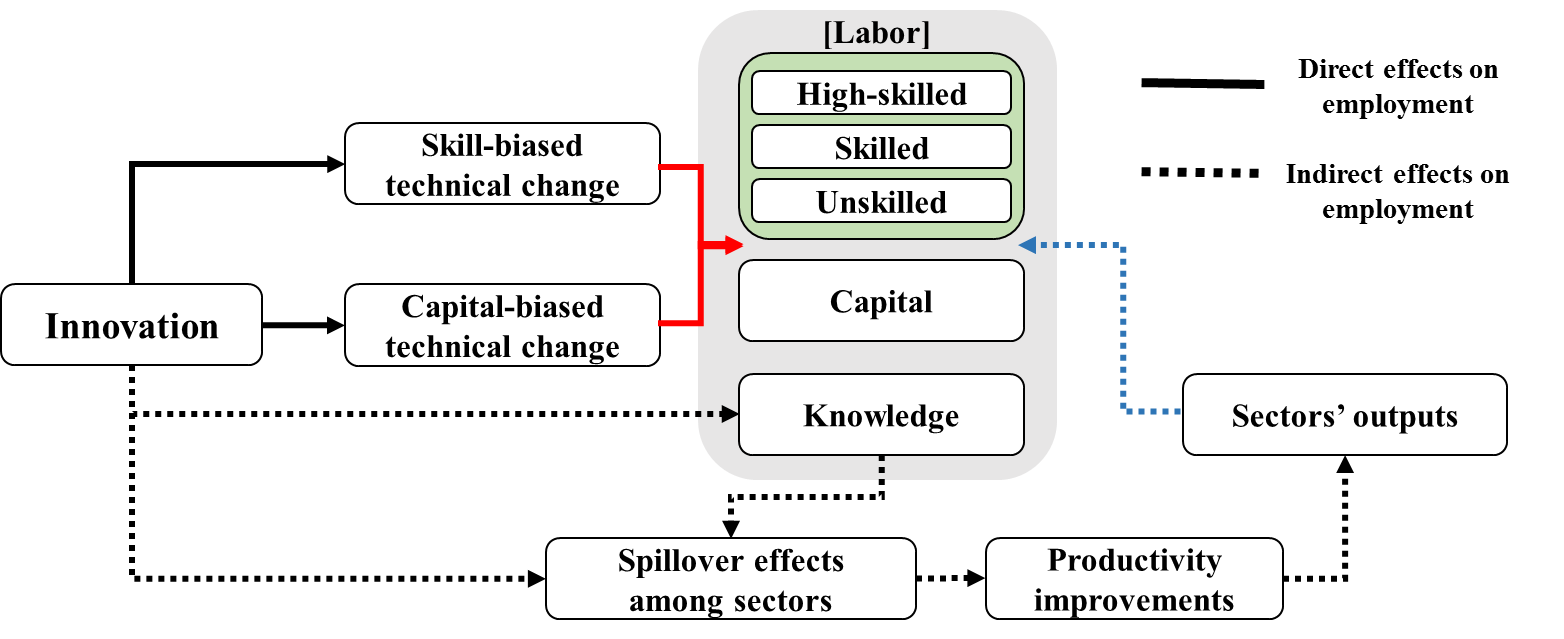


Figure 1. Methodological approaches for the analysis

**3.1 The structure of a Social Accounting Matrix (SAM)**

In this study, SAM is constructed by collecting data on overall economic activities of the national economy, including production, consumption, imports/exports, intermediate transactions among sectors, and factor incomes from a macroeconomic perspective. This SAM is used to describe baseline economy in the knowledge-based CGE model. To construct a SAM, we utilized a 2010 input–output (I–O) table from the Bank of Korea (the central bank of South Korea), and tax-related data in the 2010 Statistical Yearbook of National Tax, published by the National Tax Service in Korea. In addition, the data on household and government savings were extracted from national accounts.

Key differences of the SAM developed in this study, compared to other standard SAMs, are descriptions on R&D activities and specifications of labor and household types. We explicitly represent knowledge as a factor of production and introduce knowledge capital formation in the investment account.[[1]](#footnote-1) This study also adopts a methodological approach for constructing a knowledge-based SAM, proposed by Yang et al. (2012) and Hong et al. (2014). Within the SAM used for this study, current expenditure on 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 the knowledge capital formation account. Furthermore, the knowledge capital formation account has been classified into private and public accounts, according to who spent it. The value added from knowledge increases household income, which is a source of additional consumption and of savings that benefit industrial activities.

In addition, we have classified the labor into three types of workers, based on educational attainment levels. To be specific, labor inputs for production of final goods and knowledge production are split into three types: high-skilled, skilled, and unskilled labor. Based on these classifications, we extract information on labor inputs and wages by labor type for production activities from satellite datasets.[[2]](#footnote-2) In terms of the academic degree, we consider master’s and doctor’s degree holders as high-skilled workers. College graduates are considered as skilled workers, while unskilled workers are characterized by lower educational attainment levels, such as high school education or less. Our approaches are distinct from the other studies, which typically consider two skill groups: skilled workers with a college degree, and unskilled workers with high school diplomas (Card and DiNardo, 2002; Mallick and Sousa, 2015). These classifications are based on the current status of the Korean labor market, which is occupied by highly educated workers. Korea has reduced the share of individuals without upper secondary education, while the proportion of tertiary-educated individuals has rapidly increased over the past 30 years. Korea has also shown dramatic increases in enrollment rates at the tertiary education level (from 11.4% in 1980 to 70.1% in 2010), as well as at the upper secondary education level (from 48.8% in 1980 to 91.5% in 2010) (Statistics Korea, 2011). In addition, the relative share of jobs occupied by college graduates, master’s and doctor’s degree holders has shown an increasing trend from 2000 (37.4%) to 2010 (56.7%), while those jobs occupied by people with lower educational attainment levels have shown a decreasing trend (Statistics Korea, 2011). Those indicators allow us to more clearly understand Korea as one of the most highly educated nations in the world.

Furthermore, the household is also classified into 20 quantiles based on income levels. We use micro-level data of Household Income and Expenditure (HIE) Survey issued by Statistics Korea. Based on this dataset, we extract each household’s consumption expenditure,[[3]](#footnote-3) physical capital investment, and R&D investment levels into the SAM. Classifications of households by income level enable us to examine impacts of technological innovation on income distribution. Table 1 shows a final form of the SAM, constructed for the analysis, which incorporates those features: explicit representation of knowledge, classifications of labor by education level, and specifications of households by income level. The numbers in the cells of Table 1 indicate the size of matrix of each account.

Table 1. Construction of knowledge-based SAM

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Activity | Factor inputs | | | Institution | | Investments | | | Tax | ROW | | **Total** |
| Intermediate | Labor | Capital | Knowledge | Household | Government | Physical Capital | Knowledge capital e) | | Export | Import |
| Private | Public |
| Activity | Intermediate | | 27\*27a) |  |  |  | 27\*20 | 27\*1 | 27\*1 | 27\*1 | 27\*1 |  | 27\*1 |  |  |
| Factor inputs | Laborc) | | 3\*27 |  |  |  |  |  |  | 3\*1 | 3\*1 |  |  |  |  |
| Capital | | 1\*27 |  |  |  |  |  |  | 3\*1 | 3\*1 |  |  |  |  |
| Knowledgee) | | 1\*27 |  |  |  |  |  |  |  |  |  |  |  |  |
| Instituti-ons | Householdd) | |  | 20\*3 | 20\*1 | 20\*1 |  |  |  |  |  |  |  |  |  |
| Government | |  |  |  |  | 1\*20 |  |  |  |  | 1\*1 |  |  |  |
| Investm-ents | Physical Capital | |  |  |  |  | 1\*20 | 1\*1 |  |  |  |  |  |  |  |
| Know. Capital | Private |  |  |  |  | 1\*20 | 1\*1 |  |  |  |  |  |  |  |
| Public |  |  |  |  | 1\*20 | 1\*1 |  |  |  |  |  |  |  |
| Taxb) | | | 1\*27 |  |  |  |  |  |  |  |  |  |  |  |  |
| ROW | Export | |  |  |  |  |  |  |  |  |  |  |  | 1\*1 |  |
| Import | | 1\*27 |  |  |  |  |  | 1\*1 |  |  |  |  |  |  |
| **Total** | | |  |  |  |  |  |  |  |  |  |  |  |  |  |

1. Within the SAM, sectors are classified into 27 sectors
2. Tax account includes indirect, corporate, income, and tariffs in the SAM
3. Labor inputs for production of final goods and knowledge production are split into three types; high-skilled, skilled, and unskilled labor
4. Household is classified into 20 quantiles based on the income level
5. In this knowledge-based SAM, knowledge is explicitly presented as one of the factor inputs, and knowledge capital formation account has been added into an investment account

**3.2 The structure of the knowledge-based CGE model: Production of final goods**

As discussed in the previous section on the knowledge-based SAM, key differences between the knowledge-based CGE model and other CGE models can be summarized as follows: 1) knowledge is considered as one of production factors; 2) knowledge capital stock is accumulated through R&D investments; and 3) investments in knowledge create positive externalities, knowledge spillover effects to other sectors. Those features are reflected into the model structure in the form of a series of equations.

Our model can be understood in terms of aspects of supply and demand within the economy. From the supply-side aspects, domestic goods are produced from value-added composite and intermediate inputs. Value-added composite inputs consist of labor, physical capital, and knowledge capital. On the other hand, from the demand-side aspect, domestic goods having a substitutional relationship with imported goods are either consumed domestically or exported. Aggregate domestic demand, which is sourced by combination of import goods and domestic goods, consists of investment, intermediate demand, and final consumption by households and government. To be specific, the final goods () of each industry are produced by factors of production, including intermediate inputs (), and value-added composite (). The production of final outputs can be described as Equation (1), which follows the Leontief production function. In the equation, [[4]](#footnote-4) and , respectively, represent intermediate inputs and the value-added composite required to produce a unit of output in industry *i.* For the analysis, we consider 27 production sectors, according to the industrial classification standard in the Korean I–O table.

] Eq. (1)

*where i = 1,2, … 27*

On the other hand, a value-added composite () consists of factor inputs, including labor (: high-skilled labor, : skilled labor, : unskilled labor), physical capital (), and knowledge capital (). In the formation of the value-added composite, constant elasticity of substitution (CES) production function is chosen to capture the substitution possibilities between factor inputs. It is assumed that high-skilled labor (, physical capital (, and knowledge ( are complements, while a composite of knowledge, high-skilled labor, and capital ( has substitutive relationships with skilled and unskilled labor. In Korea, workers with a master’s or a doctor’s degree are key figures in R&D activities and are mainly engaged in highly-skilled work, such as R&D activities in public institutions or technology developments in industrial sectors. The number of master’s and doctor’s degree holders who work as R&D technicians accounted for more than 55% of the total R&D workforce in 2010 (KISTEP, 2011). Taking this fact into account, we have treated only higher degrees as skilled enough to be complementary to capital within a value-added composite production structure. The structure of the value-added composite production function in our model can be described as Figure 2, which can be also expressed by Equation (2) and (3). Values for substitution elasticities between production factors in each stage of the CES function will be discussed in detail in Section 4.

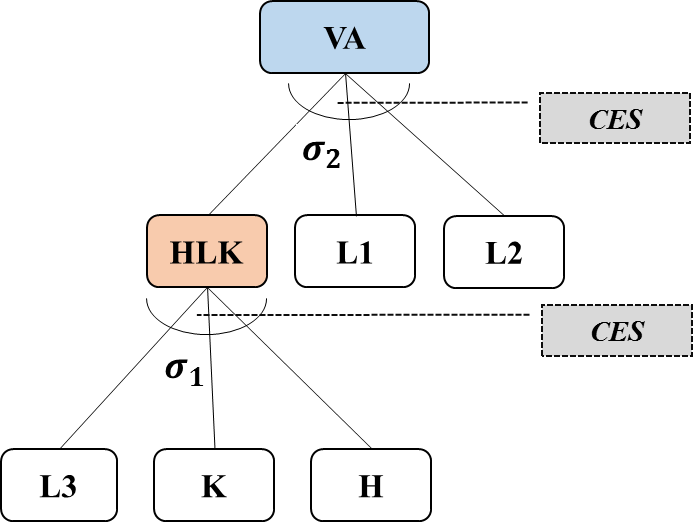


Figure 2. Structure of value-added composite production function

Eq. (2)

Eq. (3)

*where , : Share parameter for L3, K, L1, L2 in CES functions;  
: Scale parameter in each CES function;  
,*

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

Another feature of the model used for this study is that knowledge capital () is set to be accumulated through R&D investment. Therefore, it is essential to have a detailed description for R&D investment. In the model, R&D investment goods are produced through a separate process, as followed by Hong et al. (2014), Křístková (2013), and Visser (2007). It is assumed that both private and public sectors produce R&D investment goods () by combining value-added composite () and intermediate inputs () for R&D activities. In particular, the value-added composite for R&D () is generated thorough combining labor (: high-skilled labor, : skilled labor, : unskilled labor for R&D investments) and physical capital () inputs for R&D. This methodological approach reflects the fact that expenditure on R&D activities mainly consists of the following elements: wages for researchers; physical capital for research infrastructure, such as buildings or equipment, and other costs (Hong et al., 2014).

Similar to the final goods production sector, a CES functional form has been chosen as the production function of the R&D sector. The production structure of R&D investment goods can be expressed by Equations (4) and (5). To be specific, it is assumed that a value-added composite for the R&D sector () is comprised of a composite of high-skilled labor and physical capital (), skilled ( and unskilled labor for R&D activities (. Within the production structure, it is also assumed that high-skilled labor (and physical capital inputs for R&D activities () are complements, while the composite of high-skilled labor and physical capital ( has substitutive relationships with skilled ( and unskilled labor for R&D investments (. In this regard, the value of the elasticity of substitution between and is set to be less than 1 (), while that value among , , and is set to be larger than 1 (0). These methodological settings reflect the SBTC and capital-biased technical change within the R&D sector. The values of substitution elasticities are adopted from previous studies (Krusell et al., 2000; Hwang et al., 2008; Hong et al., 2014).

*]* Eq. (4)

Eq. (5)

*where : Intermediates requirement in R&D (for a unit of investment goods) ;  
 : Value-added composite requirement in R&D (for a unit of investment goods);  
 , : Share parameter for RLS3, RLS1, and RLS2 in CES function;  
 : Scale parameter in each CES function;  
 ,*

When new knowledge is created through R&D investment, newly generated knowledge is accumulated into knowledge capital stock and (pre-existing) accumulated knowledge becomes obsolete at a certain depreciation rate. In this context, the accumulation process of the knowledge capital stock is described as in Equations (6) and (7). As shown in Equation (6), the knowledge capital stock in the public sector () is accumulated through public R&D investment ( with the depreciation rate of knowledge ( In addition, private knowledge capital stock is built by private R&D investment (). is the gross R&D expenditure in the private sector, and it is distributed into R&D investments by individual sectors () to derive sector-specific knowledge capital stock (), as expressed by Equation (7).[[5]](#footnote-5) In addition, we assumed that private R&D investment in each sector is endogenously determined, following the logic of Tobin’s Q, as noted by previous studies (Hong et al., 2014; Křístková, 2012; Lemelin and Decaluwé, 2007). Along with the accumulation of the knowledge capital stock, physical capital stock is also set to be accumulated through physical capital investments ( based on the perpetual-inventory method with a depreciation rate of *kdep*, as shown in Equation (8).

Eq. (6)

Eq. (7)

Eq. (8)

Based on the descriptions of the production structure of final and R&D investment goods, we can depict key components of the production structure in the knowledge-based CGE model as shown in Figure 3. It can be understood that knowledge capital stock () is considered as an additional factor input, and it is a sector-specific asset that is accumulated through R&D investments in the sector (). These methodological settings imply that sector-specific R&D investment for knowledge accumulation bring about technological progress, which enhances the productivity of its own production process. In other words, increasing knowledge stock from R&D investments increases the productivity of other production factors, which means that increased knowledge is accompanied by reduced labor and capital requirements for the production process.

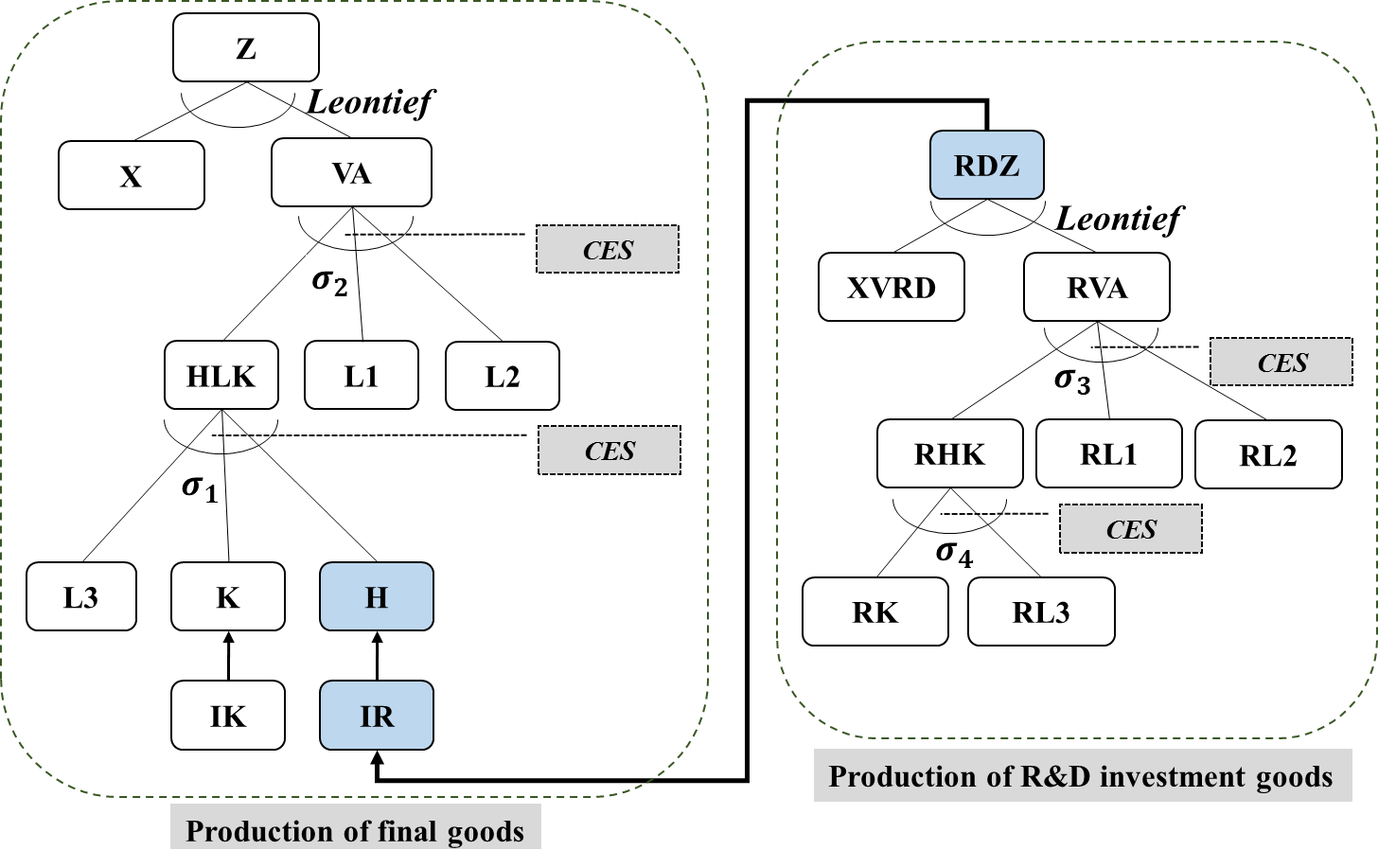


Figure 3. Production structure of final goods, including R&D investments

**3.4 The structure of knowledge-based CGE model: Knowledge spillover effects**

One of the key issues in dealing with R&D is how to deal with knowledge spillover effects, which are a typical feature of R&D. In our model, the knowledge spillover effect from other sectors is set to be proportional to the volume of intermediates’ transactions on the I–O table, using the method of Terleckyj (1980) and Hwang and Lee (2014). This methodological approach implies that industries’ innovations significantly influence the knowledge pools in external industries. For example, some industries can improve their productivity through product-embodied innovations, created from outside the sector (Hwang and Lee, 2014). As shown in Equation (9), the amount of knowledge that spilled over from *j*-th sector to the *i*-th sector is assumed to be proportional to the volume of intermediates’ transactions from the *j*-th sector to the *i*-th sector in the I–O table (Terleckyj, 1980; Hwang and Lee, 2014). The value of (i.e., the spillover knowledge from other sectors) for the *i-th* sector is derived by adding up the knowledge stock of other industries, weighted by the proportion (*other0*) of the volume of intermediates’ transactions between the given industry (*i-th* sector) and other industries.

Eq. (9)

On the other hand, public knowledge capital stock is assumed to be public goods, which can be used by all industries, thereby influencing their productivity. In general, government laboratories are primarily concerned with meeting public needs, and universities and public research institutes mainly focus on the generation of basic knowledge (Guellec and Potterie, 2003; 2001). Guellec and Potterie (2001) stated that new knowledge from basic research performed by public institutions (especially universities) enhances the stock of knowledge of the society. They also argued that industrial sectors do not fully compensate government for the benefits from public R&D in general. Hong et al. (2014) also highlighted that outcomes of public R&D activities are non-excludable and non-rival. Based on these discussions on the role of public R&D activities, we have assumed that public knowledge stock has spillover effects on all industries in the economy.

In this regard, the spillover coefficient () can be defined as a function of a government’s knowledge stock ( and other sectors’ knowledge stocks (, as shown in Equation (10). Values for elasticities of private and public knowledge stocks are drawn from previous studies (Hong et al., 2014; Hwang et al., 2008). Those two types of knowledge spillovers result in TFP changes in a production function for each sector. The relationship between the knowledge spillovers from others’ knowledge stocks and TFP changes in the production function can be described as Equations (11) and (12). In Equation (11), represents the share of value-added composites in producing final goods. This implies that increase in spillovers from others’ knowledge stocks (including government and other industries) leads to productivity improvements in each sector.

Eq. (10)

*: Calibrated coefficient for equation;  
 rdelas: Elasticity of private knowledge stocks;  
 grdelasi:Elasticity of public knowledge stocks*

Eq. (11)

Eq. (12)

**3.5 The structure of knowledge-based CGE model: Households**

In this model, households are classified into 20 quantiles based on income levels. Each income quantile of households derives income through wage, capital, and knowledge earnings. Equation (13) indicates wage incomes for each skill type (), which is the sum of payments for labor in production activities and R&D activities. Equation (14) and Equation (15) show capital and knowledge earnings, respectively. Capital earning) is the sum of returns for capital invested into production activities and R&D activities, and knowledge income) is earned from payments for the knowledge invested into production activities.

Eq. (13)

*Labor inputs for sector i by skill type;*

*Labor inputs for R&D investments by skill type;*

*: Factor price of labor by skill type*

Eq. (14)

*Physical capital inputs for sector i;*

*Physical capital inputs for R&D investments;*

*Returns of capital*

Eq. (15)

*capital inputs for sector i;*

*Factor price of knowledge capital*

Furthermore, the aggregate household earning from each primary factor described in Equations (13), (14), and (15) is divided into 20 groups of households, in proportion to the share of each income quantile, to characterize the distribution of households’ incomes. The incomes of households are either saved or paid to the government as transfer payments. The remaining incomes are then spent for consumption. Consumption expenditures of households at different income quantiles are determined by the consumption structure, drawn from micro-level data of the Household Income and Expenditure (HIE) Survey.

4. Scenario Settings

**4.1 Implementation of factor-biased technological change**

Model settings, as discussed in the previous chapter, give us information on methodological foundations to examine direct and indirect employment effects arising from innovations. A brief representation of the methodological approaches is shown in Figure 1. To account for indirect effects of technological innovations on employment structure, we have introduced R&D investments and characteristics of knowledge into our model. In this context, the CGE model is set up so that spillover effects from innovation increase productivity, influencing other sectors in the economy, as shown in Equations (9) to (12). Consequently, R&D investments and productivity improvements from knowledge accumulation can bring about expansion of outputs in industrial sectors and economic growth, resulting in indirect creation of employment.

In addition, we have explored key determinants behind the technological unemployment derived from the literature review in Section 2. To understand direct effects of technological innovations on the employment structure, it is essential to explicitly represent the SBTC and capital-biased technical change within the CGE framework. In the production structure, as shown in Figure 2, the CES functional form has been chosen as a production function in each sector.[[6]](#footnote-6) To incorporate SBTC and capital-biased technical change into the production structure, the value for elasticity of substitution among L3 (high-skilled labor), K (capital), and H (knowledge) is set to be less than 1 (), while that value among HLK (the composite of high-skilled labor, capital and knowledge), L2 (skilled labor), and L1 (unskilled labor) is set to be larger than 1 (. The elasticity of substitution larger than 1 implies substitutive relationships among HLK, L2, and LI, and represents the SBTC and capital-biased technical change. The values of substitution elasticities are adopted from Krusell et al. (2000).

**4.2 Business-As-Usual (BAU) scenario**

Using the above-mentioned methodological foundations, the model is built and calibrated on the basis of the economic situation of Korea in 2010. However, since this analysis aims to investigate the macroeconomic impacts of technological innovations on employment structure and economic growth in 2030, the BAU scenario up to 2030 is generated by expanding the base-year economy, incorporating projection data. Projection data contain forecast figures for long-term economic growth (gross domestic product (GDP) forecasts), and the forecast values for GDP growth (Table 2) are adopted from National Assembly Budget Office (NABO) (2012). It is also assumed that R&D intensity is maintained at 4% from the base year of 2010 to the target year of 2030. The level of the R&D intensity in 2010 is based on the current status of R&D investments in Korea.

Table 2. GDP projections for business-as-usual (BAU) scenario (2010 = 1)

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | ‘10 | ‘11 | ‘12 | ‘13 | ‘14 | ‘15 | ‘16 | ‘17 | ‘18 | ‘19 | ‘20 |
| **GDP level** | 1.00 | 1.04 | 1.07 | 1.10 | 1.13 | 1.16 | 1.19 | 1.22 | 1.24 | 1.26 | 1.28 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | ‘21 | ‘22 | ‘23 | ‘24 | ‘25 | ‘26 | ‘27 | ‘28 | ‘29 | ‘30 |
| **GDP level** | 1.29 | 1.31 | 1.32 | 1.34 | 1.35 | 1.36 | 1.36 | 1.37 | 1.38 | 1.39 |

**4.3 Policy scenario settings**

This study examines the effects of technological innovation on 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, and two policy 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 gradually increases from 4%, in the base year of 2010, to 5%, in 2020. For the analysis, we set the target year as 2030 and assume that R&D intensity in 2020 for each scenario is maintained until 2030. The scenarios constructed for the analysis are summarized in Table 3.

Table 3. Scenario descriptions

|  |  |  |
| --- | --- | --- |
|  | **R&D intensity in 2010** | **R&D intensity in 2020** |
| **BAU Scenario (BAU)** | 4% | 4% |
| **Scenario 1 (SCN1)** | 4% | 3% |
| **Scenario 2 (SCN2)** | 4% | 5% |

5. Main Results

**5.1 Effects on the employment structure**

Based on the scenario settings presented in the previous section, we firstly examine the changes of aggregate labor demand by scenario type. Table 4 illustrates the rate of changes in the aggregate labor demand between a base year (2010) and a target year (2030) for each scenario, as well as the changes of aggregate employment levels in 2030 relative to the BAU scenario (for SCN1 and SCN2 scenarios). Market clearance conditions of the general equilibrium framework imply that flows of goods and factors must be absorbed by production and consumption activities in the economy (Sue Wing, 2004). This suggests that, for a given factor the quantities demanded by industrial sectors must be balanced against the aggregate supply endowed to the households. Accordingly, changes of labor demand by scenario type can be understood as changes of labor supply for each scenario.

Table 4 reveals that the aggregate labor demand grows the most (53.2% increase from 2010 to 2030) under the SCN2 scenario, where higher level of R&D investments is made. The SCN2 case also reveals a significant rise in aggregate employment level, which increased by 14.4%, compared to the BAU level in 2030. On the other hand, the SCN1 scenario with decreasing R&D intensity reveals the smallest increase of employment from 2010 to 2030 (26.9% increase from 2010 to 2030). Furthermore, we can see that the SCN1 scenario shows a lower employment level relative to the BAU scenario (-5.2%, compared to the BAU level in 2030). These results imply that a higher level of innovation activities creates much more jobs by offsetting the effects of capital-biased technical change, which lowers the employment level in the economy. To investigate key mechanisms behind these results, additional analysis on changes of labor demand by skill type and by industry has been performed.

Table 4. Changes of the aggregate labor demand under different scenarios

|  |  |  |  |
| --- | --- | --- | --- |
|  | **BAU** | **SCN1** | **SCN2** |
| Total labor demand change (%) (between 2010 and 2030) | 33.9 | 26.9 | 53.2 |
| Total labor demand in 2030  (% change relative to the BAU) | - | -5.2 | 14.4 |

**5.1.2 Changes of labor demand by skill type**

Figure 4 depicts time series’ trends in changes of labor demand by skill type for SCN1 and SCN2, compared to the BAU scenario. Table 5 shows the growth rate of labor demand by skill type between 2010 and 2030 for each scenario. Table 5 suggests that, in all scenarios, demand for high-skilled labor increases more rapidly than for other types of labor. The SCN2 scenario shows greater increases in the demand for high-skilled labor, with the highest growth rate of 121.3%, from 2010 to 2030, compared to other scenarios. The SCN2 scenario also shows a significant rise in demand for all kinds of labor (unskilled labor: 42.6%, skilled labor: 44.9% growth from 2010 to 2030). On the other hand, as shown in Table 5, the SCN1 shows the lowest growth rate of labor demand by skill type (between 2010 and 2030) among all scenarios (unskilled labor: 21.9%, skilled labor: 22.5%, high-skilled labor: 61.7%). Similarly, when considering changes of the labor demand by skill type, relative to the BAU level (Figure 4), the SCN2 scenario, with increasing R&D intensity, shows greater levels in all types of labor, compared to the BAU case. We can also see that demand for high-skilled labor is more sensitive to changes in R&D intensity than for other types of labor. As shown in Figure 4(c), the labor demand for high-skilled labor of the SCN2 in 2030 increases by 26.5%, compared to the BAU level, while that of the SCN1 decreases by 7.6% from the BAU scenario. Those variations are greater than is the case with other types of workers, as shown in Figure, 4(a) and 4(b). Higher sensitivity of high-skilled labor to variations in R&D intensity implies a strong link between the level of R&D investment and the degree of skill bias in technical change, suggesting the presence of SBTC arising from technological innovations. Moreover, we can understand that a higher level of innovation favors high-skilled workers much more, and stimulates a higher degree of skill bias in technical change. Accordingly, it can be inferred that a higher level of innovation could accelerate the skill bias in technical change.

Table 5. Growth rates of labor demand by skill type from 2010 to 2030 (unit: %)

|  |  |  |  |
| --- | --- | --- | --- |
| **Skill type** | **BAU** | **SCN1** | **SCN2** |
| Unskilled labor | 28.0 | 21.9 | 42.6 |
| Skilled labor | 28.6 | 22.5 | 44.9 |
| High-skilled labor | 75.0 | 61.7 | 121.3 |

(a) Unskilled Labor

(b) Skilled Labor

(c) High-skilled Labor  
Figure 4. Changes of labor demand by skill type (% change relative to the BAU)

The rise in labor demand is linked to expansion of employment and a rise in workers’ wages. Differences in the demand of labor for particular skills cause wage differentials between workers with different skills. From the results on changes of labor demand by skill type, it is found that technological innovations disproportionately raise the demand for high-skilled labor over other types of labor, implying increases in the skill premium. Figure 5 illustrates changes of skill premium, which is defined as the ratio of the wages of either high-skilled to unskilled workers (Figure 5(b)) or skilled to unskilled workers (Figure 5(a)). It is found that, in the SCN2 scenario, the skill premium for high-skilled workers, measured by the wage ratio between high-skilled and unskilled labor, dramatically increases (17.74% from the BAU level in 2030). Furthermore, the result shows that skill premium for high-skilled workers, under the SCN2 case, steadily increases over time, as shown in Figure 5(b). On the other hand, the SCN1 scenario with a diminishing rate of R&D intensity shows a decline in skill premium for high-skilled workers (-3.13% from the BAU level in 2030). Similar trends are found in the ratio of the wages of the skilled to unskilled labor, as depicted in Figure 5(a). However, changes of skill premium for skilled workers are not as remarkable as are those of skill premium for high-skilled workers. The results imply that a higher level of innovation further increases the skill premium for high-skilled labor, with higher demand for those workers.

(a) Changes of skill premium (ratio of the wages of skilled to unskilled labor)

(b) Changes of skill premium (ratio of the wages of high-skilled to unskilled labor)   
Figure 5. Changes of skill premium (% change relative to the BAU scenario)

**5.1.3 Changes of labor demand by industry**

In this subsection, we illustrate the results representing the changes of labor demand by industry. For the analysis, we reclassify 27 industries into five types of industries: (1) primary industries, which contain agriculture, forestry, and fisheries; (2) low-tech manufacturing industries; (3) high-tech manufacturing industries[[7]](#footnote-7); (4) service industries; and (5) R&D industries. Table 6 shows that the rise of labor demand and employment level under the SCN2 scenario is greater than under the BAU scenario. However, the SCN1 case reveals losses of employment in all sectors, compared to the BAU scenario. Higher levels of labor demand in all sectors, under the SCN2 scenario, imply that an increase in R&D investments can stimulate expansions of industrial outputs, leading to higher employment levels across industries. In addition, among all industries the R&D sector shows the highest rate of increase in labor demand under all scenarios (BAU: 60.9%, SCN1: 47.4%, SCN2: 150.9% increase from 2010 to 2030), followed by the high-tech manufacturing industry (BAU: 34.5%, SCN1: 31.8%, SCN2: 78.4% increase from 2010 to 2030). This suggests that industries with higher intensities of innovation have significant potential for job creation, by requiring more workers than do other industries. Hence, the results highlight that a higher level of R&D spending (SCN2) facilitates a transition of the economy toward knowledge-intensive industries, by creating many more jobs in high-tech manufacturing and R&D industries.

Table 6. Growth rates of aggregate labor demand by industry from 2010 to 2030 (unit: %)

|  |  |  |  |
| --- | --- | --- | --- |
| **Industry** | **BAU** | **SCN1** | **SCN2** |
| Agriculture, forestry, and fisheries | 17.7 | 8.8 | 18.7 |
| Low-tech manufacturing | 27.5 | 18.9 | 53.8 |
| High-tech manufacturing | 34.5 | 31.8 | 78.4 |
| Service | 34.1 | 27.2 | 39.9 |
| R&D | 60.9 | 47.4 | 150.9 |

**5.2 Effects on the economic growth**

**5.2.1 Changes of GDP growth**

In the previous section, we have examined the employment effects of technological innovations driven by R&D investments. In this subsection, we present the main results representing the economic impacts of different levels of innovation. It is shown that scenario SCN2 stimulates the economic growth, when analyzing the macroeconomic effects in terms of GDP level, as represented in Table 7 and Figure 6. Table 7 presents the GDP growth rates (% growth rate and annual average growth rate) between the base year and 2030 for each scenario, while Figure 6 shows the changes of GDP levels in SCN1 and SCN2 scenarios, compared to the BAU scenario. Table 7 reveals that the growth of GDP level from 2010 to 2030 under the SCN2 (% growth rate of GDP: 62.0%; annual average GDP growth rate: 2.4% from 2010 to 2030) is greater than seen in other cases, while the SCN1 scenario shows the lowest GDP growth rate (% growth rate: 32.1%; annual average growth rate: 1.4% from 2010 to 2030). In addition, Figure 6 provides straightforward implications of a linkage between innovation and economic growth. We can see the GDP loss of the SCN1 (-5.3% compared to the BAU level in 2030), while the SCN2 scenario shows the GDP increase in 2030 (16.2% relative to the BAU scenario). The results highlight that a higher level of R&D spending (SCN2) boosts long-term economic growth with more innovation, while reduced R&D intensity (SCN1) hinders economic growth and causes the economy to shrink.

Table 7. GDP growth rates from 2010 to 2030 under different scenarios (unit: %)

|  |  |  |  |
| --- | --- | --- | --- |
|  | **BAU** | **SCN1** | **SCN2** |
| GDP growth (%) | 39.5 | 32.1 | 62.0 |
| Average annual GDP growth rate (%) | 1.7 | 1.4 | 2.4 |

Figure 6. Changes of GDP level   
(% change relative to the BAU scenario)

A higher level of R&D investments leads to productivity improvements, which, in turn, lowers the production costs of industrial sectors in the economy. Lower costs in producing final goods further promote price competitiveness of sectors. Enhanced price competitiveness fosters the expansion of production activities, resulting in a greater employment level. This economic mechanism is also associated with the results presented in Section 5.1.2, which show that additional R&D investments have positive effects on overall employment growth. The higher levels of aggregate employment and GDP growth suggest that a level of R&D spending should be either maintained or increased steadily to ensure quantitative expansion of the economy.

**5.2.2 Changes of value-added compositions**

This subsection describes how changes in the composition of value-added appear in different scenarios, to understand key factors behind the economic growth. Figure 7 depicts relative comparisons of three types of scenarios in terms of the compositions of value-added in the target year 2030. When comparing the absolute level of the gross value-added by scenario type (Figure 7(a)), the SCN2 scenario shows the highest value among all scenarios (1632.6 trillion KRW in 2030), indicating higher economic growth driven by additional R&D investments. On the other hand, Figure 7(a) reveals that the SCN1 has the lowest level of gross value-added (1330.7 trillion KRW in 2030), implying an economic downturn caused by reduced R&D spending. In addition, Figure 7(b) shows the relative contributions of the factors of production to the incomes received by the households as a result of these factors. Under the SCN2 scenario, three factor inputs, including knowledge, high-skilled labor, and capital, show relatively higher shares (capital: 47.6%; high-skilled labor: 8.0%; knowledge: 5.9%) in the value-added composition, compared to other scenarios. However, we can see that relative shares of skilled labor and unskilled labor in gross value-added for SCN2 are lower than are those for other scenarios.

1. Composition of gross value-added under different scenarios in 2030   
   (unit: trillion KRW)

(b) Relative share of factor inputs to the value-added in 2030 (unit: %)  
Figure 7. The composition of value-added under different scenarios

Furthermore, Figure 8 shows the changes of value-added compositions for SCN1 (Figure 8(a)), and SCN2 (Figure 8(b)) scenarios, compared to the BAU level. As shown in Figure 8(b), the SCN2 scenario shows significant increases in factor incomes compared to the BAU scenario. To be specific, the largest increases in factor incomes are found in earnings of high-skilled labor and knowledge earnings. It is shown that the labor incomes of high-skilled workers increase by 26.5%, compared to the BAU level, in 2030, under the SCN2. In addition, the value of knowledge incomes of the SCN2 in 2030 changes by 26.0%, compared to the BAU scenario. On the other hand, the SCN1 case reveals substantial declines in factor incomes, compared to the BAU level, as presented in Figure 8(a). Those results suggest that a higher level of R&D spending (SCN2) enhances the SBTC, and capital-biased technical progress, resulting in changes of the value-added composition, with higher shares of knowledge, high-skilled labor, and capital.

(a) Changes of the value-added composition in SCN1 (% change relative to the BAU scenario)

(a) Changes of the value-added composition in SCN2 (% change relative to the BAU scenario)

Figure 8. Changes of the value-added composition compared to BAU level

**5.3 Effects on income distributions**

In previous sections, we have analyzed the impacts of innovations on the employment structure and economic growth. From these analyses, it is found that innovation-driven economic growth favors high-skilled over unskilled labor, suggesting a transition of the value-added composition toward high-skilled labor, knowledge, and capital. Those results imply a close correlation between the technological innovation and the degree of SBTC and capital-biased technological change. The factor-biased technological progress driven by innovation is deeply associated with wage inequality and income polarization. Therefore, it is meaningful to observe key indicators related to the income distribution (Figure 9, 10).

Figure 9. The income share of the top 10% group (%)

Figure 10. The income share of the middle-income group (%)

To examine the income distribution among income quantile groups, an analysis of the relative income shares held by the top 10% of income-level households (Figure 9) and by the middle-income earners, between 40% and 60% of income level (Figure 10), has been performed. As shown in Figure 9, the SCN2 scenario shows increases in the share of income held by the highest 10% of households, compared to the BAU level (SCN2: 26.19% of total income in 2030; BAU: 26.08% of total income in 2030). On the other hand, the income share of the middle-income class under SCN2 shows decreases, as compared with the BAU scenario (SCN2: 26.19% of total income in 2030; BAU: 26.08% of total income in 2030), as presented in Figure 10. The results imply that a higher level of R&D spending (SCN2) can contribute to the concentration of wealth in upper income classes.

Furthermore, to analyze how the income is distributed across all households, the concept of the decile distribution ratio is adopted. The decile distribution ratio is the share of the bottom 40%, in relation to the share of the top 20%, in terms of income levels. This index is commonly used to measure the concentration of income in the upper income groups. As depicted in Figure 11, the SCN2 shows the smallest decile ratio value (SCN2: 0.326 in 2030) among policy scenarios (BAU: 0.328, and SCN1: 0.329 in 2030). We can see that the decile ratio value of the SCN2 continues to drop from the base year 2010, widening gaps between those of other scenarios. The results can be explained by the fact that the degree of SBTC and capital-biased technological progress is intensified when additional R&D investments are made. Hence, it can be inferred that people in higher income classes engage more in high-skilled works and benefit more from capital earnings than do people from lower income classes. Therefore, we can understand that the degrees of income inequality and income polarization are deepened and intensified as the transition of the value-added composition accelerates toward high-skilled labor, knowledge, and capital, with additional R&D investments. The results suggest that innovation-driven economic growth could increase disparities between the rich and poor, implying the importance of complementary policies to reduce income inequality in the economy.

Figure 11. The decile distribution ratio under different scenarios

**5.4 Sensitivity Analysis**

To test for the robustness of the results and findings discussed in previous sections, a sensitivity analysis is conducted varying key parameters in the model. The substitution elasticities among production factors can have a major influence on the simulation results (Oh et al., 2015). In this study, we adopt values for substitution elasticities between production factors from Krusell et al. (2000), Hwang et al. (2008), and Hong et al. (2014). As discussed in the section 4.1, the value for elasticity of substitution among L3 (high-skilled labor), K (capital), and H (knowledge) is set to be less than 1 (), while that value among HLK (the composite of high-skilled labor, capital and knowledge), L2 (skilled labor), and L1 (unskilled labor) is set to be larger than 1 (, to reflect SBTC and capital-biased technical progress from R&D investments into a model via the production structure. Those parameters are key factors describing intrinsic properties of technological progress, which can be summarized as labor-saving and skill-biased technological changes. For the sensitivity analysis, we change the value for the elasticity of substitution among HLK, K, and H () while the value of is fixed.

Table 8 compares key results between the original model and the models built for the sensitivity analysis with lower and higher levels of . We change the value of from 1.67 (original value) to 1.0 and 2.0, which reflect a lower and a higher substitution potential respectively. The “scenario 2 with a lower elasticity” (SCN2-LOW) and the “scenario 2 with a higher elasticity” (SCN2-HIGH) show the results from simulations with the lower ( and the higher value of the elasticity. These methodological settings capture the different degrees of factor-biased technological change. As shown in the Table 8, the results are very similar with results from the original model (SCN2), showing minor differences in the level of changes in labor demand, GDP level, and the value-added composition. Thus, from the sensitivity analysis we can conclude that our model appears to be quite robust. An increased level of substitution among HLK, L2, and L1 enables more efficient production and stimulates higher economic growth with productivity improvements. However, it tends to more disproportionately increase the demand for capital and high-skilled labor over skilled and unskilled labor, which results in increased skill premiums and capital earnings. In summary, from the sensitivity analysis it is found that these tendencies are intensified and accelerated by increasing value of .

Table 8. Comparison of macroeconomic variables resulting from a sensitivity analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Indicator** | | **Scenario** | | |
| **SCN2- LOW** | **SCN2** | **SCN2-HIGH** |
| GDP level in 2030 (% changes relative to BAU) | | 13.03 | 16.17 | 18.60 |
| Total labor demand in 2030 (% changes relative to BAU) | | 16.73 | 14.41 | 13.97 |
| Value-added composition  in 2030  (% share) | Capital | 44.43 | 47.58 | 48.71 |
| Unskilled labor | 18.23 | 16.66 | 16.13 |
| Skilled labor | 23.96 | 21.87 | 21.17 |
| High-skilled labor | 7.57 | 8.04 | 8.14 |
| Knowledge | 5.80 | 5.86 | 5.85 |
| Labor demand by skill type in 2030 (% changes relative to BAU) | Unskilled labor | 16.43 | 11.46 | 10.16 |
| Skilled labor | 17.89 | 12.73 | 11.42 |
| High-skilled labor | 13.77 | 26.51 | 30.74 |

6. Discussion and Conclusions

In this paper, we examined the economy-wide effects of innovation, in terms of employment structure and economic growth. For the analysis, we used the knowledge-based CGE model, focusing on the Korean economy. To incorporate characteristics of innovation within the CGE framework, R&D investments and knowledge capital stocks were introduced in the model. The knowledge stock as one of the factor inputs is assumed to be accumulated through R&D investments. In addition, to deal with spillover effects from R&D, we described the spillover effects as a function of government’s knowledge stock and other industries’ knowledge stock. These two types of knowledge spillover effects contribute to TFP improvements in each sector. Moreover, the CES functional form was chosen as a production function to reflect the elasticities of substitution between factors of production, and, in turn, to incorporate SBTC and capital-biased technological change into the model into the model via the production function. Those methodological considerations have enabled us to examine direct and indirect employment effects arising from innovations.

Based on those methodological settings in the CGE model, simulation results for policy scenarios were analyzed in terms of employment structure, economic growth, and social inequality. Simulation results show that an increased level of R&D investments promotes economic growth, and creates jobs with a higher aggregate demand for labor. These results indicate that indirect employment effects of technological innovations, associated with production expansion driven by productivity improvements and spillover effects in the economy, are larger than are direct employment effects of innovations, which replace workers via SBTC, and capital-biased technological change. In other words, it can be understood that higher levels of innovation in the economy create many more jobs, by offsetting the destructive impacts of technological innovations on the employment through factor-biased technological change. The results suggest that technological innovations with a higher level of R&D investments can bring growth opportunities and drive economic growth, with a higher aggregate demand for labor.

However, our analysis highlights the fact that economic growth accompanied by factor-biased technological change can generate higher inequality and income polarization within the economy. When R&D investment is increased, relative shares of unskilled and skilled labor in the composition of value-added are found to decrease, while those of high-skilled and capital are shown to increase. The increase in demand for labor is linked to higher levels of employment and wages. From simulation results, we found that innovation-driven economic growth favors high-skilled over unskilled labor, and further increases skill premium. A rise in skill premium could deepen wage inequality between workers. Results on income distribution also support the premise that more people in higher income groups are engaged in relatively high-skilled work and benefit from skill premium and capital earnings. In this regard, we can understand that technological changes disproportionately raise the demand for capital and high-skilled labor, over that for skilled and unskilled labor. Indeed, it is found that this “factor-biased” technical progress plays a central role in deepening income inequality and income polarization in the economy.

Our analysis implies that technological innovations pose both opportunities and challenges in the society. Over the past four decades, technological advances have driven productivity upward, improved living standards, and stimulated economic growth by creating new growth opportunities. However, economic growth accompanied by rapid technological change has brought new challenges in terms of employment and inequality. In this regard, our analysis demonstrates that economic growth driven by technological innovations does not automatically benefit everyone in a society. We have found that technological advances may create both winners and losers via SBTC, and by capital-biased technical change, as noticed by Brynjolfsson and McAfee (2012, 2014). A substantial increase in inequality does not bode well for social and political stability, and faster technological progress may intensify a strong relationship between technological change and higher inequality (Usanov and Chivot, 2013). Therefore, there should be faster adjustments by policymakers and institutions to address the risk of job polarization (by replacing skilled and unskilled jobs with higher skilled jobs) and the income inequality behind innovation-driven economic growth. The policy implications, in terms of employment and inequality challenges posed by technological innovations, can be summarized as the need to adopt a broad perspective when preparing policies dealing with these issues, rather than just focusing on labor market measures. In this regard, we propose policy recommendations in various dimensions, ranging from employment policy to fiscal policy. Policy recommendations, as presented below, suggest that socio-economic institutions need to be adjusted to the pace and direction of technological progress, to ensure both the quality of economic growth and the quantitative expansion:

1. Employment policy

Policymakers should prepare a variety of educational programs, to educate workforces to be able to fit in new jobs generated by technological changes, and learn more advanced skills. From the analysis, it is found that technological changes disproportionately raise the demand for capital and high-skilled labor over skilled and unskilled labor by eliminating many jobs, either through automation or upgrading the skill level required to attain or keep those jobs. Therefore, it is important to establish training-focused adjustment policies for effective worker transitions in the wake of technological displacement (Marchant et al., 2014). As noted by Cobo (2013), the concepts of “up-skilling” & “re-training” should be emphasized in educational programs, to enable workers to keep their competences in quickly adjusting to the rapid technological changes, SBTC. Those educational programs can facilitate smooth transitions of workers, either from unskilled to skilled workers or from skilled to high-skilled workers, in line with changing labor market demand. At the same time, the unemployment system can play an important role, as technological change is found to accelerate the obsolescence of many low-skilled workers. High benefit replacement rates might be a complementary policy instrument to incentivize low-skilled unemployed workers to participate in up-skilling and re-training programs that facilitate re-entry to the labor market (Bassanini and Duval, 2006).

1. Education policy

From our study, we have confirmed that technological progress leads to acceleration of skill obsolescence and may contribute to skill mismatches and job polarization. This result suggests that the existing educational system should undergo drastic changes, to mitigate the effects of non-neutral technological change, which is characterized by SBTC, on job polarization and skill mismatches, as highlighted by Redecker et al. (2010). To sustain the knowledge-based economy, with innovation as an engine of growth, the right types of skills and knowledge should be provided and built up through education, to adjust to a shift in the skill sets that people need to develop in accordance with technological changes. In other words, the educational system should keep pace with technological change and evolving labor markets. Thus, workplace-based vocational training and lifelong learning can be considered as key elements in upcoming educational systems. In addition, existing curricula, and many of the skills being taught today in schools, are tied to routine skills and manual works that can be replaced by machines (Rotherham and Willingham, 2010). Therefore, existing curricula and educational systems should be focused on offering opportunities to learn new skill sets, keep skills up to date, and remain compatible with technological progress. Along with reforms of the educational system, policymakers need to understand the existing skill base, at both country and industry level, and anticipate changing future skill requirements that may arise from rapid technological change (WEF, 2016).

1. Technology/Innovation policy

From the policy simulations, it is found that a higher level of R&D investment leads to higher productivity growth, and, in turn, lowers the production costs in sectors. Lower costs in producing outputs make sectors demand more factors of production, resulting in production and employment expansion in the economy. It can be inferred that promoting innovation within the economy is essential to drive economic growth and aggregate employment expansion. Thus, we can conclude that policy instruments in the innovation policy domain should be established, to offer industries the opportunity to promote entrepreneurship and trigger many more innovation-related activities within the economy. These would include granting R&D subsidies, lowering entry barriers to new business creation, and revising regulations that might hinder the creation of new business models.

1. Fiscal policy

To ensure the quality of economic growth, in addition to quantitative expansion, policy measures to solve rising income inequality should also be well established. Intensified inequalities among economic agents in the economy can cause social instability and may reduce economic efficiency and productivities. Therefore, problems of income polarization and inequality, driven by factor-bias technological change, should be mitigated with supplementary policy instruments. From the analysis, it is found that people at higher income groups are relatively more engaged in high-skilled works and benefit more from higher levels of skill premium and capital earnings than do other groups of people. This result suggests that technological progress is one of the major factors that widen income inequality within the economy. In this context, policy instruments related to tax and transfer mechanisms can play important roles in achieving redistribution of income and reducing inequality (OECD, 2015). For example, increase in tax rates for capital earnings and progressive labor income taxation could be policy options for resolving income inequality problems. However, those measures should not discourage incentives for innovation and investments and let the potential for innovation fall within the economy. Therefore, potential trade-offs in the design of tax instruments between economic growth and equity should be carefully take into consideration.

Acknowledgments

The authors are grateful to the editor and two anonymous reviewers who dedicated their considerable time and provided valuable comments and suggestions to improve the quality of the paper. This work is supported by the National Research Foundation of Korea Grant, funded by the Korean Government (NRF-2013R1A2A2A03014744), and Institute of Engineering Research (IOEG) of Seoul National University.

Conflicts of Interest

The authors declare no conflict of interest.

References

Acemoglu, D.. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics, 113*, 1055–1089.

Acemoglu, D.. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature, 40(1)*, 7–72.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in US wage inequality: Revising the revisionists. *The Review of economics and statistics, 90(2)*, 300-323.

Baccini, A., & Cioni, M. (2010). Is technological change really skill‐biased? Evidence from the introduction of ICT on the Italian textile industry (1980–2000). *New Technology, Work and Employment, 25(1)*, 80-93.

Bank Of Korea (BOK). *Input-Output Table 2010*; BOK: Seoul, Korea, 2013.

Bentolila, S., & Saint-Paul, G. (2003). Explaining movements in the labor share. *Contributions in Macroeconomics, 3(1)*, 1-31.

Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labor within US manufacturing: evidence from the annual survey of manufacturers. *The Quarterly Journal of Economics*, *109(2)*, 367-397.

Bassanini, A., & Duval, R. (2006). The determinants of unemployment across OECD countries: Reassessing the role of policies and institutions. *OECD Economic Studies*, 42(1), 7-86.

Bessen, J. *Learning by Doing: The Real Connection Between Innovation, Wages, and Wealth*. Yale University Press: London, United Kingdom, 2015.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-level Evidence. *Quarterly Journal of Economics*, *117*, 339–76.

Brouwer, E., Kleinknecht, A., & Reijnen, J. O. (1993). Employment growth and innovation at the firm level. *Journal of Evolutionary Economics*, *3(2)*, 153-159.

Brynjolfsson, E., & Hitt, L. M. (2014). Information technology as a factor of production: The role of differences among firms, *Economics of innovation and new technology, 3(3-4)*, 183-200.

Brynjolfsson, E., & McAfee, A. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company: New York, USA, 2014.

Brynjolfsson, E.; McAfee, A. *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. WW Norton & Company: New York, USA, 2012.

Card, D., & DiNardo, J. E. (2002). Skill biased technological change and rising wage inequality: some problems and puzzles. Available online: <http://www.nber.org/papers/w8769> (accessed on 26 August 2016)

Coad, A., & Rao, R. (2011). The firm-level employment effects of innovations in high-tech US manufacturing industries. *Journal of Evolutionary Economics, 21*(2), 255-283.

Cobo, C. (2013). Skills for innovation: envisioning an education that prepares for the changing world. *Curriculum Journal*, 24(1), 67-85.

David, H., Katz, L. F., & Krueger, A. B. (1997). Computing inequality: have computers changed the labor market?. Available online: <http://www.nber.org/papers/w5956> (accessed on 26 August 2016)

Dunne, T., Haltiwanger, J., & Troske, K. R. (1997). Technology and jobs: secular changes and cyclical dynamics. Available online: <http://www.nber.org/papers/w5656> (accessed on 26 August 2016).

Falk, M., & Seim, K. (2001). Workers' skill level and information technology: a censored regression model. *International Journal of Manpower, 22*(1/2), 98-121.

Griliches, Z. (1969). Capital-skill complementarity. *The review of Economics and Statistics*, *51(4),* 465-468.

Grossman, G. M., Helpman, E., Oberfield, E., & Sampson, T. (2016). Balanced growth despite Uzawa. Available online: <http://www.nber.org/papers/w21861> (accessed on 26 August 2016)

Guerriero, M., & Sen, K. (2012). What determines the share of labour in national income? A cross-country analysis. Available online: <http://ftp.iza.org/dp6643.pdf> (accessed on 26 August 2016)

Guellec, D., & De La Potterie, B. V. P. (2001). R&D and productivity growth: panel data analysis of 16 OECD countries, *OECD Economic studies*, *33*, 103-126.

Guellec, D., & De La Potterie, B. V. P. (2003). The impact of public R&D expenditure on business R&D. *Economics of innovation and new technology*, 12(3), 225-243.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. *Industrial and Corporate Change, 17*(4), 813-839.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2008).Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. Availiable online: <http://www.nber.org/papers/w14216> (accessed on 26 August 2016)

Haskel, J., & Heden, Y. (1999). Computers and the Demand for Skilled Labour: Industry‐and Establishment‐Level Panel Evidence for the UK. *The Economic Journal, 109(454)*, 68-79.

He, H., & Liu, Z. (2008). Investment-specific technological change, skill accumulation, and wage inequality. *Review of Economic Dynamics*, 11(2), 314-334.

Hong, C., Yang, H., Hwang, W., & Lee, J. D. (2014). Validation of an R&D-based computable general equilibrium model. *Economic modelling,* *42*, 454-463.

Hwang, S.W., Kim, B. W., Yoo, S. H., Park, K. H., Ryu, T. G., Choo, G. N., & Lee, M. K. (2008). Economic impact of basic R&D. *STEPI Policy research paper* 2008-07. (In Korean)

Hwang, W. S., & Lee, J. D. (2014). Interindustry Knowledge Transfer and Absorption via Two Channels: The Case of Korea. *Global Economic Review, 43(2)*, 131-152.

Katz, L. F., & Margo, R. A. (2013). Technical change and the relative demand for skilled labor: The united states in historical perspective. Available online: <http://www.nber.org/papers/w18752> (accessed on 26 August 2016)

Karabarbounis, L., & Neiman, B. (2013). The global decline of the labor share. Available online: <http://www.nber.org/papers/w19136> (accessed on 26 August 2016)

Korea Institute of S&T Evaluation and Planning (KISTEP). *Scientific and Technical Research Activities Survey Report.* KISTEP: Seoul, Korea, 2011. (In Korean)

Klette, J., & Førre, S. E. (1998). Innovation And Job Creation In A Smallopen Economy-Evidence From Norwegian Manufacturing Plants 1982–92. *Economics of Innovation and New Technology, 5(2-4)*, 247-272.

Křístková, Z. (2012). Impact of R&D Investment on Economic Growth of the Czech Republic-A Recursively Dynamic CGE Approach. *Prague Economic Papers, 21(4),* 412-433.

Krusell, P., Ohanian, L. E., Ríos‐Rull, J. V., & Violante, G. L. (2000). Capital‐skill complementarity and inequality: A macroeconomic analysis. *Econometrica, 68(5)*, 1029-1053.

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization, 29(2)*, 210-220.

Layard, R., Nickell, S., & Jackman, R. *Unemployment: Macroeconomic Performance and the Labor Market.* Oxford University Press: Oxford, United Kingdom, 1991.

Layard, R., Nickell, S., & Jackman, R. *The unemployment crisis*. Oxford University Press: Oxford, United Kingdom, 1994.

Lemelin, A., Decaluwé, B. Issues in recursive dynamic CGEmodeling: investment by destination, savings, and public debt. Politique économique et Pauvreté/Poverty and Economic Policy Network, Université Laval: Québec, Canada, 2007.

Machin, S., & Van Reenen, J. (1998). Technology and changes in skill structure: evidence from seven OECD countries. *Quarterly journal of economics, 113(4)*, 1215-1244.

Mallick, S.K., & Sousa, R.M. (2015). The skill premium effect of technological change: New evidence from the us manufacturing sector*. International Labour Review* (in press).

Marchant, G.E., Stevens, Y.A., & Hennessy, J.M. (2014). Technology, unemployment & policy options: Navigating the transition to a better world. *Journal of Evolution and Technology*, 24(1), 26-44.

Marouani, M. A., & Nilsson, B. (2016). The labor market effects of skill-biased technological change in Malaysia. *Economic Modelling*, 57, 55-75.

OECD. (2015). Inequality and inclusive growth policy tools to achieve balanced growth in G20 economies. Available online: <https://www.oecd.org/g20/topics/framework-strong-sustainable-balanced-growth/Inequality-and-Inclusive-Growth-Policy-Tools-to-Achieve-Balanced-Growth-in-g20-Economies.pdf> (accessed on 26 August 2016)

OECD. (2012). Education at glance 2012. Available online: <https://www.oecd.org/edu/EAG%202012_e-book_EN_200912.pdf> (accessed on 26 August 2016)

Pan, L. (2014). The impacts of education investment on skilled–unskilled wage inequality and economic development in developing countries. *Economic Modelling*, 39, 174-181.

Pianta, M. *Innovation and employment.* Oxford University Press: Oxford, United Kingdom, 2005.

Piketty, T. *Capital in the 21st Century.* Harvard University Press: Cambridge, USA, 2014.

Piva, M., Santarelli, E., & Vivarelli, M. (2005). The skill bias effect of technological and organisational change: Evidence and policy implications. *Research Policy, 34(2)*, 141-157.

Rogerson, R., Kaboski, J., & Buera, F. (2015). Skill-Biased Structural Change and the Skill Premium. Available online: <https://www.economicdynamics.org/meetpapers/2015/paper_895.pdf> (accessed on 26 August 2016)

Rotherham, A. J., & Willingham, D. T. (2010). 21st-Century Skills. Available online: <http://www.aft.org/sites/default/files/periodicals/RotherhamWillingham.pdf> (accessed on 26 August 2016)

Statistcs Korea. *The long-term population proejctions datasets 2010*; Statistkcs Korea: Seoul, Korea, 2011.

Statistics Korea. *Hosehold Income and Expenditure Survey 2010*; Statistics Korea: Seoul, Korea, 2011.

Stiglitz, J.E. (2014). Unemployment and innovation. Available online: <http://www.nber.org/papers/w20670> (accessed on 26 August 2016)

Terleckyj, N. (1980). Direct and indirect effects of industrial research and development on the productivity growth of industries. Available online: <http://www.nber.org/chapters/c3917.pdf> (accessed on 26 August 2016)

Usanov, A., & Chivot, E. (2013). The European Labor Market and Technology: Employment, Inequality, and Productivity. Available online: [www.hcss.nl/reports/download/142/2273](http://www.hcss.nl/reports/download/142/2273) (accessed on 26 August 2016)

Venables, A. J. (1985). The economic implications of a discrete technical change. *Oxford Economic Papers*, *37(2)*, 230-248.

Visser, V. (2007). R&D in WorldScan. Available online: <http://www.cpb.nl/sites/default/files/publicaties/download/memo189.pdf> (acceseed on 26 August 2016)

Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, *48*(1), 123-154.

Vivarelli, M. (2013). Skill-Biased Technological Change and Skill-Enhancing Trade in Turkey: Evidence from Longitudinal Microdata*.* Available online: http://ftp.iza.org/dp7320.pdf (accessed on 26 August 2016)

Vivarelli, M. (2012). Innovation, employment and skills in advanced and developing countries: a survey of the literature*.* Available online: <http://ftp.iza.org/dp6291.pdf> (accessed on 26 August 2016)

WEF. (2016). The Future of Jobs. Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution. Available online: http://www3.weforum.org/docs/WEF\_Future\_of\_Jobs.pdf (accessed on 26 August 2016).

Yang, H., Jung, S. M., & Lee, J. D. (2012). A study on the knowledge-based social accounting matrix. *Productivity review, 26(3)*, 257-285. (In Korean)

Zuniga, P., & Crespi, G. (2013). Innovation strategies and employment in Latin American firms. *Structural Change and Economic Dynamics*, 24, 1-17.

1. The SAM used in this study accepts the recommendation of the 2008 SNA, in order to incorporate additional accounts for knowledge capital. 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 2008 SNA extends the range of fixed assets and clarifies how to incorporate R&D spending into fixed capital formation. [↑](#footnote-ref-1)
2. We extract labor inputs and wage levels by labor types for production activities from the 2010 Household Income and Expenditure Survey (HIE Survey) micro data, from the Korea National Statistical Office, and the 2010 Wage Structure Statistics from the Ministry of Employment and Labor. [↑](#footnote-ref-2)
3. Household Income and Expenditure Survey defines 12 categories of final consumption as follows: (1) Food and non-alcoholic beverages; (2) alcoholic beverages and tobacco; (3) clothing and footwear; (4) housing, water, electricity, and gas; (5) furnishings and household equipment; (6) health; (7) transport; (8) communications; (9) recreations and culture; (10) education; (11) restaurant and hotels; and (12) miscellaneous goods and services. [↑](#footnote-ref-3)
4. Symbols with 0 indicate the parameters obtained by variable values of knowledge-based social accounting matrix of base year (year 2010). [↑](#footnote-ref-4)
5. Knowledge stocks in public and private sectors (for the year of 2010) are estimated using data in “Scientific and Technical Research Activities Survey Report”, published by the Korea Institute of Science and Technology Evaluation and Planning (KISTEP). Using equations from (6) to (7), the size of knowledge stocks in public sector is estimated to be approximately 43 trillion KRW in 2010, while that of the private sector is to be approximately 134 trillion KRW (1 U.S. dollar = 1,144.4 Korean won (KRW) in March 2016.). In addition, the industry-specific knowledge stock is estimated, and the electronic and electrical equipment sector shows the highest level of knowledge stock, with approximately 52 trillion KRW. [↑](#footnote-ref-5)
6. The CES production function has an advantage in freely choosing the substitution elasticities’ values. The values for the elasticity of substitution among primary factors measure how easy it is to substitute one for another. Therefore, biases in technical change depend on the elasticities of substitution between the different inputs. In this context, we incorporate SBTC and capital-biased technical change into the production function through different values of substitution elasticities in two-level nested CES production functions. [↑](#footnote-ref-6)
7. The classification between high-tech and low-tech manufacturing industries is based on whether the R&D intensity is higher than the average level of R&D intensity among manufacturing industries. [↑](#footnote-ref-7)