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Essays on Innovation, Human Capital, and Economic Growth in a Knowledge-based Economy

: Computable General Equilibrium Modelling for Innovation Policy Assessment

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Abstract

Essays on Innovation, Human Capital, and Economic Growth in a Knowledge-based Economy : A Computable General Equilibrium approach

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The dynamics of complementarities between technological innovation and human capital affect the growth trajectory of an economy and the role of human capital changes according to the technological level of the country. In this regard, studies analyzing the national economic growth trajectory have identified human capital as homogeneous in the economic system and focusing on the level effects of human capital, explained the relationship between technological innovation, human capital and growth, but have now expanded their discussion to include heterogeneous human capital with different properties and marginal productivity. Further, the discussion on the composition of human capital in

explaining the economic growth due to the interaction of technological innovation and human capital is including the effect on the labor market (wage, employment, etc.) and income distribution under technological innovation.

Consequently, this study focuses on the fact that the interrelationship between technological innovation and human capital defines the pattern of long-term economic growth and distribution of the economic system. Accordingly, a computable general equilibrium (CGE) model is designed and proposed as a tool to analyze the policy effects that can determine the structure of policy design and implementation to balance growth and distribution in a knowledge-based economic system based on technological innovation-driven economic growth. To overcome the methodological limitations of the existing policy effects analysis and CGE model based quantitative analysis studies, this study establishes and suggests a system that the dynamic interaction of technological innovation by knowledge capital investment and skill level change by human capital accumulation is reflected endogenously in production technology.

Based on the proposed CGE model, this empirical study tries to identify the paths through which the interaction between innovation and human capital spreads in the economy. By identifying the complementary relationship between R & D and education investment, the importance of enhancing the linkage between technological innovation through R&D investment and human capital accumulation through investment in education to improve national growth potential is found. In addition, among recent discussions on technological innovation and human capital interactions, we propose a policy mix of

innovation, education, and tax policy to solve the problems of labor market differentiation, polarization, and social inequality induced by technological innovation. Further, a quantitative policy effect analysis to identify the role of the proposed policy combination is conducted. Through these efforts, policy instruments in three policy areas, namely, increasing investment in innovation, improvement of proficiency through retraining and lifelong learning of workers in the public sector, and reform of the tax system through increasing income tax, can promote inclusive growth in the knowledge-based economy when utilized as a single policy package.

Based on the understanding of dynamics of interaction between technological innovation and human capital, the need for policy design that takes into account diverse paths that these factors use to affect growth and distribution in the economy and the interactions between institutional sectors in the associated markets is emphasized. In addition, this research contributes to the academic field focusing on innovation, human capital, and growth and distribution keywords by suggesting implications for redefining the role of innovation policy based on the empirical results of the macroeconomic model.

Keywords: Innovation, Human capital, Growth, Distribution, Computable general equilibrium model, Policy impact assessment
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Chapter 1. Introduction

1.1 Research background

For the continuous growth of an economy, there should be productivity improvements led by innovation and human capital accumulation (Acemoglu et al., 2006; Lucas, 1988; Romer, 1990). Several studies have argued that slowdowns in growth rates of industrial outputs faced by middle-income countries are strongly associated with the stagnation of total factor productivity (TFP) growth rates (Agénor & Canuto, 2015; Bulman et al., 2017; Eichengreen et al., 2013; Im & Rosenblatt, 2013; Lin & Rosenblatt, 2012; Wagner, 2015). It has been emphasized that the growth potentials for these countries should be expanded through increasing productivity improvements as there are considerable limitations of the contribution of factor accumulation to long-run economic growth. In this respect, recent economic growth theories have emphasized the importance of technological innovation and human capital to improve productivity.

The attention to technological innovation and the role of human capital as the key determinants of long-term growth of the economic system began with the endogenous growth theory (Lucas, 1988; Romer, 1990). Economic models based on the endogenous growth theory attempted to identify the possibility of long-term economic growth driven by productivity improvements through an endogenous process within the economic system, rather than considering technological advancement as an exogenous factor focused on key elements that offset the effects of diminishing marginal product of physical capital. These studies commonly assumed that as national economies approach the steady-state equilibrium, the returns to capital would decline and the growth would slow down with the diminishing marginal product of physical capital. Based on this assumption, these studies noted that long-term economic growth can be achieved by the endogenous selection of economic agents if there is adoption/selection of production technology (production function) that can offset the diminishing marginal product of physical capital. Accordingly, the role of innovation (Acemoglu et al., 2006; Aghion & Howitt, 2005; Ang & Madsen, 2011; Grossman & Helpman, 1991; Grossman & Helpman, 1994; Romer, 1986, 1990, 1994) and human capital (Becker, 1964; Kim & Lee, 2011; Lee & Lee, 2016; Lucas, 1998) as the key factors that determine the form of production function or production technology gradually began to draw attention in the growth models based on the endogenous growth theory.

Furthermore, in recent years several studies have attempted to explain the growth patterns of national economies by emphasizing the long-run economic growth driven by endogenous complementarity effects between human capital accumulation and technological innovation. These studies stressed on the importance of efficient combinations of production factors (i.e., knowledge and human capital), rather than the level of factor inputs to account for long-run economic growth (Acemoglu et al., 2006; Benhabib & Spiegel, 1994; Hall & Jones, 1999; Klenow & Rodriguez-Clare, 1997; Vandenbussche et al., 2006). From this perspective, these studies put emphasis on the role of human capital accumulation that determines the national capabilities to adopt, assimilate, and utilize knowledge (i.e., innovation capabilities) from the pool of technology and knowledge, and furthers the complementarity between the technology selection (adoption) and human capital accumulation (Benhabib & Spiegel, 1994; Nelson & Phelps, 1966).

These studies have stated that human capital plays a crucial role in establishing the national capacity to adopt technologies in low-income countries. Whereas, in countries that are close to the technological frontier level (i.e., high-income countries), the capacity to create new technological innovation is more important than the ability to imitate and adopt pre-existing technologies. Accordingly, these studies emphasized that relative stress on the width and depth of skills and knowledge required for human capital accumulation can be different in accordance with the proximity to the technological frontier and income level of the economy (Kim & Lee, 2011). Accordingly, it is noted that the dynamics of complementarity between human capital accumulation and innovation affects the growth trajectory of an economy.

The discussions on the complementarity between innovation and human capital that shapes the growth patterns of an economy have become more active in recent years. Earlier studies that focused on the relationship between innovation and human capital, and its effects on economic growth considered human capital stock a homogenous element. In other words, those studies assumed perfect substitutability between labor inputs that possess different levels of skills (knowledge) within a production function (technology) (Hamermesh, 1993; Jorgenson et al., 1994). From this point of view, the studies aimed at identifying the relationship between innovation and human capital, or labor market generally concluded that innovation can lead to higher total employment in the economic system through increased productivity and greater scale effects (Pissarides, 2000). In other words, those studies addressed the complementarity between innovation, human capital, and economic growth by focusing on the level effects of human capital rather than on the composition effects of human capital (Vandenbussche et al., 2006).

However, as recent studies on skill-biased technological change (SBTC) that shapes the relationship between innovation and labor have extended the discussions to consider heterogeneous human capital with different characteristics and marginal products. SBTC, the intrinsic property of technological progress, suggests that the relationship between labor with different skills and knowledge and innovation is not only complementary, but also substitutable (Acemoglu & Autor, 2011b; Ales, Kurnaz, & Sleet, 2015; Blanchard & Katz, 1997; Bresnahan et al., 2002; Card & DiNardo, 2002; Goos et al., 2014; Jung et al., 2017; Michaels et al., 2014; Vivarelli, 2014). STBC can be described as the non-neutral shift in production function (production technology) induced by technological innovation that disproportionately increases the demand for high-skilled labor over skilled and unskilled labor. For example, Blanchard and Katz (1997) found that the effects of the diffusion and adoption of innovation on the demand for skilled and non-skilled labor could lead to a decline in total employment, as the labor supply curve of non-skilled labor is relatively elastic, while the supply curve of skilled labor is inelastic.

Further, recent studies have theoretically and empirically demonstrated that technological innovation not only leads to skill-biased technological progress, but also leads to capital-biased, or labor-saving technological progress (Bridgman, 2017; Doraszelski & Jaumandreu, 2018; Jung et al., 2017; Karabarbounis & Neiman, 2014). This labor-saving technological progress suggests that technological innovation can possibly take place with uneven effects on the marginal productivities of capital and labor, which implies a decreases in the share of labor income in the economy (Acemoglu & Robinson, 2015; Karabarbounis & Neiman, 2014). Accordingly, the intrinsic characteristics of technological progress, which can be described as skill-biased and capital-biased (labor-saving) technological change shape the net demands for factor inputs by interacting with the labor market that accumulates heterogeneous human capital to embed in the production technology or production function.

Empirical studies from this perspective have shown that factor-biased technological progress is one of the key underlying determinants of the change in employment and wage structure in an economy (Acemoglu, 1998; Autor et al., 2017; Haltiwanger et al., 2014; Karabarbounis & Neiman, 2014; Mallick & Sousa, 2017; Mućk et al., 2018; Shim & Yang, 2016). These studies have investigated the correlation between technological advances and the relative demand for skilled and low-skilled labor and found that a shift in the production technology driven by innovation has a tendency to favor skilled over low-skilled labor, by increasing its productivity, and therefore, its relative demand. In addition, these studies have also found that this skill-biased technological progress is one of the key determinants of the change in the wage and income structure of the economy. Furthermore, studies have argued that when innovation is embodied as capital goods within the production technology, the marginal productivity of heterogeneous labor differs from the marginal productivity of capital, leading to technological unemployment (i.e., structural unemployment) and a reduction in the share of labor income in the economy (Bridgman, 2017; Brynjolfsson & McAfee, 2012a, 2014; Doraszelski & Jaumandreu, 2018). Based on empirical findings, these studies have provided the evidence for the relationship between the intrinsic attributes of technological progress and its impact on the labor market and income distribution, including the polarization of the labor market and widening income inequality.

As such, innovation induces changes in demand for labor and relevant skills (i.e., human capital) through direct and indirect channels such as, reduced production costs, spillover effects from knowledge capital accumulation, increased variety of products, and scale effects within the economy (Acemoglu, 2012; Danninger & Mincer, 2000; Uhlig, 2004). To be more specific, technological innovation has the tendency to bring about a factor-biased technological progress and plays a central role in deepening income inequality and income polarization in the economy. The changes in labor supply due to human capital accumulation also affect technology adoption and diffusion. This interrelationship between innovation and human capital accumulation shapes the patterns of long-term economic growth and distribution in the economy (Brynjolfsson & McAfee, 2014; Card & DiNardo, 2002; David et al., 2006).

From this point of view, it can be understood that the interrelation between innovation and human capital accumulation leads to a conflict between growth and distribution, explaining the economic phenomenon contrary to the Kuznets' hypothesis found in developed economies (Goos et al., 2009; Goos et al., 2014). Several empirical studies have pointed out that deepening of income inequality can undermine the economic foundations and hamper long-run growth (Joumard et al., 2012; Lahiri & Ratnasiri, 2012; Ostry et al., 2014). It is therefore important to determine what types of policy options can be used to achieve the twin objectives of growth and distribution together within a knowledge-based economy. Given that the patterns of economic growth and distribution within an economy are the outcomes of complex interactions among various actors and institutions within the economic system, policy design should be pursued with comprehensively and systematically.

To this end, it is essential to propose a wide range of policy options to spur inclusive growth in a knowledge-based economy with the understanding of the dynamic interaction between technological progress and human capital accumulation and its interrelationship with other institutional conditions (Bogliacino & Vivarelli, 2012; Vivarelli, 2013, 2014). Vivarelli (2013, 2014) highlighted that to understand the relationship between innovation and human capital and its macroeconomic impact on the growth patterns, various compensation mechanisms via various paths within an economy should be considered, as along with the direct impact of factor-biased technological progress on the labor market from an economy-wide perspective. According to Vivarelli (2013, 2014), the initial labor saving impact of innovation can be counterbalanced by various compensation mechanisms through new demand from technological innovation (Edquist et al., 2001; Nickell & Kong, 1989), increases in new investments and associated scale effects (Edquist et al., 2001; Say, 1964), increases in product varieties (Pianta & Vivarelli, 2000; Stoneman, 1983; Stoneman & Ireland, 1983), decreases in commodity prices, increases in household incomes, and so on.

In this regard, Vivarelli (2013, 2014) had highlighted that to understand the interrelationship between innovation and human capital, it is crucial to consider the indirect effects of innovation on the labor market and induced different mechanisms of compensation effects, along with an understanding of the direct effects triggered by factor-biased technological progress including skill-biased and capital-biased technical changes. Accordingly, in addition to an in-depth understanding of the relationship between technological innovation and human capital in a knowledge-based economy, evidence-based innovation policy design should be pursed, based on the quantitative analysis of the economy-wide effects of the dynamic interaction between the innovation and human capital composition.

1.2 Research motivation

Generally, the policy impact assessment of innovations policy is dominated by ex-post analysis (Edler et al., 2016; Hong et al., 2014; Liu et al., 2018; Loikkanen et al., 2013). The absence of an ex-ante analysis on innovation policy is strongly associated with the difficulties in quantitatively measuring and estimating the volume of intangible capital assets, and their impact due to the inherent uncertainty of knowledge and technological innovation and the external effects (or scale effects) triggered by technological innovation

(Jung et al., 2017; Yang et al., 2015; Yang et al., 2012; Lee et al., 2012; Hwang et al., 2015). Therefore, quantitative methodologies, like regression analysis are actively used for the ex-post analysis of the innovation policy impact assessment because of the advantages of easily acquiring the relevant statistics and being methodologically simple.

However, from the perspective of policy-makers, this ex-post analysis is somewhat insufficient as a policy impact assessment tool, as it assumes partial equilibrium making it difficult to grasp the effects of policy options on the entire economy and is limited in comparing and analyzing the effect of various policy options (Burfisher, 2017). In this regard, when it is possible to quantify the characteristics of knowledge and innovation, the ex-ante analysis of the impact of innovation policy can be a more useful approach to estimate the economy-wide effects of innovation policy with considerations of the external effects (or scale effects) triggered by technological innovation. The ripple effects of technological innovation are not just limited to the policy beneficiaries groups, and the influence is spread through inter-industry linkages and inter-institutional relationships. This is closely related to the nature of knowledge and technology innovation, including indivisibility and non-excludability. In this regard, a computable general equilibrium (CGE) model can serve as a useful methodology for the ex-ante analysis of the effect of innovation policies (Burfisher, 2017; Dixon & Rimmer, 2013; Dwyer et al., 2006). The CGE model consists of a series of equation systems describing the general equilibrium of the economy, with theoretical assumptions on production technology, preferential relations, factor inputs, government, households, enterprises, imports and exports, and so on. The exogenous changes of policy variables in the CGE model described by the equation systems allow us to grasp the economy-wide impact of the policy options. If the policy variables are considered exogenous variables within the CGE model, the new equilibrium solution can be calculated by imposing policy shocks with variants in those exogenous policy variables, and the economy-wide effects of the policy options can be quantitatively measured by comparing the new equilibrium with the initial solution. In this respect, CGE model is similar to comparative static analysis (Hosoe et al., 2010).

In other words, in analyzing the economy-wide impact of policy design alternatives, the CGE model can serve as a useful methodology with the following features: 1) the logical descriptions of the behaviors of the economic entities, 2) the evaluation of the policy impact from the economy-wide perspective with considerations of inter-industrial and inter-institutional linkages, 3) the numerical presentation of economy-wide effects with a wide range of macroeconomic variables, and 4) the availability of various policy experimentations with different assumptions on the exogenous policy variables. Accordingly, such a CGE model has been utilized as a useful analytical tool in various fields, including international trade, environment and energy and tax policies. In the 2000s, some CGE models were applied to innovation policies. However, despite the importance of innovation as an important growth engine for economic growth in the knowledge-based economy, the CGE model and other macroeconomic models for the innovation policy impact assessments were not actively developed due to the difficulty in data construction and modeling reflecting the characteristics of innovation and knowledge. The absence of such methodological foundations has provided limited perspectives in understanding the economy-wide effects of technological innovation and the relationship/interaction between innovation and other economic variables within the economy.

This study aims to present a CGE model and social accounting matrix (SAM) data that explicitly reflect the characteristics of innovation and knowledge with descriptions on knowledge as another production factor within the production function, knowledge accumulation through innovation activities, and the spillover effects in the economy, to overcome the limitations of previous studies that focused on the innovation policy impact assessments. Through this, this study aims to provide a methodological basis for the long-run economic growth rates to be endogenously determined by innovation activities within the CGE model, without considering innovation-related factors as exogenous elements.

In addition, based on the arguments suggested by previous studies that the dynamic interaction between innovation and human capital affects the growth and distribution in the knowledge-based economy, this study aims to construct the CGE model with descriptions on the endogenous interaction between knowledge accumulation and human capital accumulation within the production function. Technological progress is an endogenous process, rather than exogenous (Acemoglu, 2002; Acemoglu & Autor, 2011a). As emphasized by recent studies, the pace and direction of technological progress are determined endogenously in accordance with the distribution of skills in the economy, and the distribution of skills are affected by factor-biased technological change and human capital accumulation (Grossma et al., 2017; He & Liu, 2008; Pan, 2014). The previous studies based on this perspective had attempted to propose theoretical models to account for the contribution of the complementarity between skill upgrading via human capital investments and technological progress embodied in capital goods in the long-run economic growth (Grossman et al., 2017). However, it is hard to find empirical studies that reflect this perspective using macroeconomic models based on identifiable macroeconomic data. These were the methodological limitations for extending the understanding of how the interaction between innovation and human capital is endogenously formed through various channels within the economy and how the long-run economic growth rates appear through it. Accordingly, this study aims to provide the methodological foundations within the CGE model, where the pace and direction of technological progress are determined endogenously in accordance with the distribution of skills in the economy and the distribution of the skills are affected by the factor-biased technological change and human capital accumulation.

In addition, various studies that focused on the distribution issue within the economy based on a CGE model have tried to investigate the income distribution effects triggered by the policy scenarios with considerations of heterogeneous households and labor by preparing the SAM dataset with classifications of the households account into multi-income groups and division of labor within the production factor account in terms of years of schooling (Oh et al., 2014; Jung & Thorbecke, 2003; Jung et al., 2017; Kim & Kim, 2005; Ojha et al., 2013; Siddiqui et al., 1999; Kim & Kim, 2010; Cho & Kim, 2017; Ji, 2001). These studies have mainly focused on taxation, redistribution, and education policies to investigate the mid- to long-run economy-wide effects, driven by changes in relevant policy variables. However, these studies lack the in-depth considerations of technological progress as an endogenous process within the model. Even though technological progress was considered within the model, it reflected exogenous technological progress (Ojha et al., 2013). This study aims to extend the discussions addressed by the previous studies that focused on the income distribution issue within the economy based on the CGE analysis through reflecting the micro-level perspective in the SAM dataset and the CGE model with considerations of heterogeneous labor and households, and facilitating a comprehensive analysis of the growth and distribution effects induced by the endogenous interaction between technological innovation and human capital accumulation with relevant equation systems. Through this, this study expects to verify and enhance the usefulness of the designed CGE model that can simultaneously measure the growth and distribution effects driven by a wide range of policy options that affect the dynamic interaction between innovation and human capital accumulation.

As mentioned earlier, the dynamic interaction between innovation and human capital accumulation in the knowledge-based economy shapes the growth and distribution patterns of the economy. Therefore, it is essential to investigate what types of policy options can be used to achieve the objectives of growth and distribution within the knowledge-based economy. So, it is expected that the use of the CGE model will gradually increase as a quantitative methodology to analyze the growth and distribution effects induced by a variety of policy options to spur inclusive growth in the knowledge-based economy. Our study aims to overcome the methodological limitations of previous studies based on the CGE methodology and present an integrated CGE model that reflects the following key factors: 1) endogenizing the innovation-related elements considering the characteristics of innovation and knowledge (knowledge as a factor of production, endogenization of knowledge capital investments, and spillover effects of knowledge accumulation via productivity improvements), 2) endogenizing the decision-making process of labor on human capital accumulation (i.e., up-skilling and re-training) affected by the relative wages of workers and educational investments within the economy, 3) designing the endogenous interaction between knowledge capital accumulation (i.e., innovation) and human capital accumulation within the production function, 4) describing the intrinsic attributes of technological progress within the production structures, and 5) establishing the macroeconomic model to simultaneously estimate the growth and distribution effects with considerations of heterogeneous labor and households within the equation systems and SAM. It is expected that this study would provide a theoretical and methodological basis for analyzing the effect of various policy options and alternatives in terms of growth and distribution within the knowledge-based economy. So far, previous studies using the CGE model that explicitly considered the innovation and R&D (research and development) activities within the model have focused on the direct support measures for innovation activities and their impact on the economy, including subsidies and tax grants on R&D investments. However, it is expected that the scope of the innovation policy impact assessments will be expanded by considering the various policy instruments, such as human capital investment and tax policy. Furthermore, we also expect the proposed CGE model to be used as a tool for policy impact assessments to determine what types of policy options can achieve both growth and distribution objectives in a knowledge-based economy.

1.3 Research purpose and outline of the study

This study intends to proceed in the following steps with different objectives. Before developing the CGE model in Chapter 2, this study aims to present the theoretical background of this study and summarize the key findings of relevant theoretical and empirical studies. Through this, this study aims to promote the understanding of the key concepts to be discussed in this study, by addressing that the interaction between innovation and human capital is an important determinant of economic growth and distribution, and this interaction is an endogenous process within the national economy. To this end, this study contains a comprehensive review of previous studies that focuses on the contributions of innovation and human capital to economic growth, endogenous interaction between innovation and human capital composition, and impact of the dynamic interaction between innovation and human capital composition on the labor market and income distribution. The theoretical and empirical findings of the previous studies presented in Chapter 2 serve as the theoretical basis for establishing the equation systems in the CGE model. In addition, this study aims to conduct a systematic review of the empirical studies that have utilized CGE models and the methodology used by those studies to highlight the contribution of this study in terms of a methodological development for policy impact assessments.

In Chapter 3, this study conducts a SAM-based multiplier analysis based on the knowledge-based SAM constructed. Based on the SAM multiplier analysis, this study investigates the relationship between innovation, labor market, and income distribution by focusing on the Korean economy to verify the stylized facts proposed in previous studies. By analyzing the results of SAM-based multiplier analysis, we estimate the direct and indirect effects triggered by the increased innovation activities by calculating the multiplier effects in endogenous accounts including the industrial outputs, value-added, incomes and expenditures of households, induced by the variants in exogenous accounts within the SAM data. With this research objective, we propose methods and procedures to construct a knowledge-based SAM and provide descriptions for the methodological principles of the SAM-based multiplier analysis.

In Chapter 4, we present explanations on the main characteristics of the CGE model constructed in this study including the descriptions of key components and structures of the model with relevant equations. To be more specific, this chapter provides the descriptions of the following key elements and components of the CGE model: 1) endogenizing the innovation-related elements considering the characteristics of innovation and knowledge (knowledge as a factor of production, endogenization of knowledge capital investments, and spillover effects coming from the knowledge accumulation via productivity improvements), 2) endogenizing the decision making process of labor on the human capital accumulation (i.e., up-skilling and re-training) affected by the relative wages of workers and educational investments within the economy, 3) designing the endogenous interaction between the knowledge capital accumulation (i.e., innovation) and human capital accumulation within the production function, 4) establishing the macroeconomic model to simultaneously estimate the growth and distribution effects with considerations of heterogeneous labor and households within the equational systems and SAM. Through this, we highlight that the CGE model in this study is a suitable model for analyzing growth and distribution effects induced by the endogenous interaction between the innovation and human capital accumulation, which can be used as a methodological tool for the innovation policy impact assessments. This chapter highlights the explicit descriptions of the endogenous interactions between innovation via knowledge capital accumulation and changes in labor supply (and associated change in human capital compositions) via human capital accumulation from a dynamic perspective within the model.

In Chapter 5, this study conducts a quantitative analysis of how long-run economic growth can be achieved through the endogenous interaction between innovation and human capital accumulation via R&D investments and educational investments within the economy based on the constructed knowledge-based CGE model. This study investigates the direct and indirect paths within the economy driven by the endogenous complementarity between the innovation and human capital accumulation that shape the growth patterns of the economy. To be specific, we analyze the effects of human capital accumulation through the endogenous skill upgrading of workers on innovation activities, as well as the effects of knowledge capital accumulation through R&D investments on human capital accumulation quantitatively. Based on the policy simulation of the CGE model, this study highlights the contribution of the complementary relationship between R&D and educational investments to sustain the knowledge-based economy, by stressing that the right types of skills and knowledge to 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 to enhance the long-run productivity improvements.

In Chapter 6 we present the recent discussions on innovation and its impacts on the labor market and income distribution, including the polarization of the labor market and widening income inequality driven by factor-biased technological progress. Based on those discussions, this study proposes a policy-mix consisting of innovation, education, and tax policy, and conducts policy simulations with constructed policy scenarios to draw policy implications on policy design to mitigate the side-effects of technological progress (i.e., polarization of the labor market and widening income inequality). Through this, we quantitatively analyze the macroeconomic effects of policy options in terms of growth and distribution effects, considering the interaction mechanisms between innovation, education, and tax policy. Based on the quantitative analysis we point out the limitations of the frameworks and approaches of previous studies. We highlight the importance of the policy-mix to address the growth and distribution objectives within the economy considering the dynamically changing complementarity between technological innovation and human capital. Finally, Chapter 7 summarizes the key findings and presents policy implications and the limitations of the study to establish the direction for future research to take.

Chapter 2. Literature Review on Theoretical and Methodological Approaches

2.1 The role of innovation and human capital in growth

2.1.1 Endogenous interaction between innovation and human capital

Various studies attempted to explain the growth of the national economy put emphasis on the growth effects driven by the technological innovation and human capital accumulation. These previous studies emphasize that the efficient combination among factors of production is more important than the input levels of factors of production to account for the differences in income levels among countries (Acemoglu et al., 2006; Benhabib & Spiegel, 1994; Bernanke & Gürkaynak, 2001; Hall & Jones, 1999; Klenow & Rodriguez-Clare, 1997; Vandenbussche et al., 2006). Related studies apply the broad concept of capital that encompasses both physical and human capital as factors of production, and assume the constant returns instead of diminishing returns of capital. Based on these assumptions, those studies emphasize the role of human capital as the key element which drive the technological progress by expanding the scope of studies that attempted to explain long-term economic growth (Lucas, 1988; Uzawa, 1965). In this regard, Benhabib and Spiegel (1994) empirically prove that technological progress has a positive correlation with the accumulation of physical capital or human capital, and criticize the neoclassical economics’ assumption that technological progress is made exogenously.

With emphasis on the role of innovation activities, which are economic activities that bring about technological progress, technology adoption or transfer from the foreign countries may serve as key growth engines for low income countries far from the technological frontier level (Rustichini & Schmilz, 1991). Nelson and Phelps (1966) point out that differences in the levels of human capital accumulation play a crucial role in explaining the gaps of technological innovation and technology diffusion among national economies. In particular, Nelson and Phelps (1966) emphasize that technological catch-up speed through technology diffusion and technology adoption of the national economy can be expressed by the function of human capital accumulation level. Moreover, Romer (1990) mention that human capital may have effects on determining the national capabilities to develop and create new technologies by expressing technological progress or TFP growth within the economic system as the function of human capital level (i.e., education level).

As such, a great deal of technologies and knowledge are known and disclosed to the world, but economies' capabilities to adopt and utilize such a pool of technologies and knowledge are determined by their human capital accumulation levels (Acemoglu et al., 2006; Benhabib & Spiegel, 1994; Nelson & Phelps, 1966; Rustichini & Schmilz, 1991). In other words, the direction and pace of technological innovation are determined by the level of the human capital accumulation. Previous studies including Benhabib and Spiegel (1994), Borenztein, DeGregorio, and Lee (1998), and Acemoglu, Aghion, and Zilibotti (2006) have attempted to integrate the viewpoints of Nelson and Phelps(1966) and Romer (1990), and stated that technological progress is outcomes of innovation and imitation or technology adoption. Moreover, they claim that there is a technology gap between high-income and low-income countries, and emphasize the level of human capital accumulation as a key concept to explain the absorptive capacity of the individual national economy (Parente & Prescott, 1994). These studies expand the perspectives of Nelson and Phelps (1966) and Romer (1990), emphasizing that the source of technological progress is the dual structure of imitation and innovation.

For example, Benhabib and Spiegel (1994) examine through growth accounting that human capital can be a driving force of technological progress, and reflect two paths through which human capital affects technological progress within the growth accounting model. The first is the domestic innovation (Romer, 1990), and second is the catch-up to foreign technologies (Nelson & Phelps, 1966). In this perspective, studies including Benhabib and Spiegel (1994), Borenztein, DeGregorio, and Lee (1998), and Acemoglu, Aghion, and Zilibotti (2006) have tried to explain the long-run growth of the national economies considering the theological frontiers and the proximity to the technological frontier level of the national economies. Low-income countries are far from technological frontiers, in which case the imitation strategy becomes the best strategy to spur the long-run economic growth. On the other hand, if the national economy approaches closer to technological frontier level, those countries can achieve the long-run economic growth by switching to the innovation strategy from the imitation strategy. Based on these assumptions, those studies propose theoretical economic growth models, in which advanced countries (high-income countries) and technology leaders have higher intensities of innovation activities that create new technologies, while followers have higher intensities of imitation and technology adoption (Rustichini & Schmilz, 1991).

In this technology diffusion model, the economic growth rates of developing and low-income countries depend on how well they can absorb and apply the technologies developed by advanced countries. In other words, the inflow of new technologies from advanced countries and the ability to absorb such technologies determine the technological progress of low income countries. Accordingly, the importance of human capital is further emphasized because more workers with high level of knowledge and skills accumulated from education lead to greater understanding and applicability of new technologies. Maintaining this view, Acemoglu (2002) stress out the growth effects through the interaction between human capital accumulation and technological progress, addressing the importance of the human capital to drive the endogenous technological change. That is, if there is more accumulation of available human capital, the R&D activities for technological innovation become more active. Thus, an economic system with higher level human capital accumulation tends to has higher rates of technological progress and even economic growth. As such, studies such as Borenztein, DeGregorio, and Lee (1998), and Acemoglu, Aghion, and Zilibotti (2006) are also emphasizing the role of the human capital accumulation level in technology diffusion between developed and underdeveloped countries. Moreover, assuming that human capital serves as a driving force that leads technological progress and productivity growth, those studies especially emphasize that human capital contributes to economic growth through facilitating the technological innovation carried out endogenously within the economic system, or the spurring the imitation and adoption of technologies (Caselli & Coleman, 2001).

Those previous studies account for the contribution of the level effects of the human capital accumulation on the productivity improvements and technological progress, leading to the long-run continuous economic growth. Furthermore, the aforementioned studies emphasize the effects of technological innovation and technological catch-up driven by the changes in the level effects of the human capital accumulation. However, Krueger and Lindahl (2001) mention that the case in which the human capital accumulation level has a statistically significant positive correlation with the growth of national economy is limited only to countries with the lowest level of education. In particular, this study addresses that the effect of the human capital accumulation level on the economic growth has quite different pattern and distribution among high-income countries. To be specific, Krueger and Lindahl (2001) point out that while there is a strong positive correlation between education level and economic growth in low-income countries, and middle-income countries, such a positive correlation does not appear in high income countries. With focus on this finding, they raise the issue of whether the effect of the human capital accumulation level is suitable for explaining the stages of economic development and growth. Such empirical evidence has been raised in other studies (Durlauf & Johnson, 1995; Pantelis et al., 2001).

Based on the issue raised by Krueger and Lindahl (2001) regarding the relation between the level of human capital accumulation (i.e., average educational attainment level) and economic growth, Vandenbussche et al. (2006) emphasize that studies attempted to investigate the interrelationship between the human capital accumulation and innovation, and its effects on the economic growth had focused only on the level effects of human capital accumulation, and point out their limitations. Accordingly, Vandenbussche et al. (2006) emphasize that it is necessary to lay stress on not only the level effects, but also composition effects in discussing the relation between human capital and technological innovation to account for the economic growth. From this perspective, this study emphasizes two factors in explaining the long-run growth of national economy: 1) how far the national economy is from the technological frontier level, and 2) the composition of human capital (Vandenbussche et al., 2006). Grossmand and Helpman (1991) also put emphasis on the close correlation between the skill composition of workers and the level of innovation within an economic system. This study particularly highlights that the increase in the labor stock of the skilled labor can bring about the growth-enhancing effects, whereas the increase in low-skilled labor stock can lead to the growth-depressing effects. As an extension of Grossman and Helpman (1991), Vandenbussche et al. (2006) have tried to explain the patterns of the technological innovation and economic growth of national economies in accordance of the human capital compositions with the consideration of the distance from technological frontiers.

Accordingly, Vandenbussche et al. (2006) propose an economic model with those following assumptions. Firstly, they classify human capital into skilled and unskilled within the economy, and assume that the two different types of human capital either develop technology (i.e., innovation) or adopt technology (i.e., imitation). Secondly, they assume that two types of human capital have relatively different productivity within the production function. Thirdly, similar with previous studies including Benhabib and Spiegel (1994) and Acemoglu, Aghion, and Zilibotti (2006), they assume that technological progress within the economic system has a dual structure of technological innovation and imitation. Under those underlying assumption, Vandenbussche et al. (2006) intend to capture technological progress through investigating the dynamic change of productivity within individual industries, where the productivity change of the individual industry is determined by the relative share of unskilled and skilled labor input in the imitation sector, and the relative share of unskilled and skilled labor input in the innovation sector. Here, they set higher elasticity of demand for skilled labor in the innovation sector compared to the unskilled labor. Based on the economic model designed with those assumptions and features under the general equilibrium perspective, Vandenbussche et al. (2006) have conducted the decomposition analysis on the productivity growth and economic growth based on the panel data of 19 OECD (Organisation for Economic Co-operation and Development) countries from 1960 to 2000, and found out a positive correlation between the educational attainment level and proximity to the technological frontier level. Furthermore, they have stressed out that the closer to the technological frontier, the higher the proportion of the skilled workers with tertiary education, the more growth-enhancing effects.

Maintaining this viewpoint proposed by Vandenbussche et al. (2006), Acemoglu, Aghion, and Zilibotti (2006) have conducted an empirical analysis on over 100 countries between 1960 and 2000 based on the Schumpeterian growth theory. They emphasize that technology leaders and high-income countries focus on technological development to supplement skilled labor, and low-income and developing countries achieve great economic growth effects from technological development that supplements unskilled labor, highlighting the correlation between the modes of innovation and the composition of the human capital accumulation. Accordingly, this study addresses that the discrepancy between technology and skill can generate greater complexity in technological innovation and adoption (selection). They have also proved through a proposed theoretical model that the mismatch between technology and skill may increase in the process of switching from imitation to innovation strategy if skilled workers fail to enter the economic system due to the privileged ones (i.e., old managers with lower skills) in the existing system, which serves as a barrier for the transition into the innovation strategy, and thus the economic system may face long-term stagnation in economic growth. Based on this finding, Acemoglu, Aghion, and Zilibotti (2006) emphasize that institutional conditions and policies should be co-evolved as the economic system approaches to the technological frontier level to maximize growth effects must seek co-evolution. Similar empirical studies from this perspective include Aghion et al. (2004) and Aghion et al. (2005), etc.

For example, Aghion et al. (2004) and Aghion et al. (2005) focus on the British and Indian industries and confirm that industries and counties with low openness tend to show more rapid decrease of average growth rates as they approach to the technological frontier level, while high entry barriers for entrants within the economies and sectors lead to growth-depressing effects. Those studies prove the interaction effects between the level of entry barrier and technological development (gap), as well as the correlation between the openness of sectors and productivity growth. Based on quantitative analyses, they also emphasize the importance of interaction between technological variables and institutional and political variables.

Moreover, Krueger and Kumar (2004) claim that economic growth led by technological innovation is determined by two types of human capital in terms of the forms of learning, leading to the matter of choosing either general or vocational education. They address that general education is highly effective for workers to obtain the competencies to utilize new production technology, while vocational education is effective for workers to digest and efficiently manage the technology that is already established. Based on this underlying assumption, they distinguish workers that have received general education from those that received skill-specific education within the general equilibrium model, by assuming that only the former can be utilized with higher productivity when a new technology is introduced in the production function. Moreover, within the general equilibrium model they make an assumption that only workers who received the general education over the life-cycles can be engaged in the economic activities in high-tech industry by considering that the low-tech industry in which existing technologies are used, as well as the high-tech industry in which new technologies are used within the production function. Furthermore, this study considers the adoption costs of technology in high-tech industry as the increasing convex function of the distance between the technological frontier level ($A_{f,t}$) and current technological level of the industry (A'_t). Based on those underlying assumptions, they have proposed a general equilibrium model to account for the endogenous process of technological progress through having workers accumulate skills and make decisions about choosing the participation into the labor market, based on wage changes according to relative demand change for workers demanded by the high-tech industry. Their study also prove that the growth rate of national economy in long-run g_A can be expressed as the function of the share of workers who finished the general education (η_g); $g_A(\eta_g) = ({}^{w_a}/_{w_n})[\frac{\eta_g E_h}{(1-\eta_g)h}]$. In the equation, w_a and w_n indicate the wage level of workers in the high-tech and low-tech industries, and E_h indicates the expected level of skills that can be obtained in the next stages of the life-cycle by workers that had chosen general education in the first stage. Moreover, h indicates the level of skills possessed by workers that had chosen vocational education. Based on these methodological settings, Krueger and Kumar (2004) comparatively analyze the growth patterns of the U.S (United States) and Europe, and find out that the U.S has a relatively higher intensity of workers who received general education than Europe, which accounts for a higher economic growth rate experienced by the U.S economy.

Similar to this perspective, Kim and Lee (2011) have modeled the complementarity between human capital accumulation and technology adoption under the uncertainty of technological progress, and presented a theoretical model to account for how the dynamic interaction between the human capital accumulation and new technology adoption affects long-term economic growth trajectories of the economies. To be specific, this study analyze how the wave of technological progress affects the human capital investments, as well as the technology adoption which is endogenously determined by the compositions of the human capital in the economy. Furthermore, this study have put emphasis on the different roles of the width and depth of human capital in technology adoption, and claimed that the width of human capital determines the costs required for technology adoption, while the depth affects the level of technology that can be adopted. With this argument, this study also have addressed that the width of human capital is associated with the flexibility and adaptability of the workers, and the depth of human capital is related to the specialty of the knowledge and experiences for innovation (Kim & Lee, 2011). According to their proposed model, economic agents maximize their utility by allocating their time for human capital accumulation and labor market participation during the young period, and for technology adoption during the old period during the two-periods of life-cycles in a situation where technological progress is uncertain. Based on these underlying assumptions and methodological settings, the probability of the technology adoption within an economic system can be expressed as the function of the expected value of technology adoption costs and uncertainty of technological shocks which is endogenously determined within the model. By conducting empirical analysis based on the model, this study has found out that the economic system may have different growth paths depending on the initial structure of human capital and technological uncertainty. When there is a newly introduced technological shock, a new technology can be efficiently adopted if the adoption cost is low (in an economy with great width of human capital), which leads to greater level of human capital investment in the following periods by increasing the returns of human capital investments. However, if the probability of the technology adoption is low and uncertain due to the excessively high adoption costs (in an economy with low width of human capital), the expected returns of human capital investments increase, while the economic growth rates decrease, thereby resulting in a poverty trap.

Furthermore, to explain the growth patterns of countries that fell into the middle-income growth traps, studies including Agenor and Canuto (2015) and Agenor and Dinh (2015) have attempted to investigate the contribution of the human capital composition in the economic system on economic growth through human capital accumulation and the allocation of talents (i.e., workers with heterogeneous skills) among industrial sectors based on developed theoretical models under the general equilibrium perspective. With these objectives, those studies have proposed general equilibrium models in which workers face the choices of education (i.e., human capital accumulation) and labor supply in their entire life-cycles (assuming that the life-cycle has two stages: youth and middle/old age). They set up an economic system in which workers that accumulated advanced skills through human capital accumulation can be allocated to the industry producing new designs, whereas workers with relatively lower skills who did not accumulate human capital are distributed to an industry producing and manufacturing final goods. Moreover, they have presented the economic system in which the increase of designs and blueprints created in the design sector determines the variety of intermediate goods, thereby affecting the long-term economic growth (Agénor & Canuto, 2015; Agénor & Dinh, 2015). To be specific, they set up the general equilibrium model so that the design sector has higher productivity than the industry producing final goods, which enables to identify the productivity growth and growth-enhancing effects driven by the evolution of the human capital composition within the economic system.

Those studies conducted by Agenor and Canuto (2015) and Agenor and Dinh (2015) commonly consider the following sectors within the economic system; 1) sector producing final goods, 2) sector producing intermediate goods, and 3) sector producing designs that come up with new ideas or blueprints that determine the diversity (i.e., variety) of intermediate goods being produced. Consideration of such industrial sectors reflects the intuition of Romer (1990)'s work. With these considerations of the industrial sectors within the model, the design sector is assumed to utilize labor and public capital as production factors, and the manufacturing sector producing final goods has the production function consisting of labor, physical capital, and intermediate goods as production factors. Moreover, the industry producing intermediate goods purchases new ideas and blueprints produced by the design sector by paying a certain amount of cost to produce intermediate goods. Here, the industry producing final goods is assumed to be an industry with lower productivity, whereas the design industry is assumed to be an industry with higher productivity and higher level of technological advancement utilizing the workers with advanced skills. In particular, their general equilibrium models are commonly assuming that the long-run economic growth rate of the economy is determined by the growth rate of newly produced designs and blueprints created in the design sector.

These series of previous studies have expanded from the discussions about technological innovation (i.e., technological progress) and growth driven by the level effects of human capital accumulation, and are leading the discussions on the contribution of the human capital compositions within the economy on the economic growth. Those studies are commonly emphasizing that the composition of skills possessed by workers in the economic system is very important in determining the width and depth of the technology market that can be developed and adopted. Accordingly, the aforementioned studies provide implications that the composition of human capital determines the rates of technological innovation and technology adoption, and well explains the long-run economic growth by emphasizing the strong interrelationship between the heterogeneous composition of human capital and technological innovation.

2.1.2 Factor-biased technological change and its impacts on economy

From the literature review presented in previous section, we can understand that recent studies investigating the complementarity between innovation and human capital are expanding their scopes from the discussions on the level effects of human capital accumulation on the productivity growth (i.e., technological progress), and economic growth, to the discussions on the composition effects of human capital accumulation with considerations of the heterogeneous labor with different skills. Moreover, in addition to the discussions on the interaction between technological innovation and human capital accumulation, various studies are recently focusing on the intrinsic attributes of technological innovation that bring about factor-biased technological progress, as more attention is paid to the composition effects including consideration of heterogeneous human capital. Studies focusing on the concept of factor-biased technological progress are expanding their discussions to the matter of influence over the labor market (wages, employment, etc.) in the economic system and income distribution effects beyond the growth effects through productivity growth, based on interaction between innovation and human capital accumulation.

Earlier studies that focused on the level effects of the human capital accumulation have assumed labor to be homogenous, and focused on the growth effects according to the increase of the average human capital accumulation level in the economic system. This perspective assumes that heterogeneous labor that has different human capital can be interchangeable, which is why some studies began to point out that this approach fails to properly explains the division of the wage structure and income inequality due to technological progress (Freeman, 1979; Hamermesh, 1993; Jorgenson et al., 1994). Empirical studies conducted from this perspective commonly highlight that technological innovation generally drive productivity improvements, and enhance the complementary relation with the human capital accumulation, leading to the expansion of the employment in the labor market through scale effects (Pissarides, 2000). Likewise, studies that focused on the level effects of human capital have considered labor to be homogenous. In other words, those studies presume the perfect substitutional relationship among workers even though they possess heterogeneous skills and knowledge. However, this approach has limitations when explaining the wage and income gaps among heterogeneous workers that accumulated different human capital.

Accordingly, various studies are recently expanding the discussion and including consideration of heterogeneous human capital with different properties and marginal products. Based on this perspective a wide range of studies focus on the skill-biased technological progress (SBTC), claiming that the relation between workers with different skills (or, knowledge) and innovation is not only complementary but also substitutable (Acemoglu & Autor, 2011b; Ales et al., 2015; Antonietti, 2007; Blanchard & Katz, 1997; Bresnahan et al., 2002; Card & DiNardo, 2002; Goos et al., 2014; Jung et al., 2017; Michaels et al., 2014; Raveh & Reshef, 2016; Vivarelli, 2014). Skill-biased technological progress refers to a non-neutral shift in production function that forms differentiated demand for workers with relatively high skills and knowledge within the distribution of workers, due to the complementarity between the capital goods inherent in new technology and the labor with higher (or, advanced) skills (Jung et al., 2017).

For example, Blanchard and Katz (1997) mention that while the supply curve of labor that accumulated a relatively low level of skills is elastic, that of high-skilled labor is inelastic, and thus the influence of the technological progress over the labor market may lead to decline in employment. David et al. (1997) have conducted an empirical analysis to investigate the underlying causes for the relative labor demand change and wage differentials between workers (that accumulated heterogeneous human capital) focusing on the U.S economy. Based on the quantitative analysis, they have found that development of information and communication technology (ICT) increases the relative demand and wages of skilled workers compared to the low-skilled labor. Moreover, Machin and Van Reenen (1998) analyze the relationship between R&D intensity, the employment level and wage differentials among workers in seven OECD countries including U.S, Denmark, France, Germany, Sweden, United Kingdom, and Japan. The analysis results suggest that there is a positive correlation between technological change represented by R&D intensity and employment and relative wage increase of skilled workers in all countries. Furthermore, Bartel and Sicherman (1999) also examine the interrelationship between the technological progress with relevant proxy variables and wage differentials among workers focusing on the U.S economy, and verify that the demand for high-skilled labor is higher in industries with higher technological progress. To express the level of technological progress among industries, Bartel and Sicheman (1999) have used variables such as the number of patents produced in each industry, investment in R&D activities, ratio of scientific technicians, and total factor productivity as proxy variables. Similarly, Allen (2001) has utilized the industry-level data in the U.S from 1979 to 1989, and discovered that industries with higher levels of R&D investments and technology-intensive capital goods tend to have greater wage differentials among workers in terms of skill levels.

These various empirical studies argue that the increase in the relative demand for high-skilled labor driven by the skill-biased technological progress leads to the higher returns to high-skilled labor in the form of the increase in their relative wages, and skill premium, thereby serving as the main determinants of the deepening of income inequality (Acemoglu, 1999; Acemoglu & Autor, 2011b; Bartel & Sicherman, 1999; Berman et al., 1994;

Brynjolfsson & McAfee, 2012a, 2012b, 2014; Goos et al., 2009; Griliches, 1969; Jorgenson & Timmer, 2011; Jung et al., 2017; Machin & Van Reenen, 1998; Mallick & Sousa, 2017; Marouani & Nilsson, 2016; Rogerson et al., 2015). Moreover, Goldin and Katz (2008) have investigated the underlying causes of income inequality within the U.S economy, and considered the 'race between education and technology' as one of key factors which account for the changes in trends of income inequality experienced by the U.S economy. In this study, they have tried to understand the interaction between changes in demand for skilled labor driven by technological innovation, and changes in supply of skills coming from human capital investments (i.e., educational investments). Based on this perspective, Goldin and Katz (2008) have estimated the demand and supply curves of skilled labor using the long-term time series data of the U.S economy, and found out that the wage premium (i.e., skill premium) fluctuations of skilled labor in the U.S were mostly due to the fluctuations of supply, rather than demand for skilled labor in the last 100 years. Through the analysis, their study argue that the rapid increase in the wage premium of skilled labor since the 1980s originates mostly from the slowdown in the growth rate of the number of college graduates. Accordingly, they address that the demand for skilled labor constantly increased since the 1980s, and the supply growth rate of skilled labor decreased, thereby increasing the income inequality.

Similarly, Acemoglu and Autor (2011b) have conducted the decomposition analysis of the changes in relative demand for labor by expanding the demand-supply model proposed by Goldin and Katz (2008), and found out that technological progress is skill-biased. In addition, they have found that in the U.S economy, wage inequality has been worsening among population groups in terms of educational attainment levels, and years of experiences. Moreover, Malick and Sousa (2017) verify the positive correlation between technological progress and relative demand for skilled-unskilled labor, and highlight the acceleration of skill-biased technological progress in manufacturing sectors due to the wide deployment of the digital technologies in recent years. Based on this empirical analysis, this study have found out the trends of wage differentials between skilled and unskilled labor, and their associations with the technological progress. Furthermore, Rogerson et al. (2015) have conducted an empirical analysis on the U.S economy from 1977 to 2005, and discovered that the skill premium for educated workers in the U.S has been constantly increasing, which led to the increase in income polarization among workers with different skills. This phenomenon is not limited to advanced countries. For example, Marouani and Nilsson (2016) recently forecast that the Malaysia economy will make a transition into skill-intensive industrial structure driven by the skill-biased technological progress, addressing the need for a wide range of policies to promote skill accumulation of workers to enable them to keep their competences properly adjusting to the paces of technological changes, SBTC.

A series of relevant studies mentioned above commonly emphasize that the intrinsic attributes of technological progress driven by innovation which can be described as skill-biased technological progress are the key factors that trigger changes in the demand for skills within the economy. In addition, those studies put emphasis on coevolution of labor demand and supply on the basis of changes in labor supply driven by the human capital accumulation, and changes in labor demand driven by the skill-biased technological progress. Accordingly, recent studies come up with policy implications in terms of human capital investments and education as an extension from merely providing the empirical evidence on the existence of the skill-biased technological change, by highlighting the complementary relationship between innovation and human capital measured by skills. For example, Acemoglu (2002) stresses out the growth-enhancing effects driven by the acceleration of skill-biased technological progress through endogenously promoting the interaction between technology and education in terms of skill demand and supply. Acemoglu (2002) also emphasizes that the increase of the wage premium (i.e., skill premium) for skilled-labor induced by the SBTC has the possibility to increase the expected returns on educational investments (i.e., human capital accumulation), thereby promoting the supply of skilled labor through the human capital accumulation. This is similar to the implications provided by Goldin and Katz (2008). In addition, He and Liu (2008) have proposed a theoretical model which reflects the endogenous skill accumulation process through education, and the complementarity between skills and capital goods (with embodied technological progress). Based on this proposed model, He and Liu (2008) have found that when the government subsidizes workers in making decisions for skill accumulation, the skill premium can be reduced in the long run, while the social welfare can be improved. Through this, they stress out the role of investment in education and government supports for workers to induce skill accumulation.

Moreover, Grossman et al. (2016) also propose an endogenous growth model reflecting the complementary relation between skills and capital goods via endogenous technological progress embodied in capital goods, and skill accumulation through education. Based on the proposed growth model, they emphasize that a balanced growth can be achieved when the effects of skill-biased technological progress are counterbalanced by the increases in the returns on educational investment endogenously determined by the physical capital accumulation, and subsequent increases in the labor supply of high-skilled labor within the economy. This study also claims that capital goods inherent with technological progress have a complementary relation with years of schooling that represent the skill levels possessed by workers, addressing the importance of the educational investments to enhance the endogenous interaction between technological progress and human capital accumulation for the long-run economic growth. Furthermore, Pan (2014) also proposes an endogenous growth model based on the general equilibrium theory, and emphasizes that the expansion of educational investments reduces wage differentials between skilled and unskilled labor, and further promotes long-term economic growth. Those relevant studies reviewed above imply that the interaction between technological innovation and human capital accumulation should be understood as an endogenous process within the national economy, and it is necessary to understand the growth, and distribution patterns within the economy as the outcomes of such an interaction. Moreover, their key findings commonly suggest that economic growth and social welfare can be promoted and wage differentials can be resolved in a situation where there is economic incentives to resolve the discrepancy between skill supply and demand based on the understanding of the interaction between technological innovation and human capital accumulation.

Furthermore, various recent studies theoretically and empirically examine that technological innovation leads to not only skill-biased technological progress but also capital-biased or labor-saving technological progress (Bridgman, 2017; Doraszelski & Jaumandreu, 2018; Elsby et al., 2013; Jung et al., 2017; Karabarbounis & Neiman, 2014; Oberfield & Raval, 2014; Piketty, 2014). As such, labor-saving technological progress indicates that technological progress due to technological innovation has an uneven effects on the marginal productivity of capital and labor. In this context, capital-biased technological progress implies reduction of compensation of employees within the economic system (Acemoglu & Robinson, 2015; Karabarbounis & Neiman, 2014). This concept also suggests a non-neutral shift in production function driven by the displacement of labor with capital goods and capital deepening within the production technology (Bentolila & Saint-Paul, 2003; Guerriero & Sen, 2012), which addresses that the relative influence of capital goods within the production process becomes even greater as mentioned by Jung et al. (2017). In addition, recent studies point out that the intrinsic attributes of technological innovation referred to as capital-biased and skill-biased technological progress are the main causes of structural unemployment and income inequality recently experienced by the economies of advanced countries.

For example, Oberfield and Raval (2014) present the analysis results that the decline of the share of labor income in the national economy is due to a certain form of technological progress, rather than the relative price changes in factor inputs. This study has utilized the firm-level data in U.S, and discovered that the elasticity of substitution between capital and labor is found to be smaller than one. This finding drawn from Oberfield and Raval (2014) suggests that it is theoretically impossible to explain the decline of the labor income share with the changes in relative prices of factor inputs. Furthermore, Brynjolfsson and McAfee (2014) and Karabarbounis and Neiman (2014) have tried to examine a linkage between capital-biased technological change and the labor income share in the national economy, and pointed out that the labor income share in gross domestic product (GDP) has declined in many countries. Based on the empirical analyses, they warn that the relative price of capital goods will continuously decrease, due to the wide development and deployment of digital technologies, thereby expanding the phenomenon in which capital goods displace labor. The problem is that this capital-biased technological change may deepen income polarization. For example, Piketty (2014) addresses that capital-related income inequality is larger than is labor-related inequality. Accordingly, based on the studies mentioned above, it can be inferred that skill-biased and capital-biased technological progress tend to provide higher benefits and returns to only a sub-group of workers and capitalists, implying the possibility to intensify income inequality and polarization.

Technological innovation that appears in the form of skill-biased and labor-saving technological progress endogenously interacts with the labor market that accumulated heterogeneous human capital in the process of being embodied to production technology and function, thereby forming the net demand for production factors. Studies conducted from this perspective highlight that factor-biased technological progress including skill-biased and capital-biased technological change is the key concept in explaining the changes in employment and wage structure within an economic system (Acemoglu, 1998; Autor et al., 2017; Haltiwanger et al., 2014; Karabarbounis & Neiman, 2014; Mallick & Sousa, 2017; Mućk et al., 2018; Shim & Yang, 2016). In addition, those studies provide empirical grounds to account for the effects of the intrinsic attributes of technological progress over the labor market and income distribution (i.e., polarization of wage and employment structures, and deepening of income inequality).

Likewise, technological innovation generates the demands for labor and human capital through various direct and indirect paths within the economy, such as the reduction of production costs, spillover effects from the knowledge accumulation, increased product varieties, and scale effects. More specifically, technological innovation leads to factor-biased technological progress, thereby bringing changes in the employment and wage structures (Acemoglu, 2012; Danninger & Mincer, 2000; Uhlig, 2004). Moreover, changes in labor supply driven by human capital accumulation have influence over technology selection and adoption. Such an interrelationship between innovation and human capital accumulation shapes patterns of long-term economic growth and distribution within the economy (Brynjolfsson & McAfee, 2014; Card & DiNardo, 2002; David et al., 2006).

From this perspective, the interaction between innovation and human capital has the possibility to cause a collision between growth and distribution. There are empirical studies proving that the prolonged phenomenon of income and wage inequality damages the economic foundations and hinders growth in the long run (Joumard et al., 2012; Lahiri & Ratnasiri, 2012; Ostry et al., 2014). Accordingly, it is important to identify whether the two goals can coexist by designing and implementing a certain form of policies in a knowledge-based economy. Moreover, given that economic growth and distribution are outcomes of the complex interaction among industrial sectors, and multiple institutional elements, it is essential to design policy options to spur an inclusive growth under comprehensive and structural approaches (Bogliacino & Vivarelli, 2012; Vivarelli, 2013, 2014).

In this regard, Vivarelli (2013, 2014) highlights that to understand the interrelationship between innovation and human capital, it is crucial to consider the indirect effects of innovation on the labor market, and induced different mechanisms of compensation effects, along with the understanding of the direct effects triggered by the factor-biased technological progress including skill-biased and capital-biased technical changes. Accordingly, in addition to an in-depth understanding of the relationship between technological innovation and human capital in a knowledge-based economy, where the dynamic interaction between innovation and human capital accumulation shape the growth and distribution patterns in the national economy, the evidence-based innovation policy design should be pursed, based on the quantitative analysis on the economy-wide effects of the dynamic interaction between the innovation and human capital composition.

2.2 Knowledge-based CGE model

2.2.1 A framework for CGE model-based analysis

The following section will introduce the concepts of the Computable General Equilibrium (CGE) model to be used in this study, and examine the methodological approaches of previous studies attempted explicitly include knowledge- and innovation-related elements within the CGE model to highlight the contribution of this study in terms of the methodological development. The CGE model is a macroeconomic model consisting of mathematically expressed economic transactions of certain regions, countries or among countries. A Social Accounting Matrix is used as the baseline data for running the CGE model to describe the economic situation in the base year, assuming that values of transactions among industrial sectors and institutions describe the economic activities in the initial equilibrium state.

The characteristics of the CGE model can be summarized as follows. Firstly, CGE analysis assumes that there is "equilibrium" within the economic system. Equilibrium is the state in which supply and demand are in balance, and the economic state is maintained unless there are external shocks. This is an idea faithful to the traditional economic theory, but in contemporary economics there are theories that do not agree to this view[1]. Nonetheless, the CGE model has an advantage in consistently maintaining the objective and mathematical logic within the assumption based on certain economic theories (Dixon & Rimmer, 2013). Secondly, the CGE model assumes that there is simultaneous equilibrium states in all markets. This concept is contrary to the partial equilibrium. The

[1] For example, the behavioral economics addresses that the assumptions of the utility maximization, rational agents in the CGE model are far from the reality (Camerer et al., 2011; Dixon & Rimmer, 2013; Mullainathan & Thaler, 2000). In addition, the evolutionary economics also suggest that there are only dynamic equilibrium states, not static equilibrium states.

two concepts are the same in terms of the existence of the equilibrium state in which supply and demand are in balance within the market, but they are different in that partial equilibrium only targets a specific market for analysis. On the other hand, the CGE model generates the equilibrium states in every periods that consider multiple markets as well as the interdependent relations among variables of individual markets at the same time (Hosoe et al., 2010). Thirdly, the CGE model is a part of the comparative statics analysis. This methodological approach presumes that the economy in the steady-state unless there is exogenous shock, and even if there is exogenous shock, it converges to a new equilibrium point. If these policy variables are considered as exogenous terms in the model, it is possible to calculate a new value of equilibrium according to the changes in the relevant variables, and the effects of policy change can be captured by comparing this to the initial equilibrium point (Shin, 1999).

As such, the CGE model is an economic model that integrate the interdependent components of the domestic economy, including the production sectors, consumption, investments, institutions (i.e., households, governments, and firms), and other elements (i.e., exports and imports). The equilibrium solution driven by the external shocks in the CGE model is generated through the interactions among those components, and provides the quantitative analysis results about the considered policy options. Prior to the CGE model-based analysis, it is necessary to prepare the base-year SAM data fitted for the purpose of the analysis. SAM is considered as the base dataset for the CGE model that reorganizes statistical data on economic variables reflecting the production technology, preferential relations, factor endowments, inter-industrial transactions, and inter-institutional transactions in consistent manners. Once the SAM of the base year is constructed and prepared, it is necessary to establish a system of equations for the CGE model to describe the transactional information within the SAM data. A series of equations consists of necessary conditions to optimize the objective functions of economic agents, constraints imposed to the decision-making for economic agents (i.e., objective functions of economic agents), definitions of endogenous variables, and market clearing conditions of products and factors of production. These equations also include various parameters and exogenous variables to be determined with the assumptions of appropriate values for them. The parameter values that cannot be obtained from the SAM data can be determined through assumptions or statistical estimations.[2] The stage after that is the calibration process of the CGE model to test the validity of the CGE model for describing the base year economic situation. Through the calibration process, the analysis preparation stage based on the CGE model is completed, and macroeconomic effects of the policy shocks in the form of changes in exogenous policy variables can be calculated through the policy simulations.

The CGE model with these characteristics is a system of equations that describes the general equilibrium of economy by adopting specific assumptions and macro-level data about production technology, preferential relations, factor endowments, and government's

[2] For example, assuming a CES (Constant Elasticity Substitution) production function, the values for the elasticity of substitution between production factors, and the elasticity of transformation within the CET (Constant Elasticity Transformation) function cannot be obtained from SAM, but must be obtained outside the CGE model. For example, if the utility function of the household is assumed to be a simple Cobb-Douglas function, the ratio of the expenditure to each product in the total expenditure can be derived from the SAM data.

economic policies within the model, and thus is regarded as a useful analytical tool for the policy impact assessments from the economy-wide perspective (Lofgren et al., 2002; Robinson & Roland-Holst, 1988). This model has the advantage of comprehensively analyzing the direct and indirect effects of a certain type of policy option. Analyses based on the CGE model have been most actively conducted in the fields of energy, environment, international trade and taxation. However, due to the difficulty in establishing and modeling data related to the innovation activities and knowledge, there have not been many empirical studies attempted to develop and propose the CGE models to analyze policy effects in light of the characteristics of technological innovation, despite its importance as a key growth engine for economic growth. The lack of such a methodological foundation has had limitations in providing a systemic perspective on what mechanism technological innovation has in interacting with other economic variables, and how it affects macroeconomic variables accordingly. Thus, the following section will examine the methodological approaches of previous studies that attempted to incorporate factors related to technological innovation and knowledge within the CGE framework, and present the characteristics of those CGE models to highlight the key features of the model to be proposed in this study as well as the contributions of this study.

2.2.2 Methodological approaches for knowledge-based CGE model

To consider variables such as innovation or knowledge as the key elements within the macroeconomic systems of equations, there must be explicit expressions about them in the

SAM data. In other words, there is a need for information about knowledge accumulation (i.e., knowledge stocks) or knowledge transactions (i.e., knowledge flows) (Garau & Lecca, 2015). In this regard, this study will examine main approaches to capture the flows and interactions of knowledge and innovation within the SAM framework. Relevant studies have tried to extract the information on the knowledge flows and transactions implicitly included in the X_{ij} matrix as shown in Figure 1, and identify the investment data about innovation activities (i.e., R&D investments) by each industrial sector. Their main approaches in constructing a knowledge-based SAM, proposed by those relevant studies can be summarized as Figure 1.

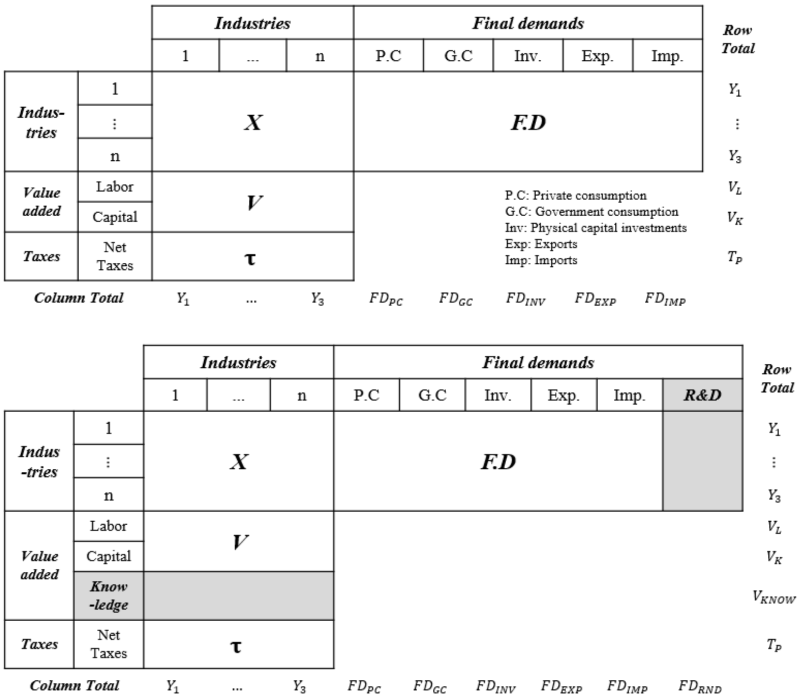


Figure 1. Methodological approaches to extract knowledge-related elements within SAM

The first approach has been initially proposed by Terleckyj (1980) in which the R&D investments in each industry are allocated according to the proportions of intermediate goods transactions among industries. This approach presumes that technological progress is embodied in intermediate goods and spread within the economic system through the intermediate goods transactions. For example, when R&D investment costs of individual industries are identified, and R&D investment cost of industry *i* is $R\&D_i$ and the demand for intermediate goods in other industries for the goods of industry *i* is identified as x_{ij}, then the knowledge spillover effects occurred when the knowledge created through the R&D of industry *i* is diffused to other industries can be calculated as $\omega_{\mathrm{ij}} = \frac{\mathrm{x_{ij}}}{\sum_{\mathrm{j}} \mathrm{x_{ij}}} R\&D_i$. Accordingly, ω_{ij} is deducted from the existing transactional information matrix X_{ij} of intermediate goods (among industries), and the relevant ω_{ij} can be newly added as a factor of production as the knowledge account.

The second approach is selecting certain knowledge-intensive industries and estimating the economic transactions between those industries and others as R&D costs for other industries (Berndt & Morrison, 1995; Goulder & Schneider, 1999; Sue Wing, 2003). Studies based on this methodological approach are Goulder and Schneider (1999), Berndt and Morrison (1995), Sue Wing (2003). Those studies specify high-technology industries and consider the total industrial outputs of those industries as the total amounts of knowledge created (i.e., knowledge flows) in the base year economy. Under this assumption, those studies consider the total assets of high-technology industries as the total amounts of knowledge capital (i.e., knowledge stocks). In this regard, the row information of the corresponding high-tech industries within the SAM data can be understood as the payments to knowledge of other industries paid to the high-technology industries, while the column information of them within the SAM can be regarded as the investments in innovation activities and R&D. Compared to the first approach, this approach is relatively simple, but its limitation is that it is ambiguous which industries to be defined as innovation-intensive industries.

The third approach is using the Yale Technology Matrix (YTM) to extract the knowledge transactional information from X_{ij} shown in Figure 1. Using the YTM data which contains the inter-industrial linkages of patents produced by individual sectors, this approach has been proposed to overcome the limitations of the approaches that regarded the transactional information of intermediate goods as that of knowledge flows among industries as previously mentioned. This is because knowledge can be embodied in the intermediate goods, in addition to being disembodied (Garau & Lecca, 2015; Meijl, 1997; Putnam & Evenson, 1994). Accordingly, by multiplying the R&D cost $R\&D_i$ of each industry with the knowledge transaction matrix (YTM_{ij}) drawn from the YTM, the knowledge transaction costs among industries $\omega_{\mathrm{ij}} = YTM_{ij}R\&D_i$ can be determined. That is, ω_{ij} is deducted from the pre-existing transactional information matrix X_{ij} of intermediate goods (among industries), and the relevant ω_{ij} is newly added as a factor of production as the knowledge account within the SAM data. One of studies from this approach in constructing a knowledge-based SAM is Garau and Lecca (2015). Based on the three approaches mentioned so far, previous studies are attempting to explicitly reflect and incorporate innovation- and knowledge- related elements within the SAM data.

Next, we will examine the methodological characteristics of empirical studies based on the CGE model in which knowledge and innovation related elements are incorporated explicitly. Such literature review can be utilized usefully as a reference for designing the model to be proposed in this study. As the economic growth model continues to develop with focus on the endogenous growth theory, the importance of technological innovation in economic growth has been widely perceived. Accordingly, there are studies that intend to reflect innovation and knowledge as factors of production in the production function in developing the CGE methodology as well. What to examine in these relevant studies is related to how they design the production function within the CGE model, as well as how they consider the knowledge spillover effects driven by the knowledge capital accumulation within the model, as they are important methodological issues that should be considered in the knowledge-based CGE models which are based on the endogenous growth theory (Garau & Lecca, 2015).

Garau and Lecca (2015) have proposed a multi-regional CGE model of a small open economy to quantitatively calculate the macroeconomic effects of R&D policies with focus on Sardinia region, Italy. Accordingly, they have reflected the endogenous technological progress and spillover effects from knowledge accumulation in the CGE model. The production functions of final goods producing sectors are assumed to be in the form of CES functions as the functions of intermediate inputs, physical capital, labor and knowledge capital considered as production factors (see Figure 2 as shown in below). This model reflects knowledge as an independent factor of production, thereby describing the substitutional and complementary relationships among other factors of production. Moreover, Garau and Lecca (2015) have claimed that given that the non-excludability of the knowledge, knowledge spillover effects occur from other regions, and reflected this within the CGE model to improve total factor productivity of the final goods manufacturing industry. Here, the knowledge spillover effects are assumed to increase when transactions with other regions increase, and the portion of domestic R&D stock increases compared to that of overseas R&D. Thus, the economic growth rate in the model is endogenously determined by the spillover effects of knowledge accumulation.

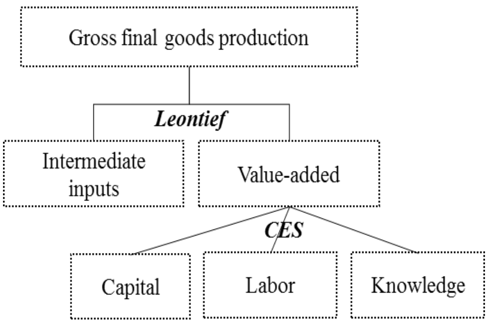


Figure 2. Final goods production structure of Garau and Lecca (2015)

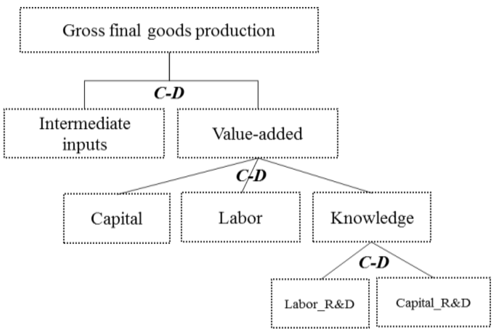


Figure 3. Final goods and knowledge production structure of Ghosh (2007)

Ghosh (2007) has designed a multi-sectoral GCE model of a small open economy to examine the efficiency of R&D policies to promote innovation activities of the private sector, focusing on Canada economy. To this end, total three industrial sectors are presumed, such as industries producing final outputs, industries producing new knowledge and designs, and industries producing differentiated capital goods using the designs. It is also assumed that industries producing final goods are such as agriculture, manufacturing and service, all of which have the production structure as shown in Figure 3. The production structure shows that for producing the outputs of individual industries, the intermediate inputs composite and value-added composite are combined in the form of the Cobb–Douglas production function, and the latter goods are produced in the technology that exhibits constant returns to scale that uses labor, capital, and R&D capital goods as input factors. In this model, it is also assumed that the productivity of value-added increases with the growth rates of the variety of differentiated capital goods (i.e., the number of newly produced patents or designs), which serve as the source of the economic growth (Ghosh, 2007). Moreover, Ghosh (2007) has also incorporated the knowledge spillover effects in the model, by having R&D activities improve productivity of firms in R&D sector (i.e., industry producing new knowledge and designs) and firms producing final goods. This study has also reflected that the knowledge spillover effects from overseas (i.e., rest of the world) influence only the productivity of R&D firms.

Křístková (2010, 2013) has designed and proposed a multi-sectoral GCE model of a small open economy focusing on Czech economy to quantitatively examine the economy-wide effects of the R&D investment in the private sector. The distinctive feature of Křístková (2010, 2013)'s work is that this study has distinguished the private R&D sector from public. The private R&D sector is assumed to be the monopolistic market. Firms in the private R&D sector produce differentiated knowledge and designs, thereby determining the variety of capital goods in the economy. The private R&D sector is assumed to produce new designs and patents by combining the value-added composite consisting of knowledge capital and capital-labor composite inputs, and the intermediate composite under the Leontief production form (see Figure 4 as shown below). Moreover, the public R&D sector is assumed to produce public knowledge instead of designs, and thus this sector plays the role of increasing productivity of the private R&D sector (Křístková, 2013). The variety of capital goods (i.e., the number of newly produced designs) is designed to increase productivity of the final goods production sector. Accordingly, the economic growth rate of the economy in this model is determined as the function of the growth rate of newly produced design (i.e., the variety of capital goods) produced by the private R&D sector, and the productivity growth experienced by the private R&D and final goods producing sectors (Křístková, 2010).

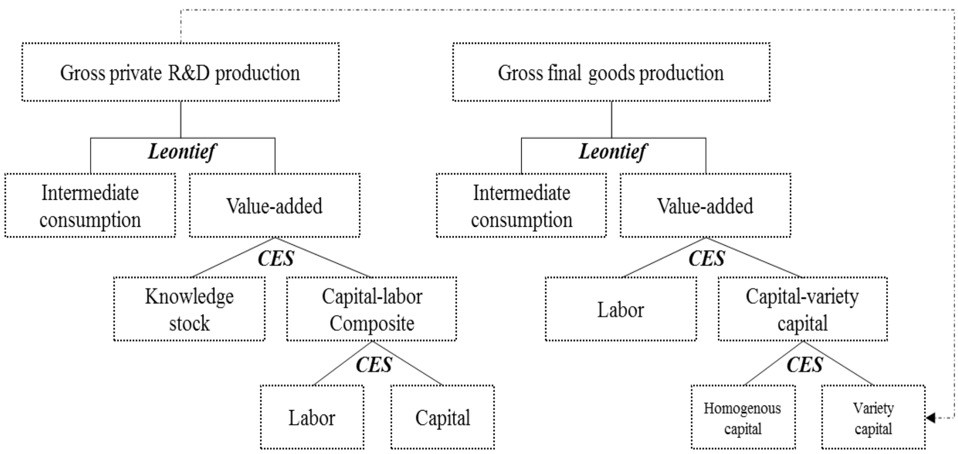


Figure 4. Production functions of R&D and final goods sectors in Křístková (2013)

Bye, Fæhn, and Heggedal (2009) have analyzed how an incentive system for innovation must be designed in order to improve economic growth and social welfare in a small open economy of Norway. This study has classifies industries into R&D industries developing new designs and patents, industries producing capital goods using the patents, and industries producing final goods. Economic growth in this model can be endogenously determined through productivity growth and the love-of-variety effects. Moreover, in order to describe the knowledge spillover effects within the CGE framework, this study has assumed that productivity of the R&D sector increases according to the accumulation of domestic knowledge stock, and the increased knowledge stock improves productivity of the final goods production sector through the love-of-variety effect.

Furthermore, Verbič et al. (2011) have designed a knowledge-based CGE model to analyze the effects of R&D policies in the Slovenia economy. In this model, it is assumed that the TFP growth rate is endogenously determined by the levels of R&D stocks and the economic openness, and that the TFP and R&D stocks indirectly affect the production of final goods. The distinct feature of this model proposed by Verbič et al. (2011) is that it has specified the production factor within the model, especially for the labor. To be specific, this study has considered the heterogeneous labor with different levels of educational attainment as the factor inputs within the CGE model. Accordingly, Verbič et al. (2011) has considered three types of labor in terms of accumulated human capital, physical capital, and knowledge capital as factors of production within the Cobb-Douglas production function of final goods producing sector. However, this study does not incorporate the endogenous process in which the skills of workers are improved according to exogenous shocks such as investment in education for human capital accumulation. Similarly, the GEM-E3 model classifies workers by the educational attainment level, but this model also fails to reflect the endogenous skill accumulation process within the model to capture the changes in the human capital decomposition within the economy (Di Comite, 2015).

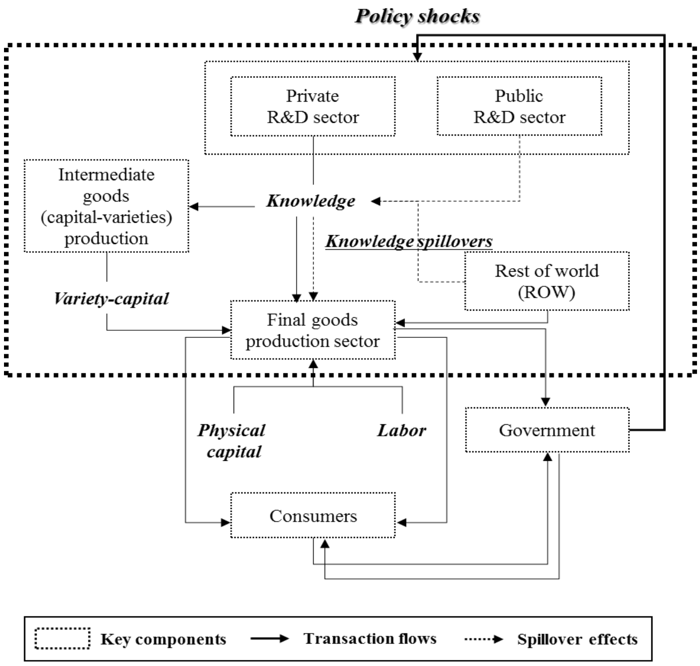


Figure 5. Key features of knowledge-based CGE model and their structures

Due to the difficulty in establishing and modeling related to the innovation activities and knowledge within the model and data, there have not been many empirical studies attempted to develop and propose the CGE models to analyze policy effects in light of the characteristics of technological innovation, despite its importance as a key growth engine for economic growth. The lack of such a methodological foundation has had limitations in providing a systemic perspective on what mechanism technological innovation has in interacting with other economic variables, and how it affects macroeconomic variables accordingly. However, as examined above, there have recently been studies attempted to analyze the policy effects by designing knowledge-based CGE models that reflect elements related to technological innovation and knowledge by explicitly representing the knowledge within the production function, and knowledge externalities from innovation activities based on the endogenous growth theory. Those studies provide methodological frameworks to conduct an ex-ante analysis on the innovation policies. Several examples of developing knowledge-based CGE models presented so far have the following common structure of the models. Firstly, they explicitly consider industries that produce new knowledge and designs along with the final goods industries within the economy. Secondly, new knowledge produced in the R&D industry is either included in the final goods production structure as a factor of production, or endogenously determines the economic growth rate by increasing the variety of capital goods. Thirdly, the spillover effects of knowledge accumulation are assumed to come from various channels (i.e., transactions with foreign countries, domestic knowledge accumulation, public R&D sector’s knowledge stock, etc.), thereby determining the productivity growth within the economic system. In summary, the key components and interactions among those components in knowledge-based CGE models proposed by previous studies can be summarized as Figure 5. The three common features mentioned above can be understood in the 'key components' of Figure 5.

2.3 Contribution of this study

As such, knowledge-based CGE models based on the endogenous growth theory commonly highlight that technological progress through knowledge creation occurs endogenously, through which economic growth is determined by the knowledge spillover effects. However, these studies are lack of consideration on the endogenous interaction between innovation and human capital accumulation. As previously examined in Section 2.1, in-depth discussions about the growth and distribution patterns of a knowledge-based economy are possible when all the following factors are comprehensively considered in the model; labor and skill demand changes caused by technological innovation, dynamic interaction between human capital composition through human capital investment and changes in skill supply, and influence over wage and income structure in the economic system accordingly.

However, as examined in Section 2.2.2, the existing knowledge-based CGE models consider homogeneous labor as a single account within the production factors account, without considerations of labor that accumulated heterogeneous human capital Secondly, previous studies that attempted to classify the single labor account in terms of years of schooling including Verbič et al. (2011) and Pan (2005) fail to capture dynamic changes in the human capital composition based on endogenous process of skill improvement (i.e., skill accumulation) according to human capital investment of workers within the CGE framework. Thirdly, proposed CGE models proposed by previous studies fail to specify the intrinsic attributes of technological progress within the production function, which can be described as the factor-biased technological change (as previously mentioned, technological progress is not just determined by exogenous shocks, but endogenously determined according to the distribution of skills given in the economy, and the direction and pace of factor-biased technological progress are determined by the endogenous interaction between technological innovation and human capital). The limitations of those methodological approaches proposed by previous studies provide a limited perspective in properly capturing the growth effects resulting from the dynamic interaction between technological innovation and human capital as examined in Section 2.1.

Furthermore, as examined in Section 2.1, studies focusing on the interaction between innovation and human capital have shown greater interests in the distribution issues along with growth effects. However, the existing knowledge-based GCE models are deeply oriented towards investigating the growth effects induced by policy shocks. On the contrary, studies focusing on the distribution issue based on the CGE framework have tried to capture the income redistribution effects induced by changes in policy variables with considerations of heterogeneous households and labor within the CGE models by classifying the households in terms of income levels, or specifying the single labor account in terms of human capital accumulation levels (Oh al., 2014; Jung & Thorbecke, 2003; Jung et al., 2017; Kim & Kim, 2005; Ojha et al., 2013; Siddiqui et al., 1999; Kim & Kim, 2010; Cho & Kim, 2017; Ji, 2001). Those relevant studies have tried to examine the mid- and long-term economy-wide effects of a wide range of policies including taxation and redistribution policies as well as education policies. However, those previous studies conducted from this perspective fail to include an in-depth consideration of endogenous technological innovation within the CGE model (Ojha et al., 2013).

Accordingly, based on the methodological limitations of previous studies in terms of methodological development, this study will present a CGE model in which the dynamic interaction between innovation and human capital is determined endogenously within the production technology. Moreover, this study aims to integrate the discussions of previous studies based on knowledge-based CGE models that focused on the growth effects, and those based on CGE models that focused on the distribution effects. To this end, this study will present a model that can simultaneously measure the growth, efficiency and distribution effects according to policy shocks by designing a CGE model and data structure SAM in which the microscopic view is more concretized, thereby facilitating analysis of policy impacts for each heterogeneous worker and income quantile in terms of distribution effects, along with the growth effects driven by the endogenous interaction between technological innovation and human capital accumulation.

From this point of view, this study aims to overcome the methodological limitations of previous studies which have been based on the CGE methodology, and present an integrated CGE model in which the following key factors are reflected; 1) endogenizing the innovation-related elements considering the characteristics of innovation and knowledge (including, consideration of knowledge as a factor of production, endogenization of knowledge capital investments, and consideration of spillover effects coming from the knowledge accumulation via productivity improvements), 2) endogenizing the decision making process of labor on the human capital accumulation (i.e., up-skilling and re-training) affected by the relative wages of workers and educational investments within the economy, 3) designing the endogenous interaction between the knowledge capital accumulation (i.e., innovation) and human capital accumulation within the production function, 4) describing the intrinsic attributes of technological progress within the production structures, and 5) establishing the macroeconomic model to simultaneously estimate the growth and distribution effects with considerations of heterogeneous labor and households within the equational systems and datasets (i..e, SAM). It is expected that this study consisting of the development of the CGE model and quantitative analyses based on the constructed model can provide a theoretical and methodological basis for analyzing the effects of various policy options and alternatives in terms of growth and distribution within the knowledge-based economy. So far, previous studies using the CGE model which explicitly considers the innovation and R&D activities within the model have deeply focused on the direct support measures for innovation activities and their impacts on the economy, including the subsidy and tax grants on the R&D investments. However, it is expected that the scope of the innovation policy impact assessments will be expanded by considering the various policy instruments such as human capital investment and tax policy in the dimension of the innovation policy. Furthermore, we also expect the proposed CGE model to be used as a tool for policy impact assessments to determine what types of policy options can achieve both growth and distribution objectives in a knowledge-based economy.

Chapter 3. Quantitative analysis on Output Growth and Distribution effects of Innovation

In this chapter, firstly, main procedures and methods of constructing the SAM used in this study are described in detail. Constructed SAM serve as the data-base for the knowledge-based CGE model to depict the economic conditions of the base year. Accordingly, in the subsection 3.1 it will represent how to construct the knowledge-based SAM to describe baseline economy in the CGE model developed in this study. Secondly, SAM multiplier analysis based on the constructed knowledge-based SAM has been conducted to analyze the relationships between technological innovation and its effects on labor markets to confirm the stylized facts covered in the Chapter 2.1 and Chapter 2.2, focusing on the Korean economy (see subsection 3.2). Through this step, this study aims to investigate whether Korean economic structure has intrinsic characteristics to drive factor-biased technological progress, which is considered as one of key underlying factors to determine the endogenous interaction between technological innovation and human capital accumulation. The SAM multiplier analysis is similar to the input-output (I/O) analysis in that it analyzes changes in the endogenous accounts due to changes in the exogenous accounts. However, it can be said that it is an advanced analytical methodology rather than the I/O analysis in that it can expand the scope of endogenous elements by covering other accounts (e.g., institutions accounts), as well as the production activities accounts within the Social Accounting Matrix (Miller & Blair, 2009).The subsection 3.2

provides brief explanations on the SAM multiplier analysis, and key results of the analysis based on the constructed knowledge-based SAM by calculating the changes of endogenous accounts(i.e., production activities in industrial sectors, incomes of institutions, value-added) triggered by policy shocks injected to exogenous accounts (i.e., R&D investments accounts). Based on those results, this study aims to comprehensively understand the direct and indirect effects of technological innovation, focusing on the Korean economy. Furthermore, this study expects to confirm the relationships between technological innovation, human capital formation, and labor markets, by addressing the stylized facts over technological innovation, growth, and distribution found in previous literature which are covered in the Chapter 2.1 and Chapter 2.2.

3.1 Construction of knowledge-based SAM

3.1.1 Concept of social accounting matrix (SAM)

Since SAM not only includes information inter-industrial transactions listed in I/O tables, but also focuses on the relationships and transactions between the economic entities (institutions) covered in national accounts, it can be considered as a dataset which consistently links I/O tables and national accounts to summarize the interdependence between productive activities, factor markets, income and consumption of households, income and consumption of the governments, balance of payments, etc. for the economy as a whole at a point in time. Thus, the Social Accounting Matrix can provide a snapshot which represent circular flows of income within the economy. In addition, this SAM serve as an underlying data-base capturing the structure of the economy in which the income and expenditure equations and associated aggregate accounting relationships are derived. This SAM is used to describe baseline economy in the knowledge-based CGE model, and particular features, modeling aspects such as, behavioral equations and equilibrium conditions are derived based on the benchmark accounting framework.

Looking at the basic configuration of the SAM, the SAM is constructed as a square matrix as shown in Table 1. In the Social Accounting Matrix, row components represent receipts or incomes, while column components represent expenditures of associated economic entities. In addition, if the income and expenditure of individual accounts are the same, the income and expenditure within the overall economic structure will also coincide, thus establishing the Walras'law (Yang et al., 2012; Yeo et al., 2018). Each column element in the matrix represents expenditure, and the sum of the columns S_j is the total expenditure of the *j-th* account. In addition, each row component represents income, and sum of rows in the SAM, S_i can be understood as total income of the *i-th* account. Thus, the individual element *S(i, j)* means the expenditure from the *j-th* account to the *i-th* account, as well as the income received by the *i-th* account from the *j-th* account. The Social Accounting Matrix should be constructed following the principle that the income and expenditure of economic agents are to be equalized. Therefore, the individual accounts are recorded so that the values of the column and row sums are necessarily the same, according to the double entry book-keeping principle (Hong et al., 2014; Hwang et al., 2014; Kim, 2005). Accordingly, SAM is a table showing the circular flows of production, consumption, and accumulation (i.e., capital formation) activities of a national economy over a specific period. In other words, SAM shows economic transactions in detail related to production and consumption of the national economy in a matrix form, thereby enabling a comprehensive understanding of the economy as a whole. The data includes information on economic activities at the base year, such as production, consumption, imports and exports, intermediate goods transactions between production sectors, incomes earned by factor inputs, and detailed transactions between economic entities such as households and governments. Based on this concept of SAM, this study firstly construct a standard form of SAM, which can be depicted as Table 1 following the methodological approaches suggested by Yang et al. (2012).

Table 1. Structure of standard Social Accounting Matrix

		Production		Factor inputs		Institutions		Invest.	Taxes				ROW (Rest of World)		Total
		Domestic	Imported	Labor	Capital	Hou.	Govt.	Fixed Capital	Indirect	Corporate	Income	Tariffs	Exports	Imports	
Production	Domestic goods	S(1,1)				S(1,5)	S(1,6)	S(1,7)					S(1,12)		S01
	Imported goods	S(2,1)				S(2,5)	S(2,6)	S(2,7)							S02
Factor inputs	Labor	S(3,1)													S03
	Capital	S(4,1)													S04
Institutions	Household			S(5,3)	S(5,4)										S05
	Government					S(5,6)		S(6,7)	S(6,8)	S(6,9)	S(6,10)	S(6,11)			S06
Investments	Fixed capital					S(7,5)	S(7,6)							S(7,13)	S07
Taxes	Indirect taxes	S(8,1)													S08
	Corporate taxes	S(9,1)													S09
	Income taxes					S(10,5)									S10
	Tariffs		S(11,2)												S11
ROW	Exports													S(12,13)	S12
	Imports		S(13,2)												S13
Total		S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	

In this study, industrial sectors are classified into 28 sectors within the SAM by aggregating industrial classifications listed in the I/O statistics as shown in Table 2. In constructing the SAM, the I/O table serves as a core dataset which summarizes economic transactions between production sectors and institutions in consistent manners. Therefore, collecting I/O tables is the starting point for the construction of Social Accounting Matrix (Bank of Korea, 2013). The main focus of the I/O table is oriented towards identifying how much products are purchased from each industrial sectors, and put intermediate goods in order to produce industrial outputs by each industry, as well as capturing how much products are distributed into the economy to satisfy the final demand. In this sense, the I/O tables focus on the production parts of the economy, and highlight the relationship between production accounts and other accounts. Accordingly, this study firstly utilize the I/O table published by the Bank of Korea for the year of 2010 to construct SAM for this year.

Table 2. Aggregation of industrial codes in I/O tables to construct SAM

Industrial classifications in SAM		Industrial codes in I/O tables for 2010 (in small-sized dimensions)
S01	Agriculture, forestry and fishing	001 ~ 029
S02	Mining and quarrying	030 ~ 044
S03	Food, beverages and tobacco products	045 ~ 084
S04	Textile and apparel	085 ~ 113
S05	Wood and paper products	114 ~ 128
S06	Printing and reproduction of recorded media	129 ~ 130
S07	Petroleum and coal products	131 ~ 141

S08	Chemicals, drugs and medicines products	142 ~ 171
S09	Non-metallic mineral products	172 ~ 187
S10	Basic metal products	188 ~ 208
S11	Fabricated metal products except machinery and furniture	209 ~ 219
S12	General machinery and equipment	220 ~ 239
S13	Electronic and electrical equipment	240 ~ 267
S14	Precision instruments	268 ~ 273
S15	Transportation equipment	274 ~ 287
S16	Furniture and other manufactured products	288 ~ 297
S17	Electricity, gas, steam and water supply	298 ~ 304
S18	Construction	305 ~ 320
S19	Wholesale and retail trade	321 ~ 322
S20	Accommodation and food services	323 ~ 326
S21	Transportation	327 ~ 340
S22	Communications and broadcasting	341 ~ 347
S23	Finance and insurance	348 ~ 353
S24	Real estate and business services	354 ~ 371
S25	Public administration and defense	372 ~ 373
S26	Education	374 ~ 376
S27	Health and social work services	377 ~ 383
S28	Other services	384 ~ 400

By utilizing the I/O tables as a core data to describe the production parts of the economy, it is possible to reclassify the industrial classifications considered in the SAM, and identify the industrial transactions in detail based on the Transaction Table of Domestic Goods and Services and the Transactions Table of Imported Goods and Services from I/O statistics. Accordingly, the values in the matrix S(1,1) and S(2,1) in Table 1 can be filled out. As mentioned earlier, in this study industrial sectors are classified into 28 sectors within the SAM as shown in Table 2. Thus, S(1,1) and S(2,1) can be understood as 28*28 square matrixes. In addition, S(3,1) represents labor inputs for industrial sectors, which can be derived from 1*28 row vector based on the ‘Compensation of employees’ account in the Total Transaction Table for the base year. The S(4,1) element in the SAM as shown in Table 1 represents the capital inputs for industrial sectors, which is derived from 1*28 row vector based on the summation of ‘Operating surplus’ and ‘Depreciation of fixed capital’ accounts in the Total Transaction Table for the base year. In addition, as the indirect taxes from industrial sectors, S(8,1) can be identified from ‘Other net taxes on production(Less subsidies)’ account in the Total Transaction Table with a 1*28 row vector. The S(9,1) element in the SAM can be understood as corporate taxes paid by industrial sectors, which can be calculated by multiplying the 1*28 row vector of ‘Operating surplus’ account and corporate tax rates by industry type estimated by Kim (2009). With calculated corporate taxes paid by industrial sectors, values of S(9,1) are deducted from S(4,1) to avoid double counting.

The products and services produced from each industry are distributed and utilized for final demand such as, intermediate goods consumption, consumption of the households and government, fixed capital formation, and exports. S(1,5) and S(2,5) with 28*1 matrixes represent respectively domestic goods/services and imported goods/services consumed by households. Values for those elements in the SAM are derived from the ‘Private consumption expenditures’ columns in the Transaction Table of Domestic Goods and

Services and the Transactions Table of Imported Goods and Services, respectively. In addition, S(1,6) and S(2,6) with 28*1 matrixes represent respectively domestic goods/services and imported goods/services consumed by the government. Values for those elements in the SAM are derived from the 'Government consumption expenditures' columns in the Transaction Table of Domestic Goods and Services and the Transactions Table of Imported Goods and Services, respectively. The S(1,7) and S(2,7) elements in the SAM as shown in Table 1 indicate the values of products and services utilized for the investment goods(domestic and imported goods distributed into the fixed capital formation account). Values for S(1,7) and S(2,7) for the 28*1 matrixes are calculated by summing the 'Gross private fixed capital formation', 'Gross government fixed capital formation', 'Increase in stocks', and 'Acquisition less disposal of valuables' columns in the Transaction Table of Domestic Goods and Services and the Transactions Table of Imported Goods and Services, respectively.

In addition, SAM accounts corresponding to the rest of world (ROW) component describe the interaction between the national (domestic) economy and other countries, which can be divided into exports and imports accounts within the SAM framework. From this perspective, S(1,12) with a 28*1 column vector indicates the exports of produced products and services for each industry whose values are derived from the 'Exports' account in the Total Transaction Table of I/O statistics. On the other hand, S(12,13) with a 1*1 matrix can be understood as the total amounts of exports summing up all values of exports for each industry. In addition, S(13,2) with a 1*28 row vector can be obtained by transposing the 28*1 column vector of the 'Imports' account in the Total Transaction Table of the I/O statistics applying the industrial classifications covered in the SAM (see Table 2). Furthermore, as balancing items calculated as the difference between S(12,13) and S(13,2), values of the balance of trade are to be written in S(7,13) to make the values of rows and columns in agreement in accordance with the principles of double-entry bookkeeping. The values of S(11,2) with a 1*28 matrix are obtained by transposing the 28*1 column vector acquired from the 'Tariffs' and 'Taxes on products (imports)' accounts in the Total Transaction Table of the I/O statistics. Thus, S(11,2) indicates the tariffs imposed to the imported goods and services.

On the other hand, in case of S(5,3) and S(5,4), the sum of S(3,1) (i.e., the value of S3) and the sum of S(4,1) (i.e., the value of S4) are reflected for those cells in accordance with the principles of double-entry bookkeeping. Accordingly, values for S(5,3) and S(5,4) indicate the household's income earned by labor and capital inputs. As the component showing the total savings of the household, S(7,5) can be derived from 'Total savings and Total investments' statistics for the 'Households and non-profit organizations' in the National Accounts statistics published by the Bank of Korea. On the other hand, S(7,5), which indicates the total savings of the government, can be obtained from 'Total savings and Total investments' statistics for the 'General government' in the National Accounts statistics. As the income taxes imposed to the household, the values of S(10,5) can be obtained from the National Tax Statistics published by the National Tax Service in Korea. In addition, the government collect its earnings (incomes) by collecting tax revenues including indirect taxes, corporate taxes, incomes taxes, and tariffs. Those tax revenues collected by the government are listed in S(6,8), S(6,9), S(6,10), and S(6,11) cells in the SAM. Those S(6,8), S(6,9), S(6,10), and S(6,11) indicate indirect taxes, corporate taxes, incomes taxes, and tariffs respectively, which are obtained by the values of sums of rows of S08, S09, S10, and S11, in accordance with the principles of double-entry bookkeeping. In addition, S(5,6) and S(6,7) are balancing items for equalizing the sum of rows and columns, representing the government transfer payments and government debt respectively.

In this way, the I/O statistics including the Transaction Table of Domestic Goods and Services, the Transactions Table of Imported Goods and Services, and the Total Transaction Table serve as the core dataset for constructing a standard SAM, but other supplementary datasets including the National Accounts statistics and the National Tax Statistics are additionally needed to capture the information on taxes, savings, and incomes for institutions. In summary, this study utilize a 2010 I/O table from the Bank of Korea, and tax-related data in the 2010 National Tax Statistics published by the National Tax Service in Korea. In addition, the data on household and government savings are extracted from the National Accounts statistics.

3.1.2 Construction of knowledge-based SAM

This subsection briefly describes how the knowledge-based SAM is constructed, based on the standard form of SAM as presented above. This study adopts a knowledge-based SAM made by the method of Yang et al. (2012), Hong et al. (2014), and Jung et al. (2017).

The detailed methodological approaches and procedures for constructing a knowledge-based SAM are presented in Yang et al. (2012)'s work. As we have seen in the Chapter 2.2, in order to consider knowledge and innovation as key elements in the macroeconomic equational systems, the SAM data should also have explicit descriptions on those elements. In other words, information on accumulation of knowledge, and knowledge flows in the economic system should be incorporated into the SAM dataset. Therefore, in this subsection, key differences of the knowledge-based SAM developed in this study compared to the standard SAM are presented, and the structure of the knowledge-based SAM constructed for this study, which is extended from the standard form of the SAM is shown in Table 3. The main objective of constructing a knowledge-based SAM is to provide an accounting framework and associated dataset that can be utilized to analyze the macroeconomic effects of innovation policies based on the CGE model, by assuming that knowledge can be used as one of factor inputs which are accumulated through knowledge capital formation activities (i.e., R&D activities). To fulfil this purpose, two additional accounts are added to the standard SAM. Firstly, 'knowledge account' is additionally considered as another value-added account along with labor and physical capital. By assuming that R&D expenditures and investments be the capitalization process of knowledge stocks, and knowledge be the products of R&D expenditures, knowledge account is taken into account as an independent production factor separated from labor and capital within the SAM framework. Secondly, the 'knowledge capital formation' which is distinguished from the 'fixed capital formation' account is additionally considered as another investment account within the SAM. Capitalization of R&D means that investments for R&D is preceded, and R&D activities are carried out by utilizing investment resources. Incorporating those features, the knowledge-based SAM has two additional accounts compared to the standard SAM; “knowledge” in value-added accounts (i.e., production factors), and “knowledge capital formation” in investment accounts. In addition, the latter is subdivided into private and public knowledge capital, according to who spent it.

Accordingly, to construct the knowledge-based SAM it is essential to check how the information on accumulation of knowledge, and knowledge flows in the economic system has been dealt with in the I/O tables and the standard SAM (Hong et al., 2014; Jung et al., 2017; Yang et al., 2012). The 2010 I/O statistics utilized for this study to construct the SAM has followed the guidelines of the 1993 System of National Accounts (SNA). Thus, within the 2010 I/O table, the current expenditure on R&D is included in intermediate goods transactions, while the capital expenditure on R&D is reflected in the fixed capital formation account. Following the methodological approaches suggested by Yang et al. (2012), within the knowledge-based SAM used for this study, current expenditure on R&D, which was initially included in intermediate consumption, 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. Therefore, it is essential to identify and reflect proper values in the newly added accounts (“knowledge” in value-added accounts and “knowledge capital formation” in investment accounts), and adjust the pre-existing values of other accounts.

As a first step to identify values for the knowledge account as another production factor, the amounts of R&D expenditures spent by each industry are identified in the intermediate goods transaction matrix by capturing values intermediate consumption expenditure for '(Public) research institute (357th sector in the most-detailed I/O table)', '(Non-profit) research institute (358th sector)', and 'research and experiment in enterprise (360th sector)' by industry. It is assumed that those 'research institute' industries in the I/O table produce R&D goods, which is knowledge. In addition, it can be understood that current expenditure on R&D by industrial sector can be identified from the transactions between each industry and those 'research institute' industries. Accordingly, those identified R&D expenditures spent by each industry are considered as the knowledge inputs for each industry, and moved to the knowledge in value-added accounts, by eliminating values from the intermediate transaction matrix to prevent double-counting. Those values are filled out in *A* cell in Table 3. In addition, these values represent the economic benefits earned by the innovation activities (R&D activities), which are allocated to the households to consist incomes of households as shown in *B* cell in Table 3. It is also assumed that the government does not earn incomes from knowledge capital inputs, and assumed that incomes earned by knowledge capital inputs are received only by households.

Secondly, for the consideration of the knowledge capital formation account, the current expenditure on R&D has been identified. To this end, the intermediate consumption columns of research institute sectors including '(Public) research institute (357th sector in the most-detailed I/O table)', '(Non-profit) research institute (358th sector)', and 'research and experiment in enterprise (360th sector)' in 403 basic sectors covered in most-detailed I/O table are moved to the knowledge capital formation account to consider the current (ordinary) expenditure in R&D (Yang et al., 2012). Thus, it is possible to record *H, I, J, K, L, M,* and *N* cells in Table 3 by identifying the expenditure structure of 357th, 358th, and 360 sectors. In this process, the expenditure columns of '(Public) research institute (357th sector in the most-detailed I/O table)', '(Non-profit) research institute (358th sector)' are summed up to be considered as the 'public knowledge capital formation' account, while the expenditure column of 'research and experiment in enterprise (360th sector)' is considered as the 'private knowledge capital formation' account to summarize the current expenditure structures of R&D.

Thirdly, for the consideration of the knowledge capital formation account, the capital expenditure on R&D has been also identified to describe the expenditure structure of the R&D. To figure out relevant values for capital expenditure as knowledge capital formation, this study utilizes the 'Survey of Research and Development in Korea, 2010' published by KISTEP (2011). The capital expenditure on R&D consists of expenditure on machinery, land and buildings, and computer software. In the 2010 I/O table, capital expenditure on R&D is initially included in the fixed capital formation account. Accordingly, in order to prevent double-counting, the amounts of capital expenditure on R&D should be deducted from the fixed capital formation, and then the same amount shall be reflected in the knowledge capital formation account. Therefore, the capital expenditure on R&D for machinery is assumed to have been spent on ‘General machinery and equipment (S12)’, ‘Electronic and electrical equipment (S13)’, ‘Precision instruments (S14)’, ‘Transportation equipment (S15)’, and ‘Furniture and other manufactured products (S16)’ sectors in the industrial classifications considered within the SAM framework. In addition, the capital expenditure on R&D for land and buildings is assumed to be expenditures on the ‘Construction (S18)’ industry, while the capital expenditure on R&D for computer software is assumed to have been spent on ‘Real estate and business services (S24)’ sector. Accordingly, based on the identifiable values for the capital expenditure on the machinery, land and buildings, and computer software in the ‘Survey of Research and Development in Korea, 2010’, the amount equivalent to capital expenditure on R&D is subtracted from the fixed capital formation account for those relevant sectors including ‘General machinery and equipment (S12)’, ‘Electronic and electrical equipment (S13)’, ‘Precision instruments (S14)’, ‘Transportation equipment (S15)’, ‘Furniture and other manufactured products (S16)’, ‘Construction (S18)’, and ‘Real estate and business services (S24)’ sectors, and added same amounts of values into the newly added knowledge capital formation accounts. At this time, the method of splitting those values into the private and public knowledge capital formation accounts is based on the proportion of private and public sectors in capital expenditure on R&D identified in the ‘Survey of Research and Development in Korea, 2010’. After proceeding third step for the consideration of the capital expenditure on R&D within the knowledge capital formation account, values for *G, H, I,* and *J* cells in Table 3 can be filled out.

In addition, capitalization of R&D accompanies with savings. As fixed capital formation is formed through the savings of economic entities including households and governments, knowledge capital formation is also accompanied with savings for R&D from institutions. In order to identify the relevant values associated with savings for R&D within the knowledge-based SAM, we utilize the relative shares of private and public sectors' financial resources in the total R&D investments in the private and public sectors identified in the 'Survey of Research and Development in Korea, 2010', and fill out values for *C, D, E,* and *F* cells in Table 3. In addition, the amounts equivalent to *C, D, E,* and *F* cells are deducted from the private savings and public savings for fixed capital formation (S(7,5) and S(7,6) cells in Table 1).

Finally, by re-balancing the balancing items of the SAM data after proceeding those steps as mentioned above, the knowledge-based SAM can be constructed as shown in Table 3. Additional accounts to construct the knowledge-based SAM in this study from the standard SAM can be summarized as *A, B, C, D, E, F, G, H, I, J, K, L, M, N,* and *O* cells in Table 3, compared to the standard form of SAM as presented in Table 1. Main steps and procedures to construct the knowledge-based SAM described above are summarized as follows; 1) consideration of knowledge in the production factor account (① step in Figure 6), 2) consideration of current expenditure on R&D within the knowledge capital formation account (②-1 step in Figure 6), and 3) consideration of capital expenditure on R&D within the knowledge capital formation account (②-2 step in Figure 6). Those main procedures are depicted in Figure 6 as below.

Table 3. Meanings of individual accounts in the Knowledge-based SAM

		Production		Factor inputs			Institutions		Investments			Taxes				ROW		Total
		Domestic goods	Domestic goods	Labor	Capital	Know.	Hou.	Govt.	Physical capital formation	Knowledge capital (private)	Knowledge capital (public)	Indirect	Corporate	Income	Tariffs	Exports	Imports	
P	Domestic goods	Intermediate transactions					Private consump-tion	Public consump-tion	Physical capital formation	**G**	**H**					Exports		S01
	Domestic goods	Intermediate transactions					Private consump-tion	Public consump-tion	Physical capital formation	**I**	**J**							S02
F	Labor	Labor inputs								**K**	**L**							S03
	Capital	Capital inputs								**M**	**N**							S04
	Knowledge	**A**																K1
I	Households			Labor income	Capital income	**B**												S05
	Government								Govt. Debt			Indirect taxes	Corporate taxes	Income taxes	Import tariffs			S06
I	Fixed capital formation						Private saving	Public saving									Balance of trade	S07
	Knowledge capital (private)						**C**	**D**										K2
	Knowledge capital (public)						**E**	**F**										K3
T	Indirect	Indirect taxes								**O**	**P**							S08
	Corporate	Corporate taxes																S09
	Income						Income taxes											S10
	Tariffs																	S11
R	Exports																Exports	S12
	Imports		Imports															S13
Total		S01	S02	S03	S04	K1	S05	S06	S07	K2	K3	S08	S09	S10	S11	S12	S13	

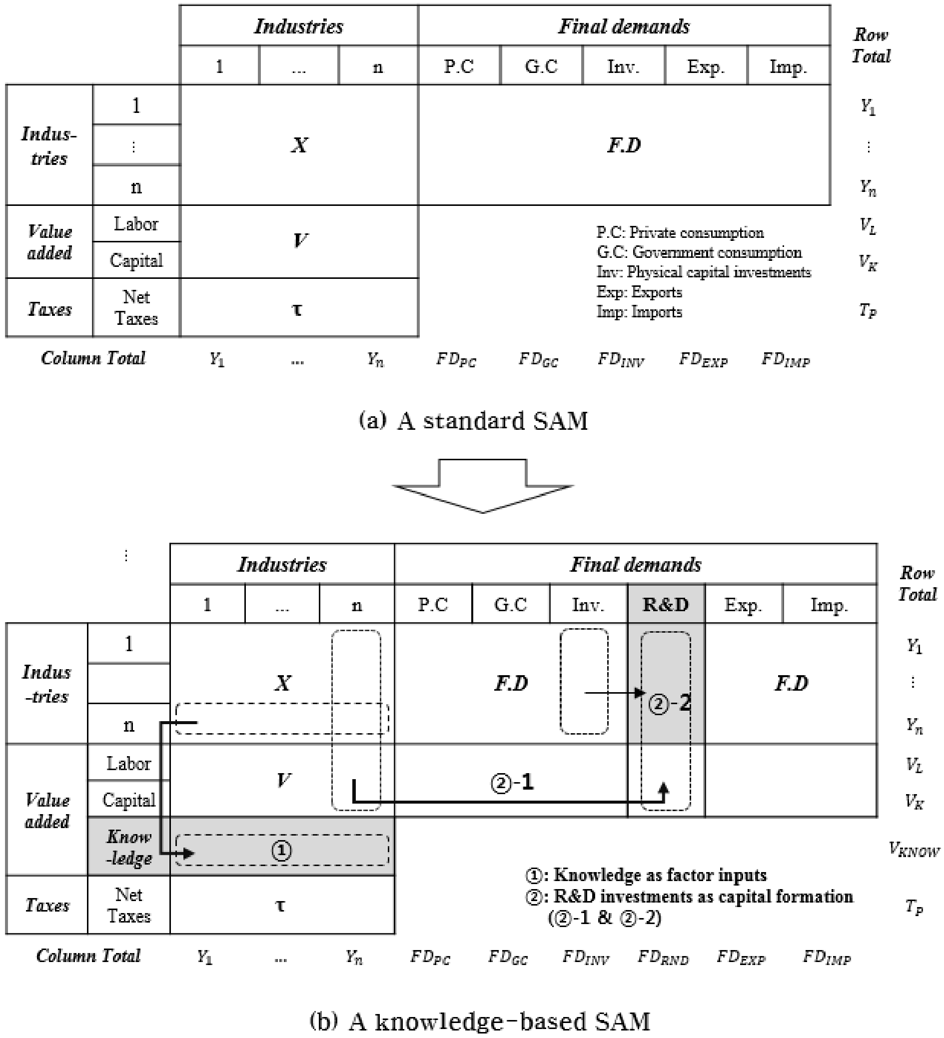


Figure 6. Main procedures to construct a knowledge-based SAM

3.1.3 Construction of micro-SAM for labor and households accounts

Based on the knowledge-based SAM data presented in the previous subsection, as the final step for constructing the SAM this study aims to develop the detailed micro-SAM with considerations of heterogeneous households with different income and consumption structures, and different types of labor with heterogeneous human capital accumulation. By constructing a micro-SAM for labor and households accounts, this study aims to construct a dataset for the CGE model, which can be utilized for capturing the different productivity of different types of labor in the production function, and analyzing the different impacts on heterogeneous labor and households triggered by policy shocks. To consider different types of labor, we have classified the single labor into three types, based on the educational attainment levels in incorporate heterogeneous human capital accumulation for workers. To be specific, labor inputs for production of final goods and knowledge production sectors are split into three types; high-skilled, skilled, and low-skilled labor followed by Jung et al. (2017)'s work. When disaggregating the single labor account into three different types of labor within the SAM, we consider workers who have finished graduate schools (i.e., master's and doctor's degree holders) as high-skilled labor. College and university graduates are considered as skilled labor, while low-skilled labor are characterized by lower educational attainment levels, such as high school education or less. Furthermore, the single household account is also disaggregated into 20 quantiles of households on the basis of income levels, to capture heterogeneous characteristics of households with different income and consumption structures.

Based on these classifications as mentioned above, the '2010 Survey Report on Labor Conditions by Employment Type' published by the Ministry of Employment and Labor in Korea has been utilized to classify the single labor into three types, based on the educational attainment levels. This raw data contains information on working days, working hours, wages, working conditions, individual characteristics of workers, etc. with a sample of 1,471,138 permanent employees. In addition, 'Survey of Research and Development in Korea, 2010' published by the KISTEP (Korea Institute of S&T Evaluation and Planning) has been utilized to figure out the information on workforce in private and public R&D sectors. Based on the above-mentioned raw datasets, we have we extract information on labor inputs by labor type in terms of educational attainment levels for industrial sectors and R&D sectors, in order to consider three different types of labor accumulated heterogeneous human capital. To measure a worker's proficiency and skills, various criteria can be used. Studies that measure the human capital accumulation of workers generally use average years of schoolings as a variable representing the skills and knowledge possessed by workers (Michaels et al., 2014). Based on the average years of schoolings, previous studies attempt to compare the levels of human capital accumulation between countries, and this approach has the advantage of having an explanatory power to account for skills and knowledge possessed by workers in intuitive manners (Barro & Lee, 2013; Lee & Lee, 2016; O'Mahony et al., 2008).

Following this approach, we consider the educational attainment level as the proxy variable to represent the skills and knowledge of workers in the process of disaggregating the labor account. Based on this assumption, matching between the industrial codes (*s2 variable*) in the '2010 Survey Report on Labor Conditions by Employment Type' published by the Ministry of Employment and Labor, and educational attainment level for workers (*f1 variable*: 1) Middle school graduates, 2) High school graduates, 3) College/University graduates, and 4) Graduate school graduates (master and doctoral degrees)), and matching between industrial codes in the '2010 Survey Report on Labor Conditions by Employment Type' which is based on the Korean Standard Industrial Classification (KSIC) and industrial classifications considered in the SAM (see Table 4) are performed.

Table 4. Matching between industrial classifications in SAM and codes in KSIC

Industrial classifications in SAM		Industrial codes in KSIC
S01	Agriculture, forestry and fishing	01, 02, 03
S02	Mining and quarrying	05, 06, 07, 08
S03	Food, beverages and tobacco products	10, 11, 12
S04	Textile and apparel	13, 14, 15
S05	Wood and paper products	16, 17
S06	Printing and reproduction of recorded media	18
S07	Petroleum and coal products	19
S08	Chemicals, drugs and medicines products	20, 21, 22
S09	Non-metallic mineral products	23
S10	Basic metal products	24
S11	Fabricated metal products except machinery and furniture	25
S12	General machinery and equipment	29
S13	Electronic and electrical equipment	26, 28
S14	Precision instruments	27
S15	Transportation equipment	30, 31
S16	Furniture and other manufactured products	32, 33, 34
S17	Electricity, gas, steam and water supply	35, 36, 37, 38, 39
S18	Construction	41, 42
S19	Wholesale and retail trade	45, 46, 47
S20	Accommodation and food services	55, 56

S21	Transportation	49, 50, 51, 52
S22	Communications and broadcasting	58, 59, 60, 61
S23	Finance and insurance	64, 65, 66
S24	Real estate and business services	62, 63, 68, 69, 70, 71, 72, 73, 74, 75
S25	Public administration and defense	84
S26	Education	85
S27	Health and social work services	86, 87
S28	Other services	90, 91, 94, 95, 96

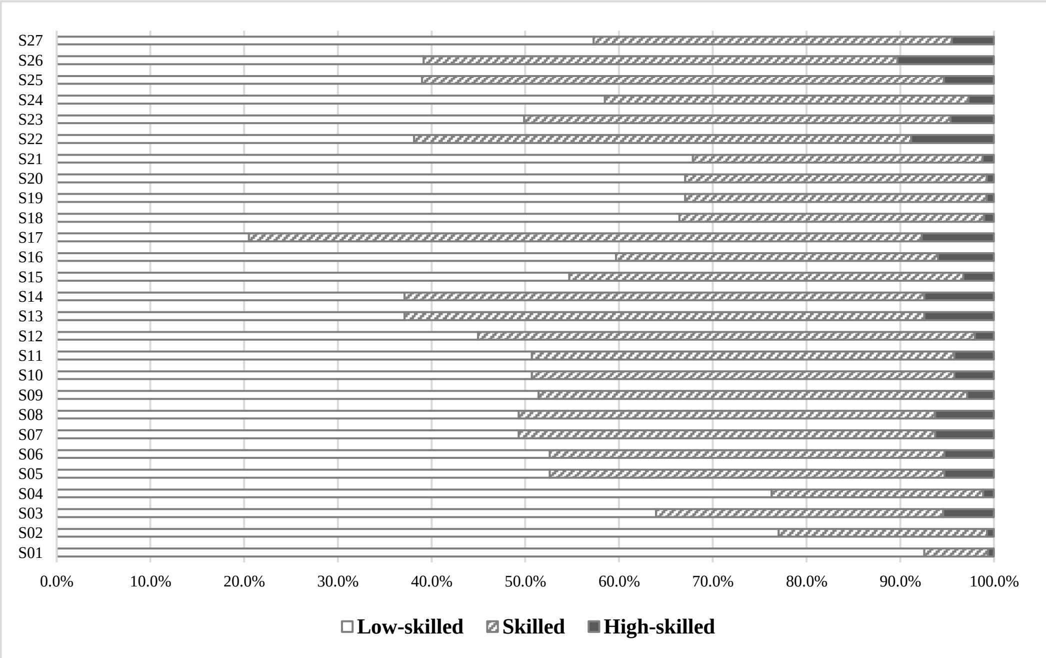


Figure 7. Relative shares of different types of labor in terms of human capital accumulation by industrial sector (Unit: %)

After proceeding those matching procedures, the share of each type of labor (low-skilled labor: high school graduates or lower levels, skilled labor: college/university graduates, high-skilled labor: masters or doctoral degree holders) in each industrial sector

($SHR\_LAB_{LOW,i}$: low-skilled labor, $SHR\_LAB_{MIDDLE,i}$: skilled labor, $SHR\_LAB_{HIGH,i}$: high-skilled labor) has been identified, as shown in Figure 7. Those relative shares of different types of labor used in industrial sectors are multiplied by total labor inputs for industrial sectors (S(4,1) in Table 3) to achieve the segmentation of the labor accounts for industrial sectors within the SAM.

As discussed above, it is attempted to segment the value of labor inputs (i.e., value-added) by industry within the SAM data, on the basis of the number of workers with different characteristics in terms of educational attainment levels. However, the relative proportions of different types of workers in accordance of the human capital accumulation are derived on the basis of the number of people used in each industrial sector, while in the case of the values of labor inputs for industrial sectors to be disaggregated are measured in terms of monetary units. Accordingly, the segmentation process of labor inputs by industrial sector based on the approach presented above has a limitation in that it cannot capture the differences in wages between low-skilled, skilled, and high-skilled workers. For example, Kim et al. (2015)'s work has tried to estimate the relative share of compensation of employees (i.e., labor inputs in value-added accounts) in the SAM framework by skill level, by capturing the wage level per worker according to the skill level (i.e., measured by the educational attainment level), as well as the number of workers in accordance of skill level in order to disaggregate the single labor account according to the skill levels. With this approach, Kim et al. (2015) utilizes raw datasets including the Report of the Census on Establishments published by Statistics Korea, Korean Labor and Income Panel Study published by the Korea Labor Institute, and datasets published by the International Labor Organization (ILO). The methodological approaches presented by Kim et al. (2015)'s work might be an appropriate approach to consider both the number of workers by industry and the per capita wages by skill level for the detailed breakdown of the single labor account based on the skill level. However, due to the limitations of data collection in capturing differences in wage levels among workers with different skill levels, this study has attempted to disaggregate the labor inputs for production of final goods into three types of labor on the basis of the relative quantities of different types of workers used in industrial sectors, not considering the per capita wages by skill level. Accordingly, this study aims to describe the different marginal productivity among different types of workers who have accumulated different levels of knowledge and skills (low-skilled, skilled, and high-skilled labor) by incorporating different values of substitution elasticities in multi-level nested CES (Constant Elasticity of Substitution) production function. Methodological approaches regarding this issue will be presented in Chapter 4.

In addition, as mentioned above, 'Survey of Research and Development in Korea, 2010' published by the KISTEP (Korea Institute of S&T Evaluation and Planning) has been utilized to figure out the information on workforce in private and public R&D sectors. From this raw dataset, the information on the distribution of workforce by sector (i.e., private and public R&D institutions and sectors) has been extracted to disaggregate the labor inputs for the knowledge capital formation account within the SAM. The distribution of workers by R&D sector and degree is shown in Table 5. As shown in Table 5, in the case of private

R&D sector, 57.9% of R&D personnel were found to be from skilled labor with college/university graduates, 28.7% of the R&D workforce were master's degree holders, and 6.5% of the R&D personnel were doctoral degree holders. On the other hand, in the case of public research institutes (public research institutes and universities), 6.2% of R&D personnel were found to be from skilled labor with college/university graduates, 37.0% of the R&D workforce were master's degree holders, and 55.8% of them were doctoral degree holders. Using these figures, the share of each type of labor (low-skilled labor: high school graduates or lower levels, skilled labor: college/university graduates, high-skilled labor: masters or doctoral degree holders) in each R&D sector ($SHR\_LAB_{LOW,RND,t}$ $t = private\ R\&D\ or\ public\ R\&D$: low-skilled labor, $SHR\_LAB_{MIDDLE,RND,t}$: skilled labor, $SHR\_LAB_{HIGH,RND,t}$: high-skilled labor) has been identified. Those relative shares of different types of labor used in R&D sectors are multiplied by total labor inputs for R&D sectors (L, and M in Table 3) to achieve the segmentation of the labor accounts for R&D sectors (i.e., knowledge capital formation account) within the SAM.

Table 5. Distribution of workforce in Korea's R&D institutions (Unit: persons (%))

	Public R&D	Private R&D
High school graduates or below	1,298 (1.08%)	15,663 (6.93%)
College/University graduates	7,385 (6.17%)	130,900 (57.88%)
Graduate school graduates (Master's degree)	44,296 (36.99%)	64,928 (28.71%)

Graduate school graduates (Doctoral degree)	66,765 (55.75%)	14,677 (6.49%)
Total	119,744 (100.00%)	226,168 (100.00%)

After proceeding those procedures to disaggregate the single labor account into the three types of labor (i.e., low-skilled, skilled, and high-skilled labor) by sectoral level, it is possible to calculate values of total labor inputs (i.e., value-added for labor, or compensation of employees) by labor type (V_{L1}: total value-added from low-skilled labor, V_{L2}: total value-added from skilled labor, V_{L3}: total value-added from high-skilled labor). In order to distribute labor incomes according to the type of households (i.e., 20 quantiles of households), the micro data of the '2010 Household Income and Expenditure Survey (HIE Survey)' published by Statistics Korea has been used, which provides incomes and expenditures of households and household conditions with a sample of 9,932 households. In allocating the labor incomes to different types of households, the labor input structure (i.e., structure of labor market participation) of households by each income quantile has been figured out based on the householder's educational attainment level after classifying the sample of 9,932 households into 20 quantiles based on the total household's income levels. Based on this approach, the share of each income quantile of households (*HH*) in total labor incomes from different types of labor (low-skilled, skilled, and high-skilled) has been identified ($SHR\_LAB_{LOW,HH}$: share of *HH*-th type of households in total labor income from low-skilled labor; $SHR\_LAB_{MIDDLE,HH}$: share of *HH*-th type of households in total labor income from skilled labor; $SHR\_LAB_{HIGH,HH}$: share of *HH*-th type of households in total labor income from high-skilled labor). Those values including, $SHR\_LAB_{LOW,HH}$, $SHR\_LAB_{MIDDLE,HH}$, and $SHR\_LAB_{HIGH,HH}$ are multiplied by total labor incomes, V_{L1}, V_{L2}, and V_{L3} in order to calculate the values of labor income by labor type for each income quantile.

In this study, in allocating the labor income to different types of households, the educational attainment level of the householder has been used as a variable to match the segmentation process of the labor account by skill level, and disaggregation process of the households account by income level. The extraction of the characteristics of the labor market participation for each type of households based on the householder's educational background has a limitation in grasping all information on the level of heterogeneous human capital accumulation and the labor market participation status of household members. However, when considering the data availability and data processing issues, it is considered as an appropriate approach to utilize the highest level of education achieved by the householder for each household to maintain consistency in the segmentation of labor and household accounts in the SAM data system. The methods of constructing a coherent SAM dataset through the mutual combination of micro data for labor (employment) and household accounts, including the '2010 Survey Report on Labor Conditions by Employment Type' and the '2010 Household Income and Expenditure Survey (HIE Survey)' can be understood as shown in Figure 8.

Survey report on Labor Conditions by Employment Type	
Industry codes (variable: s2)	1) Agriculture, forestry and fishing 2) Mining and quarrying 3) Manufacturing (total 25 sectors) 4) Electricity, gas, steam and air conditioning supply 5) Water supply; sewage, waste management, materials recovery 6) Construction 7) Wholesale and retail trade 8) Transportation and storage 9) Accommodation and food service activities 10) Information and communication 11) Financial and insurance activities 12) Real estate activities 13) Professional, scientific and technical activities 14) Business facilities management and business support services; rental and leasing activities 15) Public administration and defense; compulsory social security 16) Education 17) Human health and social work activities 18) Arts, sports and recreation related services 19) Membership organizations, repair and other personal services 20) Activities of households as employers; undifferentiated goods-and services-producing activities 21) Activities of extraterritorial organizations and bodies
Level of education (f1)	**1) Middle school graduate or below** **2) High school graduate** **3) College/University graduate** **4) Graduate school graduate(Master & Doctoral degrees)**

Household Income and Expenditure Survey (HIE Survey)	
Incomes by household (income)	1) Gross incomes 2) Wage and salary income 3) Business income 4) Property income
Expenditures by household (expend)	1) Food and non-alcoholic beverages 2) Alcoholic beverages and tobacco 3) Clothing and footwear 4) Housing, water, electricity and other fuels 5) Furnishings and household equipment 6) Health 7) Transport 8) Communication 9) Recreation and culture 10) Education 11) Restaurants and hotels 12) Miscellaneous goods and services
Saving by household (sav)	1) Non-consumption expenditure 2) Expenditure by variants of financial assets
Taxes by household (tax)	1) Regular taxes 2) Non-regular taxes
Level of education by household (school)	**1) None** **2) Elementary school graduate** **3) Middle school graduate** **4) High school graduate** **5) College/University graduate** **6) Graduate school graduate(Master & Doctoral degrees)**

Matching between "Labor" and "Households" accounts

Figure 8. Match between labor and households accounts within the SAM dataset

Table 6. Utilization of the HIE Survey for disaggregating households by income level

Household Income and Expenditure Survey (HIE Survey)	
Incomes by household (income)	1) Gross incomes 2) Current incomes 3) Wage and salary income 4) Business income 5) Property income
Expenditures by household (expend)	1) Food and non-alcoholic beverages 2) Alcoholic beverages and tobacco 3) Clothing and footwear 4) Housing, water, electricity and other fuels 5) Furnishings and household equipment 6) Health 7) Transport 8) Communication 9) Recreation and culture 10) Education 11) Restaurants and hotels 12) Miscellaneous goods and services
Saving by household (sav)	1) Non-consumption expenditure 2) Expenditure by variants of financial assets
Taxes by household (tax)	1) Regular taxes 2) Non-regular taxes
Level of education by household (school)	1) None 2) Elementary school graduate 3) Middle school graduate 4) High school graduate 5) College/University graduate 6) Graduate school graduate (Master & Doctoral degrees)

In addition to the segmentation of the labor account, the micro perspective has been reflected when classifying households into 20 income categories, based on gross income by utilizing micro data (i.e., HIE Survey) as shown in Table 6. In order to subdivide not only the labor incomes for each type of households, but also the physical capital incomes and knowledge capital incomes earned by each type of households, the income-related information (including, current incomes, labor incomes, business incomes, property incomes, non-current incomes, and other incomes) for each household quintile identified from the HIE Survey data has been utilized. Using those relevant values for each household quantile, the share of each household quantile in the total capital incomes SHR_CAP_{HH} can be identified where the capital incomes are calculated through summing up the business and property incomes in the HIE survey data, by calculating the relative share of each type of households in the total capital incomes earned by aggregate households. Those values SHR_CAP_{HH} for household quantiles are multiplied by total capital incomes (V_K) and total knowledge capital incomes (V_{KNOW}) identified from the SAM data to figure out the amounts of incomes received from the knowledge capital inputs and physical capital inputs by each household quantile. Based on this approach, we have tried to segment the income information of households within the SAM. The relative shares of each household quantile in the value-added composition, and the income structures of each household quantities for the base year of 2010 identified from the HIE survey data are shown in Table 7 and Table 8 as below.

Table 7. Relative share of each household quantile in the value-added composition for the base year of 2010 (Unit: %)

		Share of each income quantile within the value-added				
		Physical capital	Low-skilled labor	Skilled labor	High-skilled labor	Knowledge capital
H1	Quantile 1	0.10%	0.70%	0.30%	0.10%	0.40%
H2	Quantile 2	0.40%	1.60%	0.50%	0.40%	0.90%
H3	Quantile 3	0.60%	2.30%	0.70%	0.60%	1.40%
H4	Quantile 4	1.30%	2.80%	1.20%	1.00%	1.80%
H5	Quantile 5	1.70%	3.40%	1.70%	1.50%	2.30%
H6	Quantile 6	2.20%	4.00%	2.30%	2.00%	2.70%
H7	Quantile 7	2.50%	4.10%	2.60%	2.20%	3.10%
H8	Quantile 8	3.20%	4.70%	3.10%	2.50%	3.50%
H9	Quantile 9	3.60%	5.00%	3.80%	3.00%	3.90%
H10	Quantile 10	4.00%	5.10%	4.10%	3.50%	4.30%
H11	Quantile 11	4.20%	5.30%	4.30%	4.00%	4.70%
H12	Quantile 12	4.50%	5.50%	4.70%	4.50%	5.00%
H13	Quantile 13	5.50%	5.80%	5.40%	5.00%	5.40%
H14	Quantile 14	6.20%	6.10%	6.10%	5.50%	5.90%
H15	Quantile 15	6.60%	6.40%	6.60%	6.00%	6.40%
H16	Quantile 16	7.40%	6.60%	7.60%	7.00%	7.00%
H17	Quantile 17	8.00%	7.20%	8.10%	8.00%	7.70%
H18	Quantile 18	9.80%	7.30%	9.80%	9.50%	8.70%
H19	Quantile 19	12.00%	7.60%	11.40%	13.70%	10.10%
H20	Quantile 20	16.20%	8.50%	15.70%	20.00%	14.80%
Total		100.00%	100.00%	100.00%	100.00%	100.00%

Table 8. Income structure of each household quantile for the base year of 2010 (Unit: %)

		Income structure of each household quantile					Total
		Physical capital	Low-skilled labor	Skilled labor	High-skilled labor	Knowledge capital	
H1	Quantile 1	15.84%	56.86%	21.37%	1.09%	4.84%	100.00%
H2	Quantile 2	25.95%	53.22%	14.58%	1.79%	4.46%	100.00%
H3	Quantile 3	26.76%	52.60%	14.04%	1.84%	4.77%	100.00%
H4	Quantile 4	37.34%	41.24%	15.50%	1.98%	3.95%	100.00%
H5	Quantile 5	37.89%	38.86%	17.04%	2.30%	3.91%	100.00%
H6	Quantile 6	39.08%	36.44%	18.37%	2.45%	3.66%	100.00%
H7	Quantile 7	40.58%	34.13%	18.98%	2.46%	3.84%	100.00%
H8	Quantile 8	42.99%	32.38%	18.73%	2.31%	3.59%	100.00%
H9	Quantile 9	42.97%	30.61%	20.40%	2.47%	3.55%	100.00%
H10	Quantile 10	44.30%	28.97%	20.42%	2.67%	3.64%	100.00%
H11	Quantile 11	44.28%	28.65%	20.38%	2.91%	3.78%	100.00%
H12	Quantile 12	44.44%	27.86%	20.87%	3.06%	3.77%	100.00%
H13	Quantile 13	47.17%	25.51%	20.83%	2.96%	3.54%	100.00%
H14	Quantile 14	48.06%	24.25%	21.26%	2.94%	3.49%	100.00%
H15	Quantile 15	47.99%	23.87%	21.58%	3.01%	3.55%	100.00%
H16	Quantile 16	48.62%	22.24%	22.45%	3.17%	3.51%	100.00%
H17	Quantile 17	48.56%	22.41%	22.11%	3.35%	3.57%	100.00%
H18	Quantile 18	50.86%	19.43%	22.87%	3.40%	3.45%	100.00%
H19	Quantile 19	52.77%	17.14%	22.54%	4.15%	3.39%	100.00%
H20	Quantile 20	53.77%	14.47%	23.43%	4.58%	3.75%	100.00%

In addition, the share of consumption expenditure of goods and services for each income quantile $SHR\_PC_{i,HH}$ is identified to describe the heterogeneous expenditure structure of different types of households. To obtain relevant values, firstly household consumption expenditure items (i.e., products or services) covered in the HIE Survey and 28 industrial classifications of the SAM data should be matched to each other. Within the HIE Survey data, the consumption expenditure items consist of 1) Food and soft drinks, 2) Alcoholic beverages and cigarette, 3) Clothing and footwear, 4) Housing, water, electricity, gas and other fuels, 5) Household equipment and housekeeping services, 6) Health, 7) Transportation, 8) Communication, 9) Entertainment and culture, 10) Education, 11) Restaurants and hotels, and 12) Other miscellaneous goods and services. The matching process between consumption expenditure items of households covered in the HIE survey and the industrial classification in the SAM data has been made by comparing the items in the HIE survey data and the most-detailed industrial classification codes in the I/O table. After this matching process, secondly the share of consumption expenditure of goods and services for each income quantile $SHR\_PC_{i,HH}$ is multiplied by the amounts of the total consumption for each industrial outputs (i.e., products or services) PC_i to calculate the consumption expenditure for each industry in each household income quantile. The values for $SHR\_PC_{i,HH}$ identified from the HIE survey data after matching process between consumption expenditure items of households covered in the HIE survey and the industrial classification in the SAM data can be confirmed from Figure 9 as below.

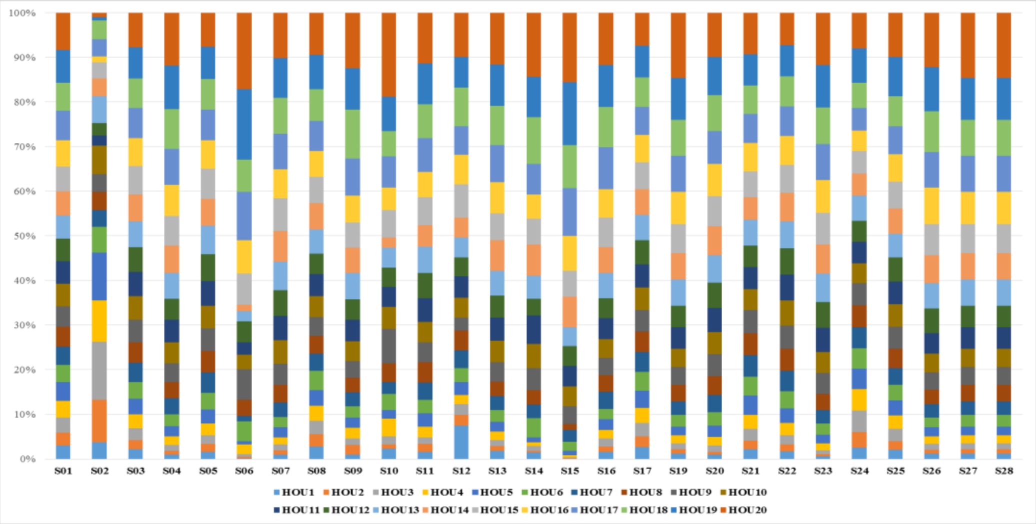


Figure 9. Share of consumption expenditure of goods and services for each income quantile identified from the HIE survey data (Unit: %)

Furthermore, the savings and income tax information by each income quantile is also extracted. In case of the saving information by each household quantile, values for the 'Expenditure by variants of financial assets' item within the HIE survey data have been utilized to calculate the share of each household quantile in the aggregate level of savings from the households (SHR_PS_{HH}). On the basis of those values for SHR_PS_{HH}, we have calculated the savings for physical capital formation, for private knowledge capital formation, and for public knowledge capital formation by each income quantile through multiplying values of SHR_PS_{HH} with the values of total private savings for physical capital formation PS_{FINV}, of total private savings for private knowledge capital formation PS_{RDC}, and of total private savings for public knowledge capital formation PS_{RDG}. On the other hand, in the case of the income tax paid by each income quantile, values for the summation of the 'Regular taxes' and 'Non-regular taxes' items within HIE survey data have been utilized to calculate the share of each household quantile in the aggregate level of income taxes paid by households (SHR_INCT_{HH}). Based on those values for SHR_INCT_{HH}, we have identified the income taxes paid by each income quantile by multiplying SHR_INCT_{HH} with the total income taxes identified from the standard SAM. In this way, the shares of savings and income tax by income quantile identified from the HIE survey data are shown in Figure 10 as below.

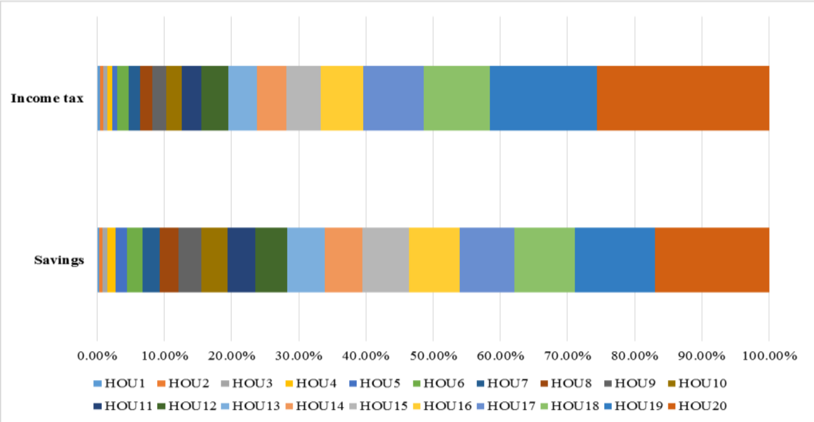


Figure 10. Shares of savings and income tax by each income quantile (Unit: %)

Through those procedures as mentioned above, we have classified the labor and households accounts to capture the heterogeneous characteristics of labor (in terms of human capital accumulation), and of households (in terms of income levels) within the SAM framework. Figure 11 shows the segmentation process of the labor accounts in the value-added for industrial sectors (① step in Figure 11), as well as the disaggregation of the labor incomes by household type (② step in Figure 11).

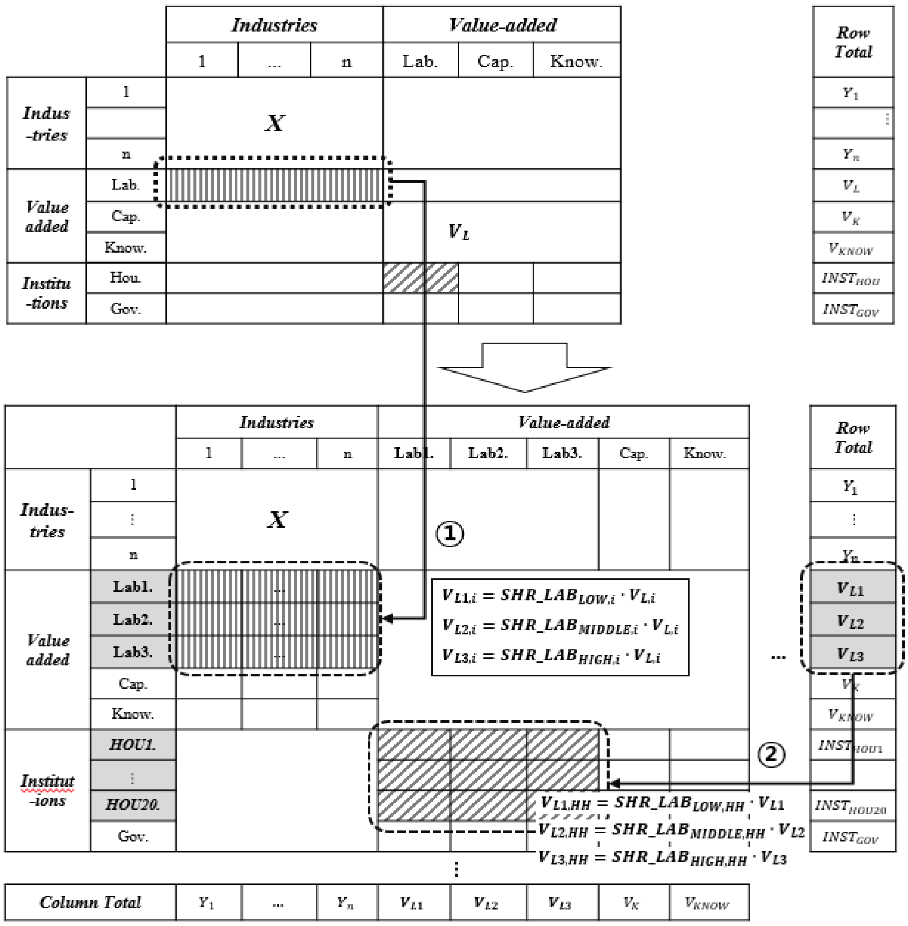


Figure 11. Procedures for segmentation of labor inputs in the value-added account

In addition, Figure 12 shows the segmentation process of the households account, including mapping the heterogeneous consumption expenditure structures for different types of households (① step in Figure 12), segmenting the labor, capital, and knowledge incomes by household type (②, and ③ steps in Figure 12), and calculating the savings and income taxes paid by each income quantile (④ step in Figure 12). The finalized form of the knowledge-based SAM that has been constructed through those procedures is shown in Table 9.

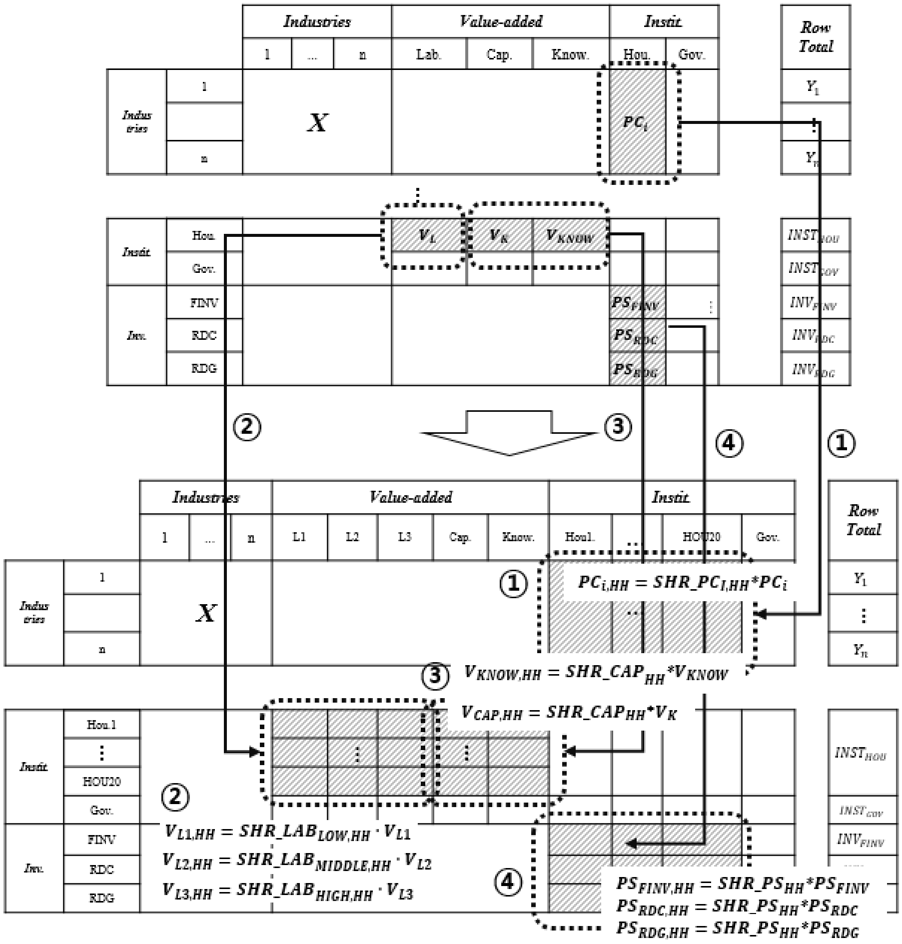


Figure 12. Procedures for segmentation of households account within the SAM

Table 9. Structure of the knowledge-based SAM and sizes of key components (matrices)

		Production		Factor inputs			Institutions		Investments			Taxes				ROW		Total
		Domestic goods	Domestic goods	Labor	Capital	Know.	Hou.	Govt.	Physical capital formation	Knowledge capital (private)	Knowledge capital (public)	Indirect	Corporate	Income	Tariffs	Exports	Imports	
P	Domestic goods	28*28					28*20	28*1	28*1	28*1	28*1					28*1		S01
	Domestic goods	28*28					28*20	28*1	28*1	28*1	28*1							S02
F	Labor	3*28								3*1	3*1							S03
	Capital	1*28								1*1	1*1							S04
	Knowledge	1*28																K1
I	Households			20*3	20*1	20*1												S05
	Government						1*20		1*1			1*1	1*1	1*1	1*1			S06
I	Fixed capital formation						1*20	1*1									1*1	S07
	Knowledge capital (private)						1*20	1*1										K2
	Knowledge capital (public)						1*20	1*1										K3
T	Indirect	1*28								1*1	1*1							S08
	Corporate	1*28																S09
	Income																	S10
	Tariffs																	S11
R	Exports																1*1	S12
	Imports		1*28															S13
Total		S01	S02	S03	S04	K1	S05	S06	S07	K2	K3	S08	S09	S10	S11	S12	S13	

3.2 SAM Multiplier analysis approaches and findings

3.2.1 Methodological approaches for SAM multiplier analysis

In this subsection, the theoretical concepts of the SAM multiplier analysis that can quantitatively measure the output growth and the distribution effects in the economic system induced by the R&D investments based on the knowledge-based SAM constructed as discussed above. In order to perform SAM multiplier analysis, a linear model should be established to capture changes in endogenous accounts due to changes in exogenous accounts. In order to analyze the SAM multiplier effects triggered by the R&D investments, we have endogenized the production activities of industrial sectors, factor inputs incomes (i.e., value-added) from knowledge, physical capital, and labor, and incomes and expenditures of households based on the constructed knowledge-based SAM with disaggregated labor inputs and households accounts. In addition, by using the linear association between the income- and expenditure-related accounts in the SAM, this study aims to investigate the structural features of Korean economy which determine the output growth and distribution effects induced by the R&D investments which is considered as the exogenous account, by analyzing the changes in production activities and relative incomes of the households induced by changes in exogenous accounts (i.e., physical capital investments and R&D investments).

When all the accounts in the SAM data are considered as endogenous accounts, the comparative static analysis cannot be performed. Accordingly, some of the accounts in the Social Accounting Matrix should be considered as exogenous accounts to analyze the effects of the changes in the exogenous accounts on the values of the remaining accounts in the SAM. Accordingly, in order to analyze the multiplier effects using a knowledge-based SAM constructed by the methods presented in the previous section 3.1, the accounts of the SAM should be classified into endogenous and exogenous accounts. There is no formal standard for classifying account into endogenous and exogenous, but endogenous accounts generally include production activities, production factors, and institutions, while exogenous accounts include investment, taxes, and the rest of world accounts (Keuning & de Ruuter, 1988; Llop & Manresa, 2004; Miller & Blair, 2009; Shin, 1999). Following this conventional approach, this study has also applied this classification criteria in considering endogenous and exogenous accounts for the SAM multiplier analysis. Table 10 shows the Social Accounting Matrix in which the endogenous and exogenous accounts are displayed separately in the form of matrix partitions.

Table 10. Classification of endogenous and exogenous accounts in SAM

<table>
<tr><td colspan="2" rowspan="2"></td><td>Production</td><td>Factor inputs</td><td>Inst.</td><td>Invest.</td><td>Taxes</td><td>ROW</td><td rowspan="2">Total</td></tr>
<tr><td colspan="3">Endogenous accounts</td><td colspan="3">Exogenous accounts</td></tr>
<tr><td>Production</td><td rowspan="3">End.</td><td colspan="3" rowspan="3">S_{11}</td><td colspan="3" rowspan="3">S_{12}</td><td rowspan="3">Y_1</td></tr>
<tr><td>Factor inputs</td></tr>
<tr><td>Institutions</td></tr>
<tr><td>Investments</td><td rowspan="3">Exo.</td><td colspan="3" rowspan="3">S_{21}</td><td colspan="3" rowspan="3">S_{22}</td><td rowspan="3">Y_2</td></tr>
<tr><td>Taxes</td></tr>
<tr><td>ROW</td></tr>
<tr><td colspan="2">Total</td><td colspan="3">Y_1</td><td colspan="3">Y_2</td><td></td></tr>
</table>

In order to perform a SAM-based multiplier analysis for the comparative statics analysis using the constructed knowledge-based Social Accounting Matrix, each column of the base year SAM is divided by the corresponding value of the column sum, and a column-stochastic matrix (*H*) with each column sum is equalized to one can be generated. For the SAM multiplier analysis, it is assumed that the coefficients matrix of the column-stochastic matrix is fixed, which means that the expenditure structure of each account does not change by exogenous shocks. Accordingly, the column-stochastic matrix *H* can be generated as shown in Equation Eq.(3.1). Here, the features of the matrix *H* are that is being a semi-positive matrix with the sum of each column is equalized as 1, and that *Y* matrix can be generated by multiplying *H* with the column sums vector of the base year SAM as shown in Table 10 $Y' = (Y_{1,} Y_2)'$. In addition, assuming that the accounts excluding the endogenous accounts in the column-stochastic matrix *H* are to be exogenous, the relational expression as shown in Eq.(3.3) can be obtained from the identity equation shown in Eq.(3.2) as shown below. The *I* matrix shown in Eq.(3.3) means the identity matrix.

$$\mathrm{H} = \begin{bmatrix} S11/_{Y_1} & S12/_{Y_2} \\ S21/_{Y_1} & S22/_{Y_2} \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} ; column - stochastic\ matrix \qquad \text{Eq.(3.1)}$$

$$\mathrm{Y} = \mathrm{H} \cdot \mathrm{Y} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \cdot \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{bmatrix} S11/_{Y_1} & S12/_{Y_2} \\ S21/_{Y_1} & S22/_{Y_2} \end{bmatrix} \cdot \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} \mathrm{S}11 + \mathrm{S}12 \\ S21 + S22 \end{pmatrix} = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} \qquad \text{Eq.(3.2)}$$

$$Y_1 = h_{11}Y_1 + h_{12}Y_2 = (I - h_{11})^{-1}h_{12}Y_2 \qquad \text{Eq.(3.3)}$$

$$\mathrm{d}Y_1 = (I - h_{11})^{-1}\,\mathrm{d}x_2 \qquad \text{Eq.(3.4)}$$

Since the components in the $(I-h_{11})^{-1}$ matrix in Eq.(3.3) is fixed, Y_1 can be expressed as the function of $h_{12}Y_2$. Here, $(I-h_{11})^{-1}$ matrix can be understood as the SAM multiplier, and $h_{12}Y_2$ be the vector of exogenous injections. With the form of the equational expression with $x_2 = h_{12}Y_2$, assuming that $\mathrm{d}Y_1$ and $\mathrm{d}x_2$ be the variants of endogenous and exogenous accounts respectively, the changes of exogenous accounts can drive variants in endogenous accounts through the $(I-h_{11})^{-1}$, the SAM multiplier matrix. Based on the outcomes derived by the Equations Eq.(3.3) and Eq.(3.4), the updated values for endogenous accounts' column sums can be calculated, and newly modified values for the components of the endogenous accounts' matrices can be derived by transposing the updated vector with column sums of endogenous accounts as shown in Equation Eq.(3.2). The SAM-based multiplier analysis conducted in this way is consistent with the Walras' law. This is because the solutions of the equational system consisting of endogenous accounts in the SAM necessarily equalize the earnings and expenditures of exogenously assumed accounts.

In addition, we would provide brief explanations on how the propagation paths of economic effects caused by changes in the exogenous accounts in the SAM are formed under the SAM-based multiplier analysis. Table 11 below shows the transactions between the endogenous and the exogenous accounts in the SAM framework. As shown in Table 11, $T_{11}, T_{21}, T_{13}, T_{32}$ indicate the transactional relations among endogenous accounts, while T_{11} indicates the inter-industrial transactions matrix, T_{13} indicates final demand accounts, T_{21} indicates the value-added for industrial sectors, and T_{32} indicates the earnings from production factors. In addition, Tx_4 is the matrix on the transactional relations among exogenous accounts, and T_{41}, T_{42}, T_{43} are expenditures on the exogenous accounts (i.e., investments, taxes, etc.) made by endogenous accounts (i.e., production, factor inputs, and institutions).

Table 11. Transactions between endogenous and exogenous accounts within the SAM

		Endogenous accounts			Exogenous accounts			Tot.
		Production	Factor inputs	Inst.	Invest.	Taxes	ROW	
End.	Production	T_{11}		T_{13}	x_1			Y_1
	Factor inputs	T_{21}			x_2			Y_2
	Institutions		T_{32}		x_3			Y_3
Exo.	Investments	T_{41}	T_{42}	T_{43}	Tx_4			Y_4
	Taxes							
	ROW							
Total		Y_1	Y_2	Y_3	Y_4			

Based on the transactions between the endogenous and exogenous accounts in the SAM, it is possible to express the transactions information of each account within the endogenously assumed components in the form of a matrix as shown in Equation Eq.(3.5). The corresponding column-stochastic matrix H for this matrix can be expressed as Eq.(3.6). In addition, equilibrium conditions for individual endogenous accounts can be expressed as Eq.(3.7) in the form of linear equations. Such a series of linear equations can be expressed as Eq.(3.8) as shown in below, which contains information on how the first and second-order effects are arrived to endogenous accounts caused by changes in the exogenous accounts. This equational form as shown in Eq.(3.8) can be depicted as Figure 13. This figure illustrates how the economic impacts of changes in the exogenous accounts considered in the SAM-based multiplier analysis spread. In this way, the multipliers address the relative size of changes in exogenous accounts in final demand to the total effects of that change. Given direct changes in exogenous accounts, indirect inter-industrial effects are driven through the forward- and backward-linkages among industries respond to increases in exogenous accounts. In addition, induced effects from increased earnings or expenditures of households generated by the direct and indirect inter-industrial effects, and from changes in inter-institutional transactions can be driven. Those multiplier effects are specific to a particular economic structure, and dependent on the intrinsic attributes of economic structure, as any spending outside of the domestic economy does not contribute to the form of the SAM multiplier matrix.

$$\mathrm{T} = \begin{bmatrix} T_{11} & 0 & T_{13} \\ T_{21} & 0 & 0 \\ 0 & T_{32} & 0 \end{bmatrix} \qquad \text{Eq.(3.5)}$$

$$\mathrm{H} = \begin{bmatrix} T_{11}/Y_1 & 0 & T_{13}/Y_3 \\ T_{21}/Y_1 & 0 & 0 \\ 0 & T_{32}/Y_2 & 0 \end{bmatrix} = \begin{bmatrix} h_{11} & 0 & h_{13} \\ h_{21} & 0 & 0 \\ 0 & h_{32} & 0 \end{bmatrix} \qquad \text{Eq.(3.6)}$$

$$\mathrm{Y}_n = H_n y_n + x_n, where\ n = 1, 2,3$$

$$\mathrm{Y}_1 = h_{11}Y_1 + h_{13}Y_3 + x_1 \qquad \text{Eq.(3.7)}$$

$$(Total\ incomes\ of\ production\ sectors\ in\ endogenous\ accounts)$$

$\mathrm{Y}_2 = h_{21}Y_1 + x_2$

$(Total\ incomes\ of\ production\ factors\ in\ endogenous\ accounts)$

$\mathrm{Y}_3 = h_{31}Y_1 + x_3$

$(Total\ incomes\ of\ institutions\ in\ endogenous\ accounts)$

$$\mathrm{Y}_1 = (I - h_{11})^{-1}h_{13}Y_3 + (I - h_{11})^{-1}x_1$$
$$\mathrm{Y}_2 = h_{21}Y_1 + x_2 \qquad \text{Eq.(3.8)}$$
$$\mathrm{Y}_3 = h_{32}Y_2 + x_3$$

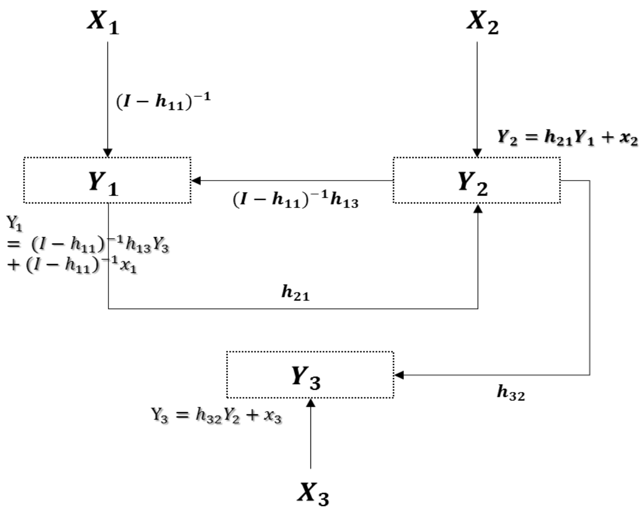


Figure 13. Circular flows of first and second order effects triggered by changes in exogenous accounts under the SAM-based multiplier analysis

In this study, we intend to analyze the changes of endogenous accounts triggered by exogenous accounts including knowledge capital formation and physical capital formation accounts in the constructed knowledge-based SAM by increasing one trillion KRW (Korean Won) respectively by controlling other exogenous accounts as fixed with no policy shocks. Based on this methodological approach, this study aims to understand whether Korean economic system has inherent structures in which the intrinsic attributes of technological innovation (i.e., factor-biased technological progress including capital- and skill-biased technological change) would be appear, by analyzing the variants in industrial outputs, compositions of value-added, and income distribution within the economy induced by the innovation activities (i.e., R&D investments) compared to the changes in those variables triggered by physical capital investments.

3.2.2 Results analysis and key findings

In this subsection, key findings drawn from the SAM-based multiplier analysis are presented. As mentioned above, to understand the relationship between the technological innovation (i.e., R&D investments) and changes of endogenous accounts including industrial production activities, factor inputs, and institutions, physical capital formation and knowledge capital formation accounts are considered as the exogenous accounts for the comparative statics analysis. We are to analyze the gross income growth effects by calculating the increments in absolute incomes of endogenous accounts, and income distribution effects by examining relative incomes (or, shares) of elements (i.e., industrial sectors, production factors, households) within individual endogenous accounts.

The I/O analysis is simply a static partial-equilibrium analysis that grasps the effects of gross income increase in each industry when the final demand for an industrial sector changes. On the other hand, in the case of SAM multiplier analysis undertaken for this study, it is also based on a static linear model similar with the I/O analysis, but it is possible to analyze changes in absolute gross income in other endogenous accounts, as well as how these gross income growth effects are redistributed to individual economic entities (i.e., endogenous accounts) within the SAM framework (Keuning & de Ruuter, 1988; Pyatt, 1999). For example, if research interests focus on income distribution in the households account, this households account within the SAM can be endogenized by segmenting a single households account into several groups in terms of income levels, occupations, and so on (Keuning & de Ruuter, 1988). In this study, as mentioned in the previous chapter, we are to examine the distribution effects induced by exogenous variables by dividing the 'households' in the institution account into 20 quantiles based on income levels when constructing the knowledge-based SAM. Based on this constructed SAM, this study aims to empirically estimate the socio-economic effects driven by R&D investments by examining the changes in production sectors, factor markets (i.e., value-added), and income distribution through the comparative static analysis. Policy scenarios considered for the SAM-based multiplier analysis can be summarized as Table 12.

Table 12. Policy scenarios considered for the SAM multiplier analysis

Scenario name	Explanations on scenarios
BASE	A base-year SAM(with no exogenous shocks)

SCN1	1 trillion KRW increases in physical capital formation
SCN2	1 trillion KRW increases in knowledge capital formation (maintaining the relative shares of private and public R&D investments)

Table 13 shows the changes in the endogenous accounts and the absolute level of each account induced by changes in the exogenous account including increases in physical capital and knowledge capital investments with 1 trillion KRW through the SAM multiplier analysis. As shown in Table 13, when the investment in physical capital is increased by 1 trillion KRW (SCN1 scenario), the total outputs growth in the economy increases by about 3,847 billion KRW compared to the BASE scenario, while it is confirmed that the total output increases by about 5,149 billion KRW for the case of SCN2 scenario (with exogenous increases in the R&D investments of 1 trillion KRW) relative to the BASE scenario. Firstly when looking into the output growth effects of industrial production activities, it is found an increase of 2,482 billion KRW and 2,553 billion KRW, respectively, in the SCN1 and SCN2 scenarios. Considering the difference in the total output growth effects between scenarios (SCN1: about 3,847 billion KRW increase, SCN2: about 5,149 billion KRW increase), it can be seen that the difference between the output growth effects in production sectors is not remarkable. However, when examining changes in production volumes by industry and by industrial group in detail, different patterns are found between those sectors.

Table 13. Comparison of endogenous accounts among BASE, SCN1 (changes in physical capital formation), and SCN2 (changes in knowledge capital formation) scenarios

		BASE scenario	SCN1 scenario	SCN2 scenario
		Gross outputs (Unit: million KRW)	Gross outputs (Unit: million KRW)	Gross outputs (Unit: million KRW)
Production activities		3,686,530,995	3,689,013,006 (+ 2,482,011)	3,689,084,024 (+ 2,553,029)
Production factors	Physical capital	477,543,050	477,860,409 (+ 317,359)	477,983,697 (+ 440,647)
	Low-skilled labor	244,895,079	245,082,023 (+ 186,944)	245,069,748 (+ 174,668)
	Skilled labor	214,722,561	214,856,045 (+ 133,483)	214,890,088 (+ 167,526)
	High-skilled labor	32,915,892	32,927,849 (+ 11,957)	33,379,643 (+ 463,751)
	Knowledge capital	36,454,878	36,474,796 (+ 19,919)	36,475,675 (+ 20,797)
Institutions	Households	1,006,531,461	1,007,201,122 (+ 669,661)	1,007,798,851 (+ 1,267,390)
	Government	243,406,948	243,432,566 (+ 25,618)	243,468,103 (+ 61,155)
Total		5,943,000,865	5,946,847,816 (+3,846,951)	5,948,149,830 (+5,148,965)

Table 14, Figure 14, and Figure 15 show the changes in the production volume by industrial sector considered in the SAM data, and the changes in production volume by the reclassified industrial group. For the analysis, to increase the ease of understanding, based on the input structure including the knowledge capital inputs, and R&D investment level by industrial sector within the knowledge-based SAM, we reclassified those sectors with higher levels of knowledge capital inputs and R&D investments compared to the average levels as high-tech manufacturing and high-tech service sectors. On the other hand, those sectors with lower levels compared to average levels are considered as the low-tech manufacturing and low-tech service sectors. New income inducing effects generated by the output multipliers of industrial sectors indicate the production inducement effects generated through the forward- and backward-linkages among industries triggered by the exogenous changes in the final demand (i.e., changes of one unit in physical capital and R&D investments). As shown in Figure 14 and Table 14, they show that under the SCN1 scenario with an increase of 1 trillion KRW for physical capital formation, the ‘construction’ industry is the industry with the greatest increase in outputs (416.7 billion KRW) triggered by the multiplier effects, followed by the ‘real estate and business service’ industry(233.8 billion KRW), and ‘electronic and electrical equipment’ industry (179.2 billion KRW) are found to be industries with higher levels of multiplier effects among 28 sectors. On the other hand, in the SCN2 scenario where R&D investment increases with 1 trillion KRW, it shows that the ‘real estate and business service’ industry (234.5 billion KRW), ‘electronic and electrical equipment’ industry (182.2 billion KRW), and ‘chemicals, drugs, and medicines products’ industry (156.1 billion KRW) are those with the largest increase in outputs due to the multiplier effects.

Table 14. Production inducement effects induced by physical and knowledge capital formation (Unit: million KRW)

		SCN1 scenario		SCN2 scenario	
		Outputs (in absolute level)	Deviations from BASE scenario	Outputs (in absolute level)	Deviations from BASE scenario
S01	Agriculture, forestry and fishing	64,690,459	45,429	64,714,949	69,919
S02	Mining and quarrying	137,803,867	75,584	137,824,016	95,733
S03	Food, beverages and tobacco	113,493,248	75,229	113,543,657	125,638
S04	Textile and apparel	69,956,534	36,079	69,969,110	48,655
S05	Wood and paper products	34,331,239	23,900	34,337,945	30,606
S06	Printing and reproduction of recorded media	8,869,120	4,925	8,883,731	19,536
S07	Petroleum and coal products	171,141,517	78,677	171,166,173	103,333
S08	Chemicals, drugs and medicines products	280,888,657	101,594	280,943,125	156,062
S09	Non-metallic mineral products	41,558,450	51,461	41,522,587	15,598
S10	Basic metal products	270,931,565	176,716	270,845,279	90,430
S11	Fabricated metal products except machinery and furniture	80,972,227	80,628	80,923,963	32,364
S12	General machinery and equipment	158,735,939	171,743	158,675,006	110,810
S13	Electronic and electrical equipment	425,577,231	179,193	425,580,213	182,175
S14	Precision instruments	33,253,328	30,788	33,254,562	32,022
S15	Transportation equipment	236,181,704	101,873	236,193,750	113,919
S16	Furniture and other manufactured products	23,645,681	19,563	23,649,303	23,184
S17	Electricity, gas, steam and water supply	77,280,493	47,935	77,333,468	100,910

S18	Construction	188,761,379	416,675	188,373,729	29,025
S19	Wholesale and retail trade	162,748,775	111,911	162,777,551	140,687
S20	Accommodation and food	89,460,901	53,629	89,525,272	118,000
S21	Transportation	138,606,913	60,276	138,633,557	86,920
S22	Communications and broadcasting	61,992,316	41,363	62,023,951	72,998
S23	Finance and insurance	137,913,714	88,839	137,974,588	149,713
S24	Real estate and business	266,001,818	233,781	266,002,518	234,481
S25	Public administration and defense	92,754,973	10,868	92,769,367	25,262
S26	Education	182,713,510	77,588	182,782,600	146,678
S27	Health and social work	82,751,255	53,344	82,804,146	106,235
S28	Other services	55,996,195	32,422	56,055,908	92,135
Total		3,689,013,006	2,482,011	3,689,084,024	2,553,029

In this way, based on the understanding of the increase in production volumes by each industry, the changes in industrial outputs of reclassified industrial groups[3] (see Figure 15 as presented below) show that under the SCN2 scenario there has been a relatively larger increase in output growth in the high-tech manufacturing and high-tech service industries

[3] Based on the values of knowledge capital inputs and R&D investments in 28 industries considered in the SAM framework for the base year of 2010, the reclassifications of 28 industries has been conducted as follows: 1) Low-tech manufacturing industry consisting of ‘S02 Mining and quarrying’, ‘S03 Food, beverages and tobacco products’ , ‘S04. Textile and apparel products’, ‘S05. Wood and paper products’, ‘S06. Printing and reproduction of recorded media’, ‘S07. Petroleum and coal products’, ‘S09. Non-metallic mineral products’, ‘S10. Basic metal products’, ‘S11. Fabricated metal products except for machinery and furniture’, and ‘S16. Furniture and other manufactured products’ sectors; 2) High-tech manufacturing industry consisting of ‘S08. Chemicals, drugs, and medicines products’, ‘S12. General machinery and equipment’, ‘S13. Electronic and electrical equipment’, ‘S14. Precision instruments’, and ‘S15. Transportation equipment’ sectors; 3) Low-tech service industry consisting of ‘S18. Construction’, ‘S19. Wholesale and retail’, ‘S20. Accommodation and food services’, ‘S21. Transportation’, ‘S25. Public administration and defense’, ‘S26. Education’, ‘S27. Health and social work’, and ‘S28. Other services’ sectors; 4) High-tech service industry consisting of ‘S17. Electricity, gas, steam, and water supply’, ‘S22. Communications and broadcasting’, ‘S23. Finance and insurance’, and ‘S24. Real estate and business service’ sectors.

compared to the SCN1 scenario. Under the SCN2 scenario, the output growth of the high-tech manufacturing and high-tech service industries is estimated to be about 595.0 billion KRW, and about 558.1 billion KRW, respectively. On the other hand, under the SCN1 scenario, it is shown that the output growth effects of those corresponding industrial groups are about 585.2 billion KRW and 411.9 billion KRW respectively. Furthermore, it is shown that under the SCN1 scenario low-tech manufacturing and low-tech service industries have relatively larger output growth effects than those shown in the SCN2 scenario.

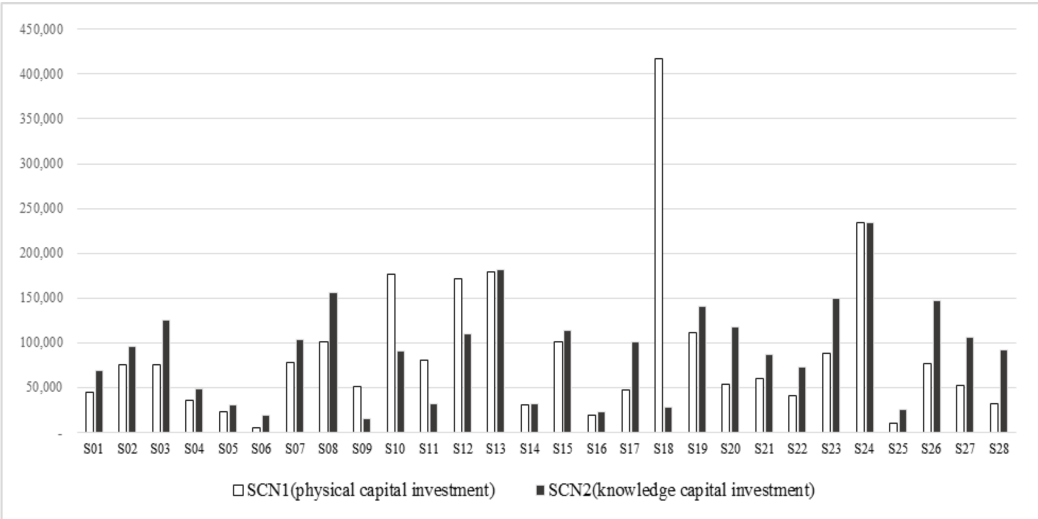


Figure 14. Changes of industrial outputs by industry for each scenario (Unit: million KRW)

As can be seen in Figure 15, in the SCN1 scenario with an increase of one trillion KRW in the physical capital formation, the output growth effects of the low-tech manufacturing industry and the low-tech service industry are each amounted to about 628.9 billion KRW, and about 816.8 billion KRW, respectively. On the other hand, output growth effects for those industries are shown to be 585.1 billion KRW (for low-tech manufacturing industry), and 744.9 billion KRW (for low-tech service industry). From those results, it can be understood that the relative contributions of the low-tech manufacturing and service industries under the SCN1 are relatively larger than the SCN2 scenario to the output growth in industrial production activities due to changes in the exogenous accounts. Furthermore, it is noted that the larger output growth effects from industrial sectors shown in SCN2 compared to SCN1 scenario, are driven by relatively larger production inducement effects in high-tech manufacturing and service industries as shown in Figure 15.

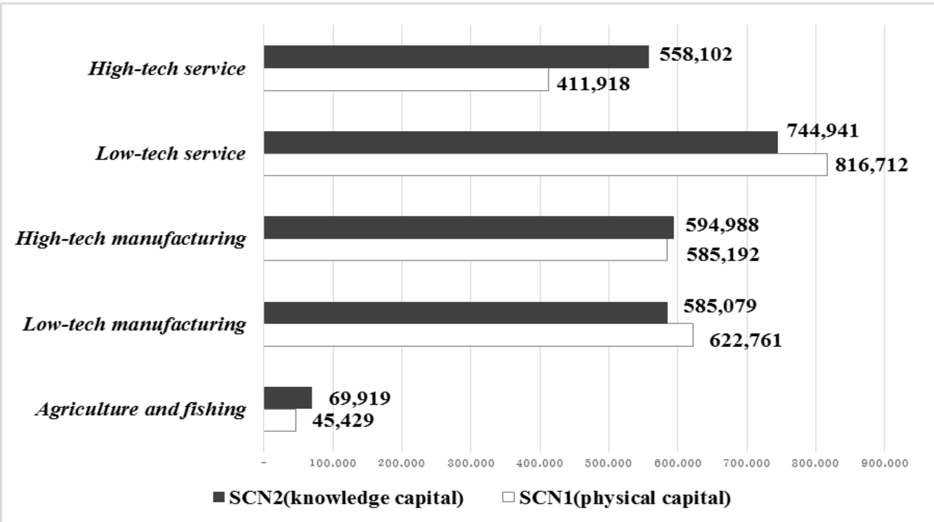


Figure 15. Changes of outputs by industrial group for each scenario (Unit: million KRW)

In addition, as shown in Table 13 and Figure 16, under the SCN1 scenario assuming the increase of one trillion KRW in physical capital investment, it is shown that compensations for production factor increase as follows: 1) physical capital: 317.4 billion KRW, 2) low-skilled labor: 186.9 billion KRW, 3) skilled labor: 133.5 billion KRW, 4) high-skilled labor: 12.0 billion KRW, and 5) knowledge capital: 19.9 billion KRW increases compared to the BASE scenario. On the other hand, in the SCN2 scenario with the exogenous injection of one trillion KRW in knowledge capital investment, it is found that the value-added growth effects for physical capital, low-skilled labor, skilled labor, high-skilled labor, and knowledge capital can be calculated as 440.6 billion KRW, 174.7 billion KRW, 167.5 billion KRW, 463.8 billion KRW, and 20.8 billion KRW, respectively. In particular, it is noted that as shown in Figure 16, when the R&D investment is increased by one trillion KRW, the increases in earnings from the high-skilled labor and physical capital are remarkable. On the contrary, it is found that when the investment of physical capital is increased by same amounts as an exogenous shock, the increase in the value-added for the low-skilled labor is relatively higher compared to the SCN2 scenario.

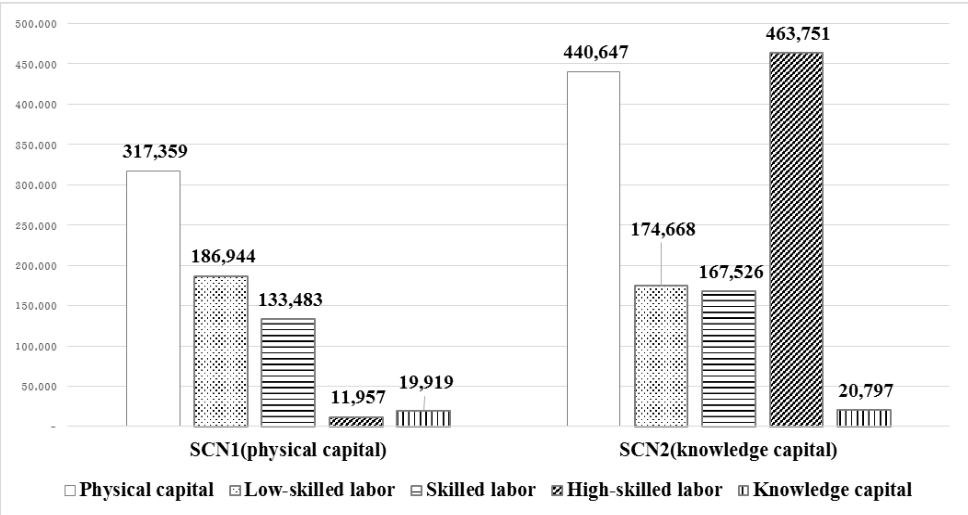


Figure 16. Changes of value-added compositions for each scenario (Unit: million KRW)

Accordingly, it can be inferred that growth in total value-added of 1,267.4 billion KRW under the SCN2 is mainly driven by the formation of incomes earned by high-skilled labor and physical capital inputs. In addition, it can be understood that the total value-added increase of about 669.6 billion KRW in SCN1 scenario is led by the income growth inducement effects in physical capital and low-skilled labor. Those results suggest that the investment in innovation activities represented by R&D investment spur the greatest demand for high-skilled labor and physical capital, thereby changing the relative demand and incomes for the production factors and the changes in the compositions of the value-added in the economy. This can be easily understood by comparing the SCN1 results with those of the SCN2 scenario, which are driven by the exogenous injection of the same amount of increase in the physical capital investment. It is also noted that the higher level of innovation activities through increased R&D investments in the Korean economy has the possibility of creating and accelerating skill-biased and capital-biased technological progress by forming differential demand among the factors of production, with the relative shares of high-skilled labor and physical capital increased.

The changes in the value-added as the endogenous accounts within the SAM-based multiplier analysis framework induced by the variants in physical capital and R&D investments are strongly linked to changes in households' incomes. Table 15 and Figure 17 present the changes of households' incomes for constructed scenarios (i.e., SCN1 and SCN2 scenarios) driven from the SAM-based multiplier analysis relative to the BASE scenario. The classification of the single household into 20 income quantiles in the SAM makes it possible to analyze the distributive effects driven by the exogenous accounts' changes. As a result, it can be seen that both SCN1 and SCN2 scenarios show that the higher the income quantile, the greater the income growth increase. This can be interpreted as being affected by the higher the income quantile, the more directly and indirectly engaged in economic activities with greater income-induced effects. However, for the SCN2 scenario assuming the increase of one trillion KRW in knowledge capital investment, it is shown that the increases in households' incomes are relatively higher compared to those values in SCN1 scenario. In particular, the increase in income in the highest income quantile (i.e., H20, income quantile 20) households is shown to be about 208.4 billion KRW for SCN2, while that for SCN1 is found to be about 93.6 billion KRW.

Table 15. Changes of households' incomes by income quantile for each scenario

(Unit: million KRW)

		SCN1 scenario		SCN2 scenario	
		Outputs (in absolute level)	Deviations from BASE scenario	Outputs (in absolute level)	Deviations from BASE scenario
H1	Income Quantile 1	3,016,830	2,118	3,017,425	2,713
H2	Income Quantile 2	7,367,019	5,155	7,369,301	7,437
H3	Income Quantile 3	10,716,256	7,489	10,719,674	10,908
H4	Income Quantile 4	16,638,579	11,440	16,644,781	17,641
H5	Income Quantile 5	21,441,807	14,658	21,450,861	23,712
H6	Income Quantile 6	26,901,275	18,307	26,913,339	30,371
H7	Income Quantile 7	29,436,262	19,950	29,449,692	33,381

H8	Income Quantile 8	35,570,740	24,076	35,586,489	39,825
H9	Income Quantile 9	40,031,958	26,980	40,050,664	45,686
H10	Income Quantile 10	43,143,588	28,976	43,165,140	50,528
H11	Income Quantile 11	45,329,724	30,391	45,353,828	54,496
H12	Income Quantile 12	48,386,957	32,371	48,413,804	59,218
H13	Income Quantile 13	55,715,338	37,179	55,745,882	67,723
H14	Income Quantile 14	61,646,612	41,055	61,680,484	74,927
H15	Income Quantile 15	65,714,593	43,712	65,751,355	80,474
H16	Income Quantile 16	72,724,328	48,199	72,766,916	90,786
H17	Income Quantile 17	78,720,865	52,151	78,768,813	100,099
H18	Income Quantile 18	92,078,653	60,698	92,136,172	118,218
H19	Income Quantile 19	108,658,142	71,158	108,737,869	150,885
H20	Income Quantile 20	143,961,597	93,598	144,076,360	208,361
	Total	1,007,201,122	669,661	1,007,798,851	1,267,390

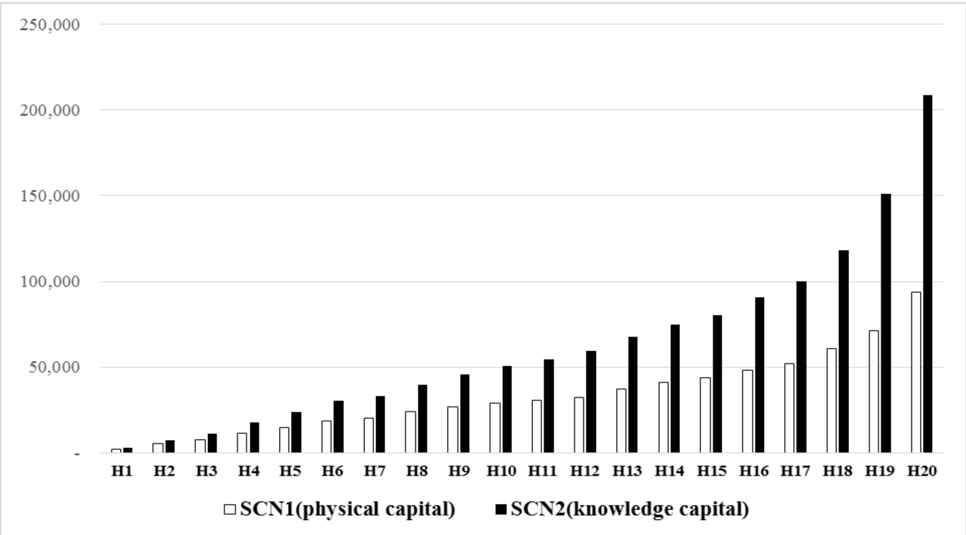


Figure 17. Variants of households' incomes by income quantile for each constructed scenario compared to BASE scenarios (Unit: million KRW)

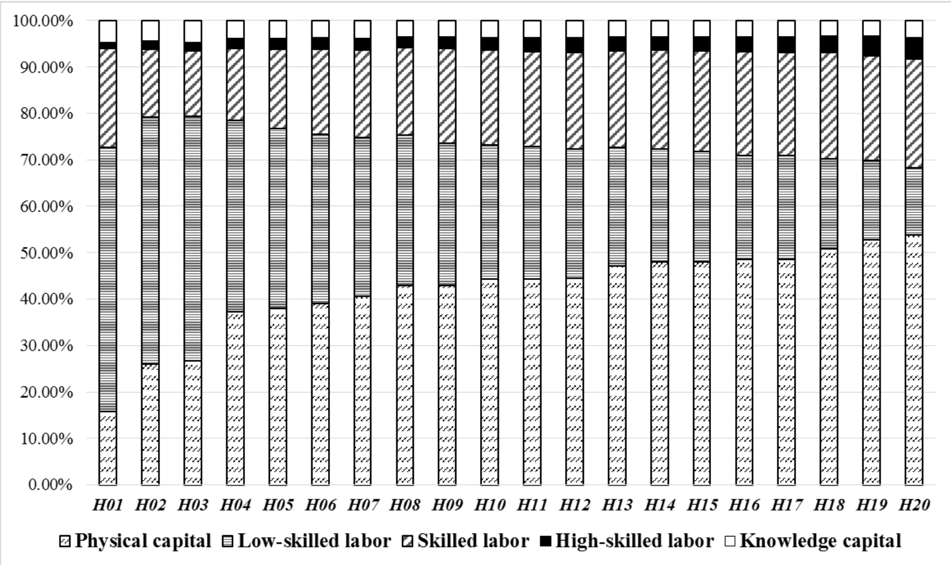


Figure 18. Income structure by each income quantile of households in a base year (Unit: %)

In order to understand the gross income growth effects of each household income quantile, we examine the share of each income quantile within the value-added composition, and income structure by income quantile. Table 7 shows the relative shares of the value-added earned by each income group within the total incomes earned by individual factor inputs, which suggests that the higher the income quintile, the higher the shares of incomes (i.e., value-added) from physical capital and high-skilled labor inputs. In addition, Table 8 and Figure 18 illustrate the income structure of the households identified in the base year SAM, which suggests that households in higher income quintiles have relatively higher shares of physical capital, skilled-labor, and high-skilled labor within the total incomes of each income quantile. In contrast, the proportions of the incomes earned by low-skilled labor within the total incomes of income quantiles are found to increase as households belong to lower income quantiles. For example, in the case of the highest income quantile (H20), the shares of incomes from the factor inputs of physical capital, low-skilled labor, skilled labor, high-skilled labor, and knowledge capital within the total incomes of that income quantile are found to be 53.77%, 14.47%, 23.43%, 4.58%, and 3.75%, respectively. On the other hand, in the case of the lowest income level (H1), the shares of earnings from the production factors of physical capital, low-skilled labor, skilled labor, high-skilled labor, and knowledge capital within the total incomes of that income quantile are found to be 15.84%, 56.86%, 21.37%, 1.09%, and 4.84%, respectively.

Underlying reasons for the result that under the SCN2 scenario there are greater gross income growth effects for households in higher income quantiles compared to the SCN1 scenario is associated with the income formation structures of those households affected by their participations in economic activities. As we have seen above, under the SCN2 scenario given the increase of one trillion KRW in the R&D investments, high-tech industries including high-tech manufacturing and service industries have shown relatively higher production inducement effects among reclassified industrial groups, coming through forward- and backward-linkages among industries and direct and indirect inter-industrial effects. In addition, the larger production inducement effects for those industries raises relative demand for physical capital and high-skilled labor more compared to other factor inputs. As shown in Figure 19, the proportions of physical capital and high-skilled labor within the input structures of high-tech industries are relatively higher than those of other industrial sectors. Thus, these production inducement effects driven by changes in the exogenous account (i.e., R&D investment) generate the induced effects on value-added and earnings or expenditures of households. In other words, it can be understood that the increases in demand for physical capital and highly skilled labor resulting from the increase in R&D investment lead to increases in the incomes of households belonging to the high income quintiles.

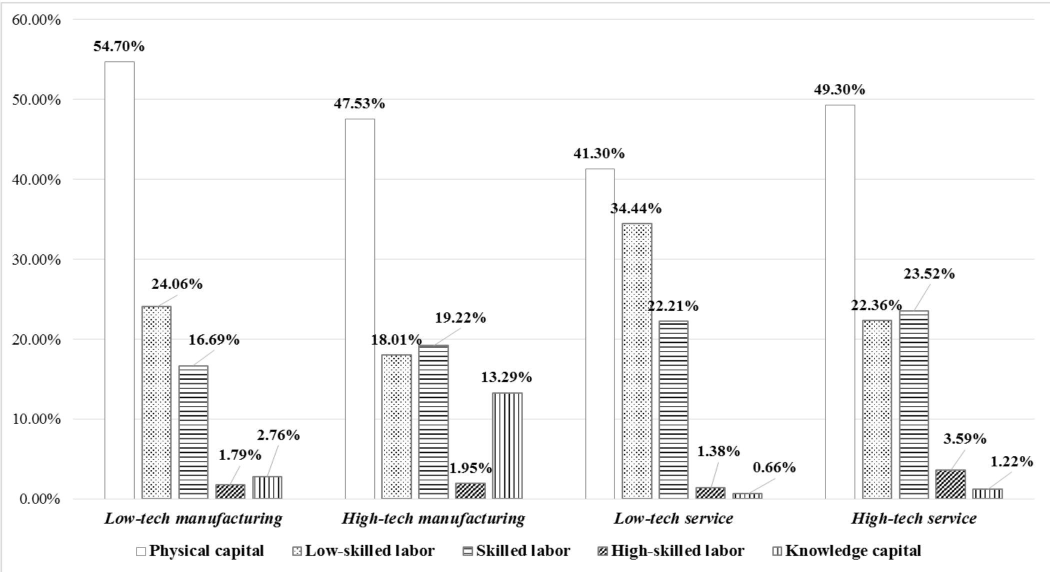


Figure 19. Relative shares of production factors in the value-added compositions for industrial sectors (Unit: %)

On the other hand, given the changes in physical capital investment (SCN1 scenarios), the production inducement effects of the low-tech manufacturing has shown relatively higher than those values of SCN2 scenario. As can be seen in Figure 19, that low-tech manufacturing industry can be understood as having the highest level of capital intensity within the input structure among industrial sectors. Accordingly, the higher the income growth effects for richer income quantiles can be understood as the outcomes generated by the higher increases in earnings from the physical capital inputs, coming from larger production volumes in the low-tech manufacturing industry. In addition, when looking at the gross income growth effects of the value-added account, it has been found that under the SCN1 scenario, the increase in value-added income resulting from lows-skilled labor inputs is relatively greater than the SCN2 scenario. It can be also interpreted that the proportion of low-skilled labor in the production factor inputs structure of low-tech manufacturing and low-tech service industries is relatively larger compared to other industries, as shown in Figure 19.

In addition, based on the values of households' incomes by each income quantile drawn from the SAM-based multiplier analysis, the proportion of each income quantile in total gross income of households is calculated for each scenario, BASE, SCN1, and SCN2, and the percentage change (%p) in the proportion of each income quantile in the SCN1 and SCN2 scenarios relative to the level of BASE scenario is calculated as shown in Figure 20. The left-hand axis of Figure 20 indicates the relative proportion of each income quantile in total gross income of households is calculated for each scenario, BASE, SCN1, and SCN2, while the right-hand axis represents the changes of those relative shares of individual income quantiles in SCN1 and SCN2 scenarios compared to the BASE scenario whose unit is measured by the percentage change (%p). As can be seen in Figure 20, it can be understood that the increase of physical capital investment in the Korean economy leads to increases in the shares of low-income households in the total gross income of the economy, but to decreases in the shares of high-income households. On the other hand, when the R&D investment is increased by 1 trillion KRW, it is found that the shares of low-income households in gross household income decreases, while the proportions of high-income households increases.

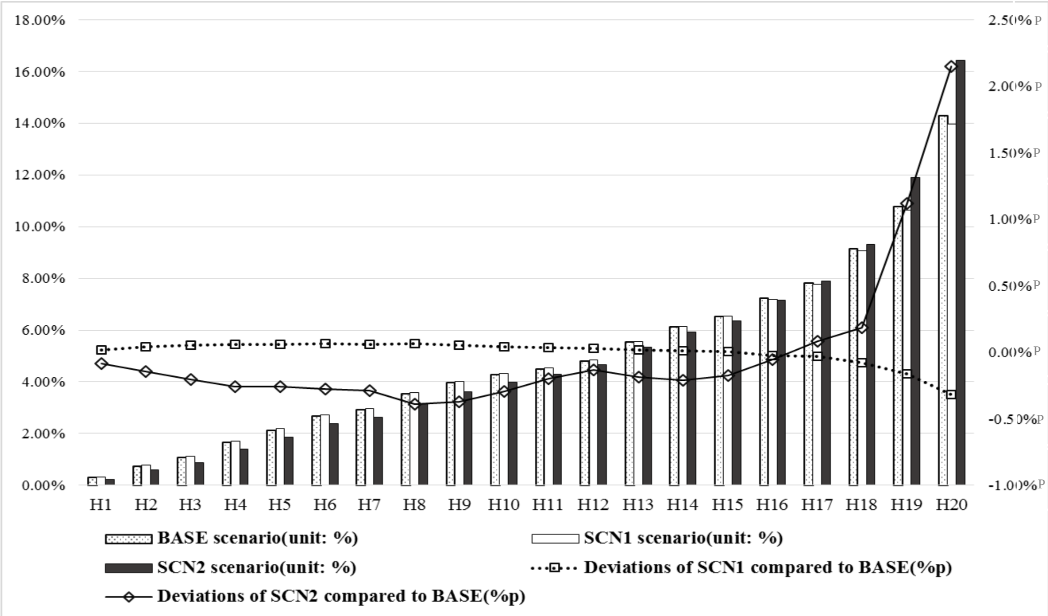


Figure 20. Income share of each income quantile (left-axis, %) and changes in the relative share of each income quantile by scenario compared to BASE (right-axis, %p)

The increase in the relative share of low-income households in the SCN1 scenario compared to the BASE scenario is related to the increases in the value-added from the low-skilled labor inputs triggered by the increase in physical capital investment. This is because, as shown in the income structures of households, it is confirmed that the households belonging to the low-income quintiles have relatively larger portions of the earnings from the low-skilled labor inputs. On the other hand, when increasing R&D investment, it is found that the relative shares of low-income households in the economic system decrease, while the relative proportions of high-income households in the SCN2 scenario in comparison to the BASE scenario increases. It can be interpreted that the corresponding accounts showing the greatest gross income growth effects in the value-added driven by the changes in knowledge capital investments are those including the physical capital and high-skilled labor, and earnings from those production factors are concentrated on the high-income households.

In addition, the Gini index is calculated based on the income growth effects by income percentile and their relative shares in the gross income, derived from the SAM multiplier analysis, in order to investigate and compare the income distribution effects among constructed scenarios. As income inequality increases, the Gini coefficient approaches 1, and when income inequality is relaxed, it approaches zero. Relevant figures are presented in Table 16 containing the values of Gini index for individual scenarios including BASE, SCN1, and SCN2. As can be seen in Table 16, the Gini coefficient is found to be about 0.3078 in the BASE scenario in the case of no change in the exogenous account. On the other hand, in the SCN1 scenario assuming an increase of 1 trillion KRW in physical capital investment, the Gini coefficient is found to be about 0.2995, while the corresponding coefficient is about 0.3524 in the SCN2 scenario assuming an increase in R&D investment of 1 trillion KRW. If there is an increase in physical capital investment, it can be understood that the gross output and income growth effects within the economic system are relatively lower than the scenario with the assumption of an increase in R&D investment, but income concentration can be eased to improve the income distribution. On the other hand, if there is an increase in R&D investment, a relatively higher level of economic growth can be achieved with larger gross output and income growth effects. However, results suggest that in terms of the income distribution within the economic system, more economic gains would be reallocated and redistributed to higher income households when additional R&D investments are made.

Table 16. Comparisons of Gini index for constructed scenarios

	BASE Scenario	SCN1 (1 trillion KRW increase in Physical capital investments)	SCN2 (1 trillion KRW increase in Physical capital investments)
Gini index	0.3078	0.2995	0.3524

In this chapter, the knowledge-based Social Accounting Matrix has been constructed based on the datasets including 2010 I/O tables, National Accounts Statistics, National Tax Statistics, and Survey of Research and Development in Korea, HIE Survey, and Survey Report on Labor Conditions by Employment Type, etc. Based on the constructed knowledge-based SAM, the SAM multiplier analysis has been undertaken to empirically investigate the production and income growth inducement effects and income distribution effects. Especially we have tried to find out how the increases in the level of innovation activities in the economic system represented by R&D investment affect the industrial outputs, value-added compositions, and income structure within the economy through the multiplier effects including the direct and indirect impact channels. In addition, by analyzing empirically the effects of production inducement, relative demand on labor inputs including low-skilled, skilled, and high-skilled labor and income distribution triggered by the technological innovation, this study aims to confirm the relationships between technological innovation, human capital formation, and labor markets, by addressing the stylized facts over technological innovation, growth, and distribution found in previous literature which are covered in the Chapter 2.1 and Chapter 2.2.

Based on the key findings of the SAM multiplier analysis in this study, it is found that in the case of Korean economy, technological innovation represented by R&D investment can lead to increases in output and gross income growth, but may have negative impacts on income distribution in the economic system by further inducing relative demand for high-skilled labor and physical capital. This study suggests that the Korean economic structure has inherent possibility that leads to skill-biased and capital-biased technological progress by creating differential demand among the factors of production in the factor inputs market when there is expansion of technological innovation through additional R&D investments.

However, the SAM-based multiplier analysis used in this chapter assumes a linear system, which limits the analysis of nonlinear economic changes. In addition, even though exogenous accounts can be also influenced by other accounts of the economy in the SAM framework, those accounts are simply treated as exogenous elements within the SAM multiplier analysis, not taking into account the feedback loop effects they receive from other accounts. In addition, this methodological approach is based on a static viewpoint, and there are limitations of this methodology in that it cannot capture the accumulation of knowledge capital stocks, and not take into account the spillover effects from the knowledge capital accumulation, and dynamic interaction between endogenous changes in economic actors' decisions. In particular, the SAM multiplier analysis assumes the behavior of economic agents only linearly without considering price variables, so there is a limitation to investigate and understand the mid- and long-run impacts of policy shocks.

Accordingly, in the next chapter, we are to overcome those limitations of the SAM-based multiplier analysis, and design and propose a non-linear knowledge-based CGE model that assumes specific preferential systems, production functions, and endogenous interactions among economic actors along with the considerations on the price variables. To be specific, this study will provide descriptions on the CGE model which can capture the induced changes in skills demand triggered by technological innovation, endogenous interaction between the human capital compositions and innovation, and changes in wage and income structures within the economic system with the considerations of heterogeneous human capital and households. In the next chapter, we will present the key components and relevant equational systems of the knowledge-based CGE model designed and proposed in this study.

Chapter 4. Structure of Knowledge-based Computable General Equilibrium model

4.1 Overall structure of knowledge-based CGE model

This section provides an overview of the knowledge-based CGE model designed in this study. The main characteristics of the CGE model used in this study can be summarized as follows. Firstly, we explicitly represent knowledge as a factor of production and introduce knowledge capital formation in the investment account, which has led to endogenization of innovation-related components within the CGE model. Secondly, we describe the structure in which knowledge stocks are accumulated with the endogenous investment decisions on R&D investments for individual sectors. The third is that knowledge spillover effects from the knowledge stock accumulation has been incorporated within the model that affect the productivity within the production function of industrial sectors. This is related to the intrinsic nature of knowledge that exerts positive externalities. The fourth characteristic of the model is that it has reflected the endogenous process of the skill accumulation of workers driven by education investments and changes in relative wages of workers. This methodological feature enables us to capture the endogenous interaction between changes in skill demand triggered by knowledge accumulation, and changes in skill supply induced by skill accumulation within the CGE framework. Finally, the fifth characteristic is that this model considers heterogeneous labor (i.e., three types of labor: low-skilled, skilled, and high-skilled labor) and households (i.e., 20 income quantiles) to capture the distribution effects induced by changes in wage structure and income distribution, as well as the growth effects.

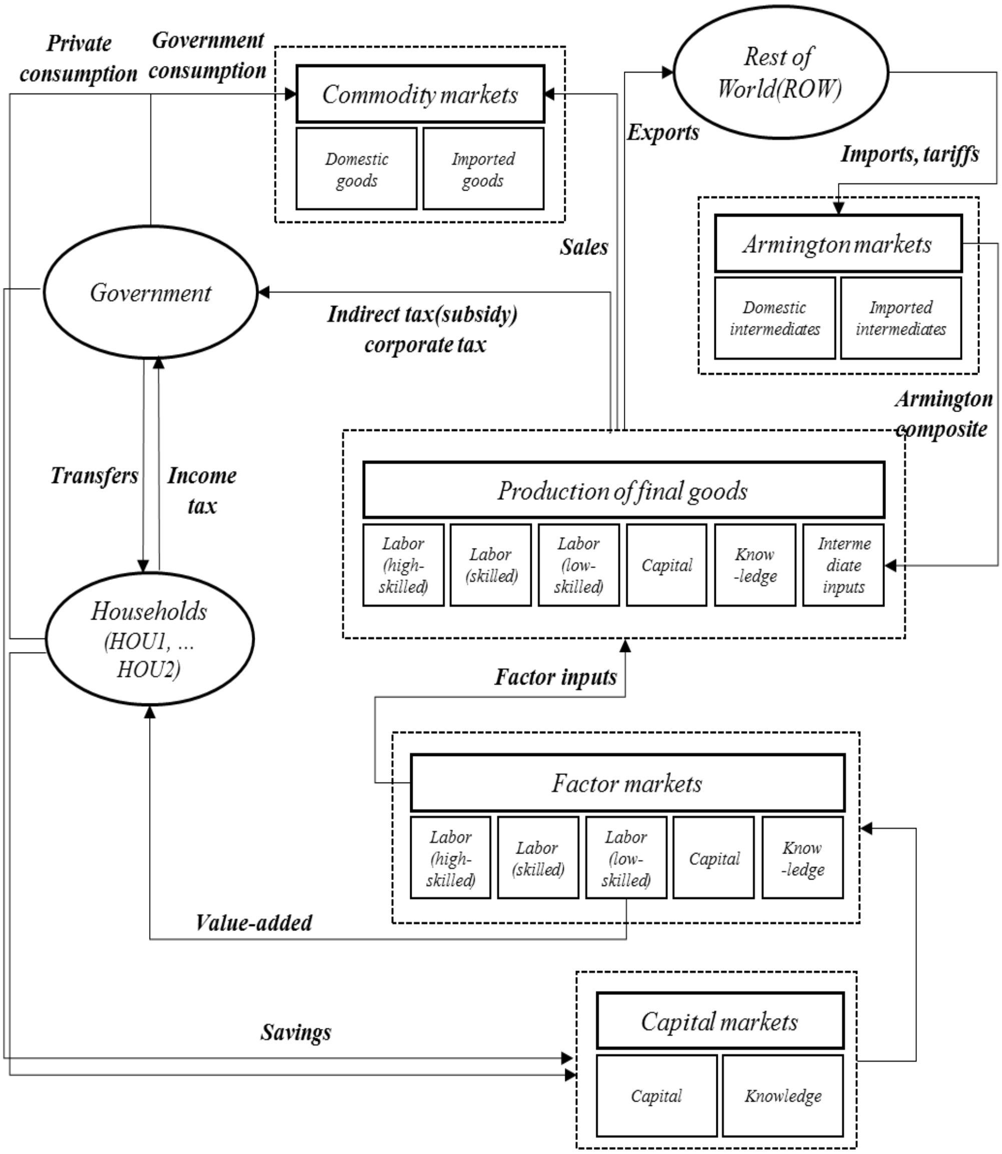


Figure 21. Overall structure of the knowledge-based CGE model proposed in this study

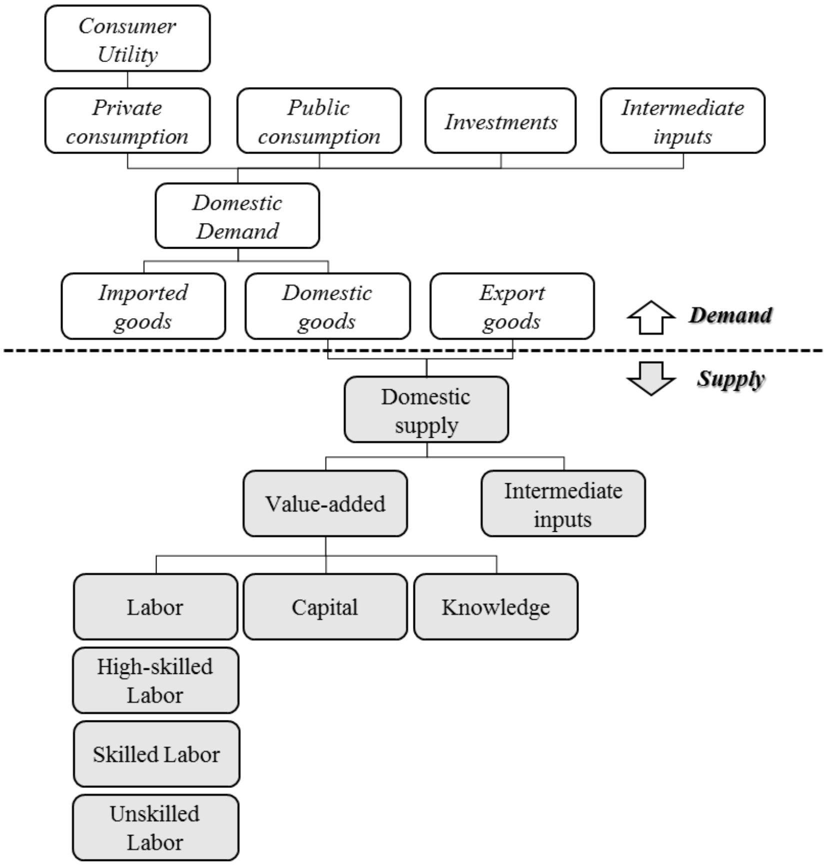


Figure 22. Structure of the knowledge-based CGE model proposed in this study in terms of supply- and demand-side

The overall structure of the knowledge-based CGE model developed in this study which incorporates those features mentioned above, and the relationships between key elements (i.e., economic transaction relationships) can be expressed as Figure 21 and Figure 22. As shown in Figure 21 and Figure 22, the model can be divided into demand- and supply-sides. Looking at the supply side, domestic outputs are produced with value-added composite and intermediate inputs. In addition, value-added composite is assumed to be produced under the multi-level production functions with high-skilled, skilled, low-skilled labor, physical capital, and knowledge capital. On the other hand, from the demand side of the economy, the produced domestic outputs are exported abroad or distributed domestically to form domestic demands with imported goods. Aggregate domestic demand, which is sourced by combination of import goods and domestic goods, consists of investment (including, physical capital formation and knowledge capital formation), intermediate goods demand, and final consumption by households and government. Based on this structure, we can systemize the knowledge-based CGE model by specifying a series of equations that express the behaviors of each economic actors (i.e., production sectors, households, government, and rest of world) and their interactions with the markets of production factors and final goods. In addition, the knowledge-based CGE model developed in this study includes households, government, and 28 industries as key economic actors. Each industrial sector produces a single commodity under the competitive market with the problem of profit-maximization, while each household faces with the problem of utility-maximization. In addition, physical and knowledge capital stocks are each accumulated through endogenously determined investments, and investments resources are financed by government and households' savings. Production factors are considered as labor (i.e., three types of labor: low-skilled, skilled, and high-skilled labor) physical capital, and knowledge capital. The main sources of earnings for the households consist of factor incomes, and the government transfers. The government imposes income tax, corporate tax, indirect tax, and import tariffs to households and production sectors, and tax revenues serve as income sources for the government. In addition, this model assumes the small open economy, focusing on Korean economy. In the CGE model of this study, it is also assumed that production sectors are in perfectly competitive markets seeking to maximize the profits, and all sectors are in full employment. In the following subsection, we will present key components of the model with relevant equations that make up the knowledge-based CGE model constructed for analysis.

4.2 Production structure of final goods

Within the knowledge-based CGE model, it is assumed that the industrial final goods (Z_i) of each industry i are produced by intermediate inputs ($X_{j,i}$), and value-added composite (VA_i). The value-added composite (VA_i) is produced by factor inputs, including labor (i.e., high-skilled labor, skilled labor, unskilled labor), physical capital, and knowledge capital under the multi-level CES production functions. Similar with other standard CGE models, it is also assumed that the final goods production function for each industry in this model is set to follow the Leontief production function, which means that there is no substitutability between the value-added composite VA_i and intermediate inputs $X_{j,i}$. Thus, each industrial sector seeking to maximize profits are faced with the following optimization problem, as producers seeking to maximize profits under the production function as shown in Equation Eq.(4.1). Faced with the profit-maximization problem, the industrial sector determines the levels of outputs, value-added composite and intermediate inputs within the production function following equations Eq.(4.2), Eq.(4.3), and Eq.(4.4). In addition, the unit cost function of each final goods producing sector can be derived as shown in Eq.(4.5). In this equation, $\tau_{Z,i}$ indicates the indirect taxes or subsidies imposed to each sector. In addition, PZ_i, PVA_i, PQ_j indicate prices of final goods, value-added composite, and Armington composite, respectively, while $ax0(n,i)$ and $AVA(i)$, respectively represent intermediate inputs and the value-added composite required to produce a unit of output (i.e., technical coefficients within the Leontief production function obtained by variable values of knowledge-based social accounting matrix of base year) in industry *i*

$$Max_{Z_i,VA_i,X_i}\ \pi_i^Z = PZ_i \cdot Z_i - PVA_i \cdot VA_i - \sum_j PQ_j \cdot X_{j,i}\ \ldots\quad \text{Eq.(4.1)}$$

$$s.t.\ \ Z(i) = \min[X(1,i)/ax0(1,i), \ldots X(n,i)/ax0(n,i),\ VA(i)/AVA(i)]$$

where i = 1,2, … 28

$$X_{j,i} = \mathrm{ax0}_{j,i} \cdot Z_i\ for\ \forall i,j\ \ldots\quad \text{Eq.(4.2)}$$

$$VA_i = AVA_i \cdot Z_i\ for\ \forall i\ \ldots\quad \text{Eq.(4.3)}$$

$$Z(i) = \min[X(1,i)/ax0(1,i), \ldots X(n,i)/ax0(n,i),\ VA(i)/AVA(i)]\ \ \ldots\quad \text{Eq.(4.4)}$$

$$\left(1-\tau_{Z,i}\right) \cdot PZ_i = AVA_i \cdot PVA_i + \sum_j \mathrm{ax0}_{j,i} \cdot PQ_j\ \ldots\quad \text{Eq.(4.5)}$$

On the other hand, the value-added composite (VA_i) is assumed to be produced by the multi-level nested CES (constant elasticity of substitution) production function, as shown in Figure 23. Within the two-level nested CES production function, as the first stage the composite of knowledge, high-skilled labor, and capital (HLK_i) is produced with high-skilled labor ($L3_i$), physical capital (K_i), and knowledge (H_i) assuming that those factor inputs are complements within the production function (see Eq.(4.6)). The knowledge capital that is used as a production factor in the production function of HLK_i in each industry is considered as a sector-specific asset. On the other hand, in the second stage of the two-level nested CES production function, the value-added composite VA_i is assumed to be produced with HLK_i composite, skilled labor ($L2_i$), and low-skilled labor ($L1_i$) (see Eq.(4.7)), assuming that HLK_i has substitutive relationships with skilled labor $L2_i$ and low-skilled labor $L1_i$. This form of the production function for each industrial sector producing final goods is chosen to describe the factor-biased technological progress within the production function by capturing the substitution possibilities between factor inputs (Jung et al., 2017). To incorporate factor-biased technological change (i.e., skill-biased and capital-biased technological progress) into the production structure, the value for elasticity of substitution among $L3_i$ (high-skilled labor), K_i (physical capital), and H_i (knowledge capital) is set to be less than 1 ($\sigma_1 = 0.67$), while that value amongHLK_i (the composite of high-skilled labor, capital and knowledge), $L2_i$ (skilled labor), and $L1_i$ (low-skilled labor) is set to be larger than 1 ($\sigma_2 = 1.67$) (Jung et al., 2017; Křístková, 2010, 2013; Krusell et al., 2000). Moreover, in this study, to explain the different marginal productivity among high-skilled, skilled, and low-skilled labor, we have considered this form of the production function (i.e., multi-level nested CES production function) with those values of elasticity of substitution among factor inputs. Under the production function for each final goods producing sector (as shown in Eq.(4.6) and Eq.(4.7), the demand functions for factor inputs (including, physical capital, knowledge capital, high-skilled labor, skilled labor, and low-skilled labor) can be derived as Eq.(4.8), Eq.(4.9), Eq.(4.10), Eq.(4.11), and Eq.(4.12) with first order conditions, as shown below. The production function of final goods for each sector specified in the CGE model can be described as Figure 23.

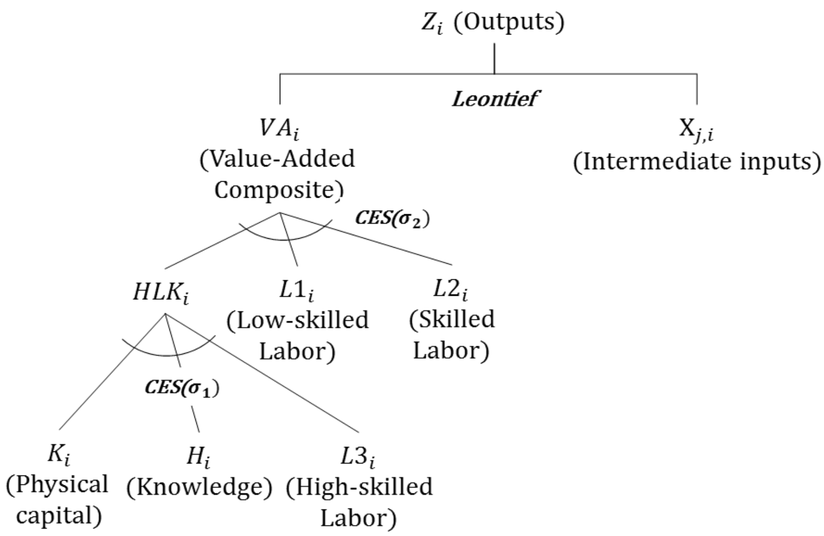


Figure 23. Production structure of final goods in CGE model

$$HLK_i = \theta 10_i \cdot (\beta 10_i \cdot L3_i^{-\rho 1} + \beta 20_i \cdot K_i^{-\rho 1} + (1 - \beta 10_i - \beta 20_i) \cdot H_i^{-\rho 1})^{-1/\rho 1} \quad \text{... Eq. (4.6)}$$

$$VA_i = \theta 20_i \cdot (\beta 30_i \cdot L1_i^{-\rho 2} + \beta 40_i \cdot L2_i^{-\rho 2} + (1 - \beta 30_i - \beta 40_i) \cdot HLK_i^{-\rho 2})^{-1/\rho 2} \quad \text{... Eq. (4.7)}$$

where $\beta 10_i$, $\beta 20_i, \beta 30_i, \beta 40_i$: *Share parameter for L3, K, L1, L2 in CES functions;*

$\theta 10_i, \theta 20_i$: *Scale parameter in each CES function;*

σ_1, σ_2: *Elasticities of substitution among factors of production*

$$K_i = HLK_i \cdot [(PHLK_i \cdot \beta 20_i \cdot \theta 10_i^{-\rho 1})/((1+\tau_{cap,i}) * PK)]^{1/(1+\rho 1)} \quad \text{...Eq.(4.8)}$$

$$H_i = HLK_i \cdot [(PHLK_i \cdot (1-\beta 10_i - \beta 20_i) \cdot \theta 10_i^{-\rho 1})/(PH_i)]^{1/(1+\rho 1)} \quad \text{...Eq.(4.9)}$$

$$L3_i = HLK_i \cdot [\frac{PHLK_i \cdot \beta 10_i \cdot \theta 10_i^{-\rho 1}}{PL3}]^{1/(1+\rho 1)} \quad \text{...Eq.(4.10)}$$

$$L2_i = VA_i \cdot \left[\frac{PVA_i \cdot \beta 40_i \cdot \theta 20_i^{-\rho 2}}{PL2}\right]^{\frac{1}{1+\rho 2}} \quad \text{...Eq.(4.11)}$$

$$L1_i = VA_i \cdot \left[\frac{PVA_i \cdot \beta 30_i \cdot \theta 20_i^{-\rho 2}}{PL1}\right]^{\frac{1}{1+\rho 2}} \quad \text{...Eq.(4.12)}$$

4.3 Production of R&D investment goods

Another characteristic of the CGE model developed for this study is a detailed description of R&D activities. Followed by previous studies including Hong et al. (2014, 2016), Jung et al. (2017), and Křístková (2013), R&D investment goods are assumed to be produced with a distinctive production function, assuming that the R&D investment goods produced from the R&D sector are accumulated into pre-existing knowledge capital stocks. To be specific, it is assumed that both private and public R&D sectors produce R&D investment goods ($RDZ_{rdt}, where\ rdt\!: private\ or\ public$) under the Leontief production function consisting of the value-added composite (RVA_{rdt}) and intermediate inputs ($XVRD_{rdt}$) for R&D activities, as shown in Eq.(4.13). The demand functions for RVA_{rdt} and $XVRD_{rdt}$ can be expressed as Eq.(4.14) and Eq.(4.15) as shown below. In addition, considering those equations including Eq.(4.13), Eq.(4.14), and Eq.(4.15), the unit cost function of the R&D sector can be derived as shown in Eq.(4.16). In this equation, τ_{rdt}

indicates the indirect taxes or subsidy imposed to the corresponding R&D sector. In addition, the total (production) amounts of R&D investment goods in the model is set to be exogenously determined with the parameter rdi_{rdt} which represents the R&D intensity as shown in Eq.(4.17).

Similar with the production function of the value-added composite within the final goods producing sector, it is also assumed that the value-added composite for R&D (RVA_{rdt}) is generated by the two-level nested CES production function, as shown in Figure 24 and Eq. (4.19). Within the two-level nested CES production function, as the first stage the composite of high-skilled labor and physical capital (RHK_{rdt}) is produced by combining the high-skilled labor ($RLS3_{rdt}$) and physical capital inputs for R&D activities (RK_{rdt}), as shown in Eq.(4.18). In addition, within the second stage of this multi-level nested CES production function for the R&D sector, it is assumed that the value-added composite for the R&D sector (RVA_{rdt}) is generated by combining the composite of high-skilled labor and physical capital (RHK_{rdt}), skilled ($RLS2_{rdt}$) and unskilled labor for R&D activities ($RLS1_{rdt}$), as shown in Eq.(4.19). In this regard, the value of the elasticity of substitution between $RLS3_{rdt}$ and RK_{rdt} is also set to be less than 1, while that value among RHK_{rdt}, $RLS2_{rdt}$, and $RLS1_{rdt}$ is also set to be larger than 1, followed by the previous studies (Jung et al., 2017; Křístková, 2010, 2013; Krusell et al., 2000). These assumptions on values for elasticity of substitution within the R&D investment goods production function are also associated with the descriptions of the factor-biased technological progress within the R&D sector. Under the production function for the R&D investments goods producing sector (i.e., R&D sector) as shown in Eq.(4.13), Eq.(4.18), and Eq.(4.19), the demand functions for factor inputs in the R&D sector (including, physical capital, high-skilled labor, skilled labor, and low-skilled labor) can be derived as Eq.(4.20), Eq.(4.21), Eq.(4.22), and Eq.(4.23) with first order conditions, as shown below. The production function of the R&D sector specified in the CGE model can be described as Figure 24.

$$RDZ_{rdt} = min[XVRD_{j,rdt}/axrd0_{j,rdt},\ RVA_{rdt}/arva0_{rdt}] \quad \text{... Eq. (4.13)}$$

$$XVRD_{j,rdt} = axrd0_{j,rdt} \cdot RDZ_{rdt} \quad \text{... Eq. (4.14)}$$

$$RVA_{rdt} = arva0_{rdt} \cdot RDZ_{rdt} \quad \text{... Eq. (4.15)}$$

$$(1+\tau_{rdt}) \cdot PRDZ_{rdt} = arva_{rdt} \cdot PRVA_{rdt} + \sum_j \mathrm{axrd}_{j,rdt} \cdot PQ_j \quad \text{... Eq. (4.16)}$$

$$RDZ_{rdt} \cdot (1+\tau_{rdt}) \cdot PRDZ_{rdt} = rdi_{rdt} \cdot GDP \quad \text{... Eq. (4.17)}$$

$$RHK_{rdt} = \varphi 10_{rdt} \cdot ((1-\Psi 10_{rdt}) \cdot RK_{rdt}^{-\rho 4} + \Psi 10_{rdt} \cdot RLS3_{rdt}^{-\rho 4})^{-1/\rho 4} \quad \text{... Eq. (4.18)}$$

$$RVA_{rdt} = \varphi 20_{rdt} \cdot (\Psi 20_{rdt} \cdot RLS1_{rdt}^{-\rho 3} + \Psi 30_{rdt} \cdot RLS2_{rdt}^{-\rho 3} + (1-\Psi 20_{rdt} - \Psi 30_{rdt}) \cdot RHK_{rdt}^{-\rho 3})^{-1/\rho 3} \quad \text{... Eq. (4.19)}$$

where $axrd_{rdt}$*: Intermediates requirement in R&D (for a unit of investment goods) ;*

$arva_{rdt}$*: Value-added composite requirement in R&D (for a unit of investment goods);*

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

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

σ_3, σ_4*:: Elasticity of substitution among inputs in each CES function*

$$RK_{rdt} = RHK_{rdt} \cdot [(PRHK_{rdt} \cdot (1-\Psi 10_{rdt}) \cdot \varphi 10_{rdt}^{-\rho 4})/(PK)]^{1/(1+\rho 4)} \quad \text{... Eq. (4.20)}$$

$$RLS3_{rdt} = RVA_{rdt} \cdot [(PRHK_{rdt} \cdot (\Psi 10_{rdt}) \cdot \varphi 10_{rdt}^{-\rho 4})/(PL3)]^{1/(1+\rho 4)} \qquad \text{... Eq. (4.21)}$$

$$RLS2_{rdt} = RVA_{rdt} \cdot [(PRVA_{rdt} \cdot (\Psi 30_{rdt}) \cdot \varphi 20_{rdt}^{-\rho 3})/(PL2)]^{1/(1+\rho 3)} \qquad \text{... Eq. (4.22)}$$

$$RLS1_{rdt} = RVA_{rdt} \cdot [(PRVA_{rdt} \cdot (\Psi 20_{rdt}) \cdot \varphi 20_{rdt}^{-\rho 3})/(PL1)]^{1/(1+\rho 3)} \qquad \text{... Eq. (4.23)}$$

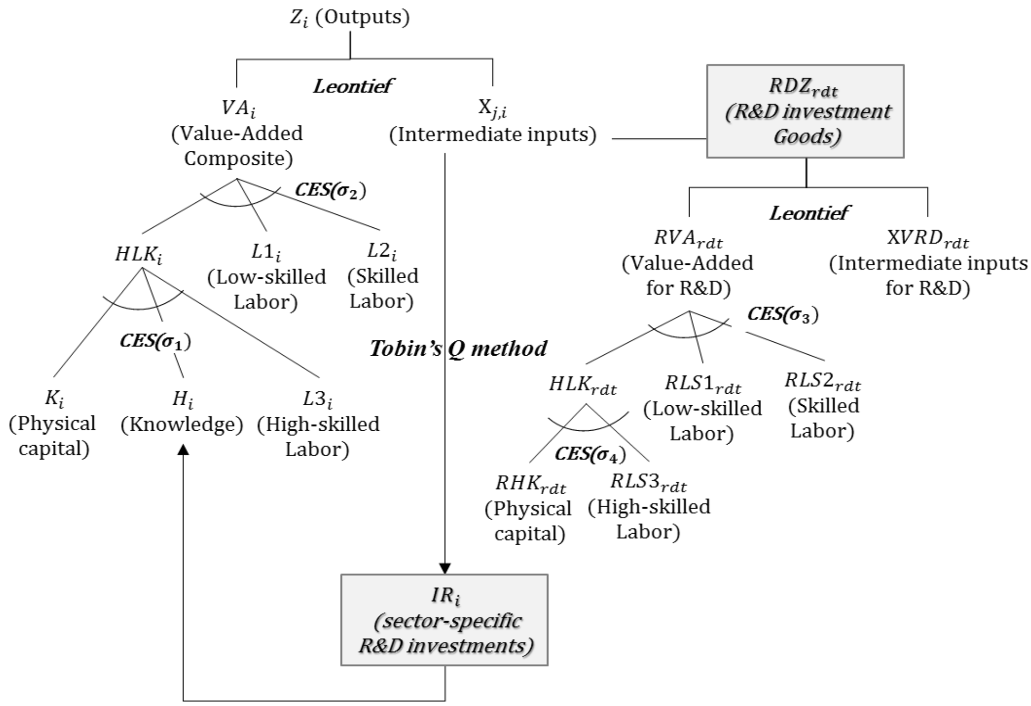


Figure 24. Production structure of R&D investment goods and its relationship with the final goods production function

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 Eq.(4.10). To be specific, public knowledge stock $H_{public,t}$ is accumulated through public R&D investments $RDZ_{public,t}$ with the knowledge depreciation rate δ_{know} (as expressed by Eq.(4.25)), while the private knowledge stock is accumulated through the private R&D investments $RDZ_{private,t}$. $RDZ_{private,t}$ can be understood as the gross private R&D expenditure, and it is assumed to be allocated to individual sectors with $IR_{i,t}$ which can be understood as the sector-specific R&D investments. Here, this allocated sector-specific R&D investment affects the accumulation process of the sector-specific knowledge capital stock ($H_{i,t}$), as expressed by Eq.(4.26).

It is also assumed that the sector-specific R&D investment $IR_{i,t}$ is set to be endogenously determined within the model, following the logic of Tobin's Q as addressed by the previous studies' approaches including Tobin (1969), Lewellen and Badrinath (1997). Accordingly, the sector-specific R&D investment $IR_{i,t}$ is determined as expressed by Eq.(4.24). In this equation Eq.(4.24), the right-hand side component represents the Q ratio of the market value (i.e., the market value of knowledge) of the unit of knowledge capital to the knowledge capital costs for one unit, while $\aleph^h$ indicates the knowledge capital investment elasticity. In addition, $Pinvrd,\ \delta_{know},\ ir,\ PH_i$, each represents the price of R&D investment good, knowledge depreciation rate, interest rate, and the price of knowledge, respectively. Accordingly, the knowledge capital investment level by industry for the period (t) is endogenously determined by the level of knowledge capital stock, the return on knowledge capital investments and the user costs of knowledge capital. Based on this methodological setting, the sector-specific knowledge capital (H_i) is set to be accumulated through the sector-specific R&D investments IR_i which is determined by Eq.(4.24). Figure 24 contains the relationship between the production structure of the R&D sector and the production structure of the final goods, describing that how the newly produced knowledge from the R&D investments is incorporated into the pre-existing knowledge capital stock for each industry.

$$IR_{i,t} = H_{i,t} \cdot \gamma^h \cdot \left[\frac{PH_{i,t}}{Pinvrd_t(\delta_{know} + ir)}\right]^{\aleph^h}$$
$$Pinvrd = \left(RDZ_{private} \cdot PRDZ_{private}\right) / \sum_i IR_i \qquad \text{... Eq. (4.24)}$$

$$H_{public,t} = (1 - \delta_{know}) \cdot H_{public,t-1} + RDZ_{public,t-1} \qquad \text{... Eq. (4.25)}$$

$$H_{i,t} = (1 - \delta_{know}) \cdot H_{i,t-1} + IR_{i,t-1} \qquad \text{... Eq. (4.26)}$$

4.4 Spillover effects from knowledge accumulation

Industry-specific knowledge capital H_i has direct impacts on the industry by being utilized as a factor input for the production function. However, the economic importance of knowledge capital is to create positive external effects, spillover effects. The knowledge capital accumulated in a particular industry can be utilized by other sectors at no costs, thereby affecting productivity of other sectors. In this regard, this model reflects the spillover effects from the knowledge capital accumulation. In the case of private knowledge capital, industry *i* can obtain knowledge spillover effects from knowledge capital stock accumulated by other sectors $j \ (j \neq i)$. In the model, it is assumed that the positive knowledge spillover effects from other sectors to the individual sector are proportional to the amounts of intermediate goods transactions identified from the I/O table based on the approach proposed by Terleckyj (1980), and other previous studies including Hong et al. (2016), and Jung et al. (2017). As expressed by the Eq.(4.27),). The value of the knowledge spillover effects embodied in intermediate goods $INTINDST_i$ from other sectors to the i-th sector can be calculated by multiplying the relative proportions of other sectors' intermediate goods utilized by the i-th sector $other0_{j,i}$ with the other sectors' (j ($j \neq i$))' knowledge capital stocks.

$$INTINDST_i = \sum_{j,j \neq i} other0_{j,i} \cdot H_j \qquad \text{... Eq. (4.27)}$$

On the other hand, within the CGE model knowledge capital stock of the public sector is assumed to be public goods, being non-rivalry and non-exclusive which can affect all industrial sectors' productivities (Guellec & Potterie, 2003). In this context, the i-th sector can enhance tis productivity within the production function driven by the spillover effects $SPCOEFF_i$ which can be represented as the function of other sector's knowledge stocks $INTINDST_i$ and the public knowledge capital stock, as expressed by the Eq.(4.28). In this equation, $rdelas_i$ and $grdelas_i$ each represents the elasticity of private (i.e., other industries) knowledge capital stocks and elasticity of public knowledge capital stocks for determining the spillover effects. The knowledge spillover effects from the private and public knowledge capital stocks lead to productivity changes within a production function for each sector. Accordingly, the productivity improvement effects from the knowledge spillover effects within the production function are captured by the changes in the input coefficients for the value-added composite. As expressed by the Eq.(4.3), AVA_i indicateds the input coefficients for the value-added composite for producing final goods for each industrial sector, which represents the ratio of the value-added composite inputs (VA_i) to the total industrial outputs of each industry (Z_i). Based on this setting, it is assumed that the value of AVA_i for each industry can be expressed as the function of the knowledge spillover effects ($SPCOEFF_i$) as expressed by Eq.(4.29). In Eq.(4.29), $ava0_i$ represents the initial vale of the share (i.e., input coefficients) of value-added composite in producing final goods calibrated based on the base year SAM data, while, AVA_i indicates the newly updated value for the input coefficients for the value-added composite with the consideration of the knowledge spillover effects. Those systems of equations suggest that the external effects of knowledge accumulation can be described in terms of increasing productivity by industry in accordance in accordance with accumulation of knowledge capital in the economic system. This can be easily understood from Figure 25 as shown in below.

$$SPCOEFF_i = spc0_i \cdot INTINDST_i^{rdelas_i} \cdot H_{public}^{grdelas_i}$$

where $spc0_i$*: calibrated coefficient for equation;* ... Eq. (4.28)

rdelas: Elasticity of private knowledge stocks;

grdelas$_i$: Elasticity of public knowledge stocks

$$AVA_i = ava0_i / SPCOEFF_i \qquad \text{... Eq. (4.29)}$$

$$VA_i = AVA_i \cdot Z_i \qquad \text{... Eq. (4.30)}$$

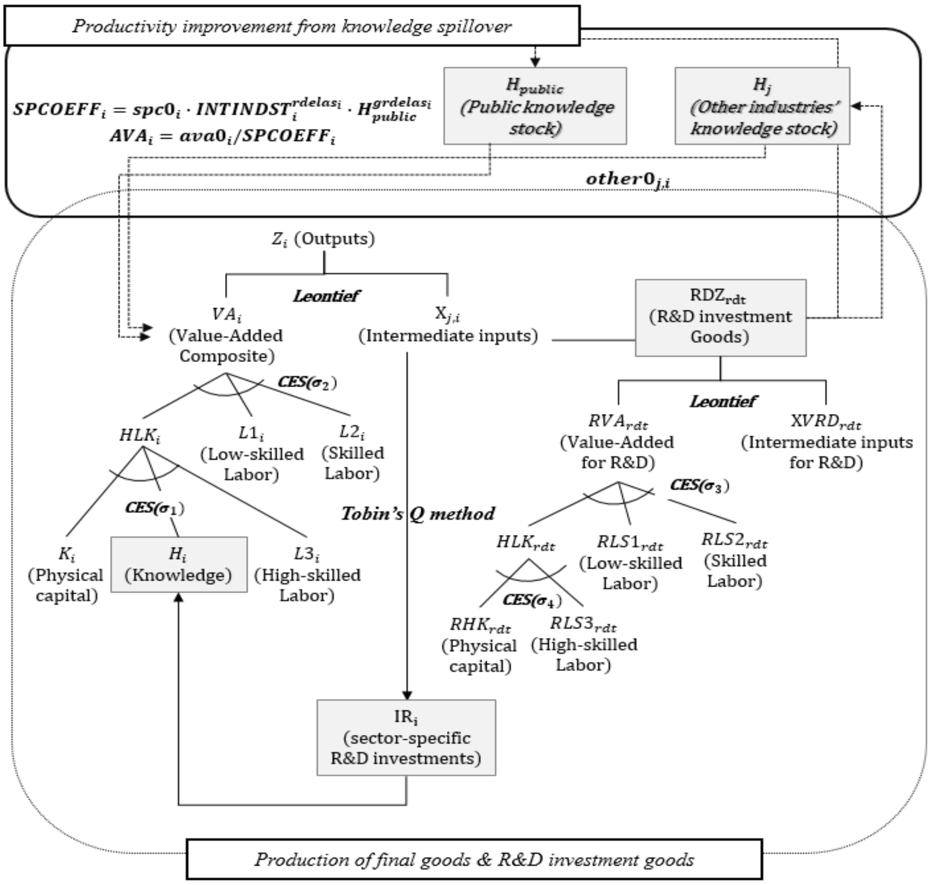


Figure 25. Productivity improvements from the knowledge spillover effects in the model

4.5 Investments and savings

In this section, we will provide explanations on the way in which the physical capital investment is endogenously determined, as well as how investments resources for physical capital and knowledge capital investments are secured from institutions (i.e., the relationships between investments and savings). It is also assumed that within the model, the gross physical capital investment is set to be endogenously determined within the model, following the logic of Tobin's Q, as expressed by Eq.(4.31), similar with the sector-specific R&D investments. In this equation Eq.(4.31), the right-hand side component represents the Q ratio of the market value (i.e., the market value of physical capital) of the unit of physical capital to the physical capital investments costs for one unit, while $\aleph^K$ indicates the physical capital investment elasticity for Q value. In addition, $Pinvk,\ \delta_{cap},\ ir,\ PK$, each represents the price of physical capital investment good, physical capital depreciation rate, interest rate, and the price of physical capital, respectively. Accordingly, the gross physical capital investment level within the economy for the period (t) is endogenously determined by the level of physical capital stocks (KS_t), the return on physical capital (PK_t) and the user costs of knowledge capital ($Pinvrd_t(\delta_{cap} + ir)$). Physical capital investment goods can be also considered as the Armington composite consisting of domestic and imported goods (or, services). Accordingly, it is assumed that the demand for physical capital investment by industry is determined by applying the proportion of physical capital investment by industry (λ_i) in the base year derived from the calibration process, as expressed by Eq.(4.32). Furthermore, the perpetual inventory method (PIM) has been also applied to describe the dynamic accumulation process of the physical capital stocks, as expressed by the Eq.(4.33).

$$INVK_t = KS_t \cdot \gamma^K \cdot \left[\frac{PK_t}{Pinvk_t(\delta_{cap} + ir)}\right]^{\aleph^K} \qquad \text{... Eq. (4.31)}$$

$$Pinvk = \sum_i \lambda_i \cdot PQ_i$$

$$Xv_i = \lambda_i \cdot INVK \quad \text{... Eq. (4.32)}$$

$$KS_t = (1 - \delta_{CAP}) \cdot KS_{t-1} + INVK_t \quad \text{... Eq. (4.33)}$$

When the values for the physical capital and knowledge capital investments levels are determined, the total amounts of investment levels ($INVRES$) within the economy can be expressed as Eq.(4.34). The total amount of physical capital investment can be derived by multiplying the quantity of physical capital investment ($INVK$) by the price of the physical capital investment good ($PINVK$). In addition, the total amount of knowledge capital is calculated through multiplying the quantity of R&D investment good produced by the R&D industry (RDZ_{rdt}) with the price of the R&D investment good ($PRDZ_{rdt}$). Investments in physical capital and knowledge capital are made through the savings of institutions including households and the government. Accordingly, if the total demand for investment goods is determined, as in Eq.(4.34), then the amount of institutions' saving is allocated in accordance with Eq.(4.35). Here, it is assumed that households and governments all are involved in financing resources for physical capital and knowledge capital investments, and the propensity of savings for institutions is fixed by the ratio of each intuition's savings in each type of investment in the base year. In the equation Eq.(4.36), rp_{rdt} and rg_{rdt}, respectively, indicate the household's saving for the R&D investment (i.e., private or public R&D investments) in total savings of households, and the government's saving for the R&D investment in its total savings. When the household and government savings are determined in this way, the total savings can be expressed as the sum of the trade balance (*SF*) together with the total savings of the household and the government, as expressed by Eq.(4.35).

$$INVRES = INVK \cdot Pinvk + \sum_{rdt} RDZ_{rdt} \cdot (1 + \tau_{rdt}) \cdot PRDZ_{rdt} \qquad \text{... Eq. (4.34)}$$

$$TOTSAV = \sum_{hh} SP_{hh} + SG + SF \qquad \text{... Eq. (4.35)}$$

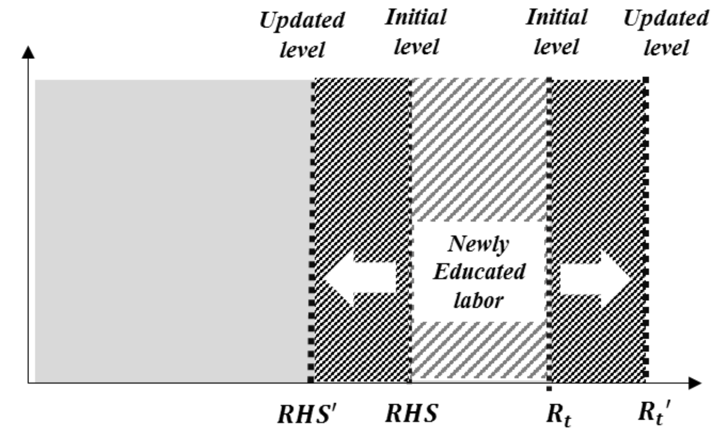
$$\sum_{rdt} RDZ_{rdt} \cdot (1 + \tau_{rdt}) \cdot PRDZ_{rdt} = rp_{rdt} \cdot \sum_{hh} SP_{hh} + rg_{rdt} \cdot SG \qquad \text{... Eq. (4.36)}$$

4.6 Endogenous skill accumulation from learning

In the designed CGE model for this study, we have modeled that the skill accumulation process of workers is endogenously determined according to the changes in educational investment level for the human capital accumulation and relative wages among workers, referring to other previous studies including Jung and Thorbecke (2003) and Ojha et al. (2013). For example, following the approaches proposed by Jung and Thorbecke (2003) and Ojha et al. (2013), the expected lifetime income of workers after completing the skill accumulation (B_t^u) can be expressed as Eq.(4.37), where *s*, τ, and R_t ($R_t = \varphi \cdot EDU_t^{\rho E}$) respectively represent the period of working, labor income tax rate, and the expected return on educational investments. R_t can be expressed as $R_t = \varphi \cdot EDU_t^{\rho E}$, where EDU_t, ρE, and φ respectively indicate the level of educational investment at time *t*, parameter for the return on educational investment, and scale parameter in this equational form.

On the other hand, the expected lifetime income of workers not engaged in the skill accumulation (B_t^l) can be expressed as Eq.(4.38). With these equational settings, when workers choose to undertake the skill accumulation when $B_t^u/B_t^l \geq 1$ is satisfied. Here, when specifying the expected lifetime income of workers (i.e., B_t^u and B_t^l), the growth rate of the wage levels w_t^u (i.e., wage level when completing the skill accumulation), and w_t^l (i.e., wage level when not completing the skill accumulation) are assumed to be determined by the economic growth rate g_t and discount rate (i.e., interest rate) ir_t. Accordingly, the expected lifetime income of workers after completing the skill accumulation (B_t^u) is endogenously determined by the expected wage rate w_t^u and the parameter value of R_t (i.e., wage growth rate taking into account the return on educational investment) (see Eq.(4.37)), while the expected lifetime income of workers not engaged in the skill accumulation (B_t^l) is solely determined by the expected wage rate w_t^l (see Eq.(4.38)).

With these equational settings and underlying assumptions, Jung and Thorbecke (2003) and Ojha et al. (2013) have tried to describe the endogenous skill accumulation process of workers assuming that workers proceed into the learning process, when $B_t^u/B_t^l \geq 1$ is satisfied by comparing the expected lifetime income of workers not engaged in the skill accumulation (B_t^l) and the expected lifetime income of workers after completing the skill accumulation (B_t^u). Accordingly, constraint equations for $B_t^u/B_t^l \geq 1$ can be derived as expressed by Eq.(4.39) with considerations of Eq.(4.37) and Eq.(4.38). As mentioned above, the left-hand side component within the Eq.(4.39) represents the availability of education facility, while the right-hand side component indicates the relative wage rate at the skill level l relative to the wage level at the skill level u. Accordingly, within this equation Eq.(4.39), the difference between the left-hand side R_t and the right-hand side can be understood as the supply of newly educated workers who completed skill accumulation (Jung & Thorbecke, 2003; Ojha et al., 2013). This can be understood as shown in Figure 26.



$$R_t \geq \left(W^l_{t-1} \big/ W^u_{t-1} \right) \cdot \left(\frac{(ir_{t-1} - g_{t-1}) + (1 + g_{t-1}) \left[1 - \left(\frac{1 + g_{t-1}}{1 + ir_{t-1}} \right)^T \right]}{(1 + g_{t-1}) \left[1 - \left(\frac{1 + g_{t-1}}{1 + ir_{t-1}} \right)^T \right]} \right)$$

Figure 26. Conceptual frameworks proposed by Ojha et al. (2013), and Jung and Thorbecke (2003)

$$B^u_t = R_t \sum_{s=1}^{T} w^u_{t-1} (1 + g_{t-1})(1 - \tau)\left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^s \qquad \text{... Eq. (4.37)}$$

$$where\ R_t = \varphi \cdot EDU_t^{\rho E}$$

$$B_t^l = \sum_{s=1}^{T} w_{t-1}^l \, (1+g_{t-1})(1-\tau)(\frac{1+g_{t-1}}{1+ir_{t-1}})^s \quad \text{... Eq. (4.38)}$$

$$R_t \geq \left(W_{t-1}^l / W_{t-1}^u\right) \cdot \left(\frac{(ir_{t-1} - g_{t-1}) + (1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]}{(1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]} \right) \quad \text{... Eq. (4.39)}$$

By imposing the constraints that *T* as infinity, and *ir* > *g*, Eq.(4.39) can be expressed as the form of Eq.(4.40). Within the Eq,(4.39), as the difference between the left-hand side R_t and the right-hand side $\left(W_{t-1}^l / W_{t-1}^u\right) \cdot \left(\frac{(ir_{t-1} - g_{t-1}) + (1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]}{(1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]} \right)$ is getting larger, the supply of newly educated workers is getting increased. Accordingly, as the value of R_t becomes larger, and the value of $\left(W_{t-1}^l / W_{t-1}^u\right) \cdot \left(\frac{(ir_{t-1} - g_{t-1}) + (1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]}{(1+g_{t-1})\left[1 - \left(\frac{1+g_{t-1}}{1+ir_{t-1}}\right)^T\right]} \right)$ is smaller, the supply of workers who have completed the skill accumulation increases. This logic can be also understood with Figure 26. Based on this, the level of supply of workers who have their skills through the learning process from the skill level *l* to the skill level *u* at the time of *t* can be expressed by Eq.(4.40) by imposing the constraints that *T* as infinity, and *ir* > *g* into Eq.(4.39). Accordingly, in this study we intend to reflect the endogenous process of skill accumulation within the model which is determined by the level of education investment spending in the economic system (EDU_t) and the wage differential (relative wage) between workers.

As expressed by Eq.(4.40), it is designed that the labor supply of workers ($LS_{u,t}$) who have their skills through learning from the skill level *l* to the skill level *u* at the time of *t* can be described as the function of by the level of education investment spending in the economic system (EDU_t) and the relative wage rate ($^{w_{t-1}^{u}}/_{w_{t-1}^{l}}$) at the skill level l relative to the wage level at the skill level u in the previous period. Within the CGE model, the level of spending on education investment in the economic system has been estimated as the level of total expenditures on education sector (i.e., S26 education sector within the model) by the public and private sectors. With the consideration of the Eq.(4.40), we have also assumed the economic growth rate g_t and discount rate (i.e., interest rate) ir_t with exogenous projection data. In addition, we have also assumed the value of the parameter ρE which represents the elasticity parameter determining the return on education investment, and the labor supply through the skill accumulation affected by the educational investment expenditure, as 0.5 by referring the values used by Jung and Thorbecke (2003) and Ojha, Pradhan, & Ghosh (2013). Moreover, within the equation Eq.(4.40), $\emptyset_1$ and $\emptyset_2$, respectively represent the relative weight of each component, and those values are assumed to be same values in Jung and Thorbecke (2003) and Ojha, Pradhan, & Ghosh (2013).

$$LS_{u,t} = \emptyset_1 \cdot EDU_t^{\rho E} + \emptyset_2 \cdot \left(^{w_{t-1}^{u}}/_{w_{t-1}^{l}}\right) \cdot [\frac{1+g_t}{1+ir}] \qquad \text{... Eq. (4.40)}$$

As mentioned above, the level of education investment expenditures of the private and public sectors (EDU_t) is considered as one of variables that affects the endogenous skill accumulation process of workers. Therefore, the private and government education investments considered in the CGE model consist of formal education, formal learning (i.e., general education), as well as the non-formal learning (Boeren, 2011; Colardyn & Bjornavold, 2004). To be specific, within the CGE model the economic actors who undertake decision-making process based on the level of education investment expenditures of the private and public sectors (EDU_t) are workers who are engaged in economic activities (i.e., production sectors). Accordingly, when considering the reality, it can be understood that the level of education investment expenditures of the private and public sectors (EDU_t) considered in the model as the investment expenditures for learning (i.e., retraining and up-skilling) for workers who are already engaged in economic activities. For example, the public expenditures to promote the learning process of workers consist of planning and supporting of the public vocational training programs for employees (if employees voluntarily participate in those programs to improve their skills, the public sector may support some of the costs or operate the programs themselves), providing learning-related infrastructure to support workers to systematically accumulate their knowledge, experiences, and know-hows, supporting for operating expenses of On-the-Job (OJT) programs for private sectors, supporting degree acquisition by employees curing their working days (with supports of tuition fees), and so on (Boeren, 2011; Colardyn & Bjornavold, 2004; Kang et al., 2011; Yoo, 2008; Lee, 2003; Kim et al., 2001). In addition, the private expenditures to promote the learning process of workers can be considered as an example of general training and firm-specific training programs under the employer-provided training program (Cho, 2010; Stevens & Margaret, 1996). Other examples of the private sector's investment to induce workers' skill accumulation include on-site training and retraining programs provided by employers, supports for workers' learning, educational programs and life-long learning programs for employees in private schools and private institutions, expenses and supports of employees' self-development, and so on (Kang et al., 2011; Kim, 2008; Görg & Strobl, 2006).

As such, the categories and dimensions of formal and informal learning and training for employees are very diverse and wide, making it difficult to identify relevant statistics and indicators in terms of the private and public sectors' investment expenditures on a wide range of learning programs (Kang et al., 2011). Accordingly, this study assumes that the total expenditure level for the education sector in the economy consisting of expenditures on 1) formal education prior to participation in labor market, 2) formal education (learning) for workers, and 3) informal learning for workers, represent a proxy variable describing the availability of the learning conditions of the economy which spur and promote the skill accumulation of workers. Through this, it is assumed that the economic, social, and cultural conditions surrounding the skill accumulation and learning process of workers are determined by the level of total education investment expenditures of the private and public sectors (EDU_t). This study also assumes and reflects the optimal situation with smooth transitions of workers, either from low-skilled to skilled labor, or from skilled to high-skilled labor.

As mentioned above, it is designed that the labor supply of workers ($LS_{u,t}$) who have their skills through learning from the skill level *l* to the skill level *u* at the time of *t* can be described as the function of by the level of education investment spending in the economic system (EDU_t) and the relative wage rate ($^{w_{t-1}^u}/_{w_{t-1}^l}$) at the skill level l relative to the wage level at the skill level u in the previous period. This methodological characteristic implies that the workers conduct learning-related decision making based on the expected returns (i.e., earnings) within the model. In addition to this approach, Charles and Luoh (2003) point out that the detailed decision-making process of economic agents in terms of skill accumulation should incorporate two aspects including the expected returns (i.e., earnings), as well as the costs accompanied by the skill accumulation. This study addresses that the possible cots related to the human capital accumulation includes examples of tuition fees, opportunity costs during the periods of labor market absence, psychological costs, and other miscellaneous costs. Charles and Luoh (2003) also suggest that the decision-making process whether to improve the skills (or, accumulate human capital) of the economic actor can be converted into the utility maximization problem of the economic agent during the life-cycle, thereby choosing the level of periods (or, levels) for skill accumulation by comparing the expected returns to the gross possible costs. Thus the net return on human capital investment is related to the wage premium in terms of skill level, as well as the economic costs, including the ineffectiveness of skill accumulation.

Chang and Hornstein (2007) also assume that consumer's utility is determined by the utility from consumption, as well as the disutility coming from the possible costs of skill accumulation, which shapes the patterns of human capital accumulation within the economy. In addition, the internal rate of return (IRR) is a methodological approach to estimate the return on education investment. This approach estimates the return on education investment by calculating both economic costs and benefits involved in this human capital investment. This approach has been proposed to overcome the pre-existing approach, which is to estimate the rates of return to human capital investments (education) with econometrical earnings functions not considering the total costs associated with the human capital investment.

In this regard, in order to comprehensively understand the human capital accumulation process as an endogenous process, it will be an elaborated approach to consider both costs (i.e., disutility) of education, and economic benefits of skill accumulation, which captures more realistic and detailed process of endogenous decision-making process associated with the human capital accumulation. However, this study adopts previous studies' approaches which highlight following variables to account for the endogenous skill accumulation process of workers; 1) Kaufman et al. (2001)'s approach which highlight that relative wages among different types of labor can promote investments in human capital, 2) Chanda (2008)'s approach suggesting that changes in interest rates and savings rates affect the changes in rates of return on educational investments, and 3) approaches proposed by Jung and Thorbecke (2003) and Ojha et al. (2013) arguing that the institutional conditions for learning shaped by the level of educational investment affect the endogenous skill accumulation of workers. By synthesizing those approaches covered by previous studies, this study focuses on the expected returns of educational investment in describing the endogenous decision-making process undertaken by workers on the human capital accumulation. Thus, the economic costs accompanied by the skill accumulation (i.e., skill upgrading), including the tuition fee, and opportunity costs due to the labor market absence are not taken into considerations in describing the endogenous decision-making process of workers on skill upgrading and human capital accumulation within the CGE model. Accordingly, it is noted that the effects of human capital accumulation drawn from the CGE analysis can be overestimated.

In the CGE model designed in this study, the total labor stock (LS_t) in the economic system is assumed to be evolved in accordance with exogenously determined growth rate of labor force (gl_t) with prediction data published by the Statistics Korea (see Eq.(4.37)). To be specific, the dynamic evolution of the human capital composition can be captured through changes in the labor stocks of each labor type. The labor supply of workers who have completed the skill accumulation from low-skilled labor (*l*) to skilled labor (*s*) is incorporated into the pre-existing skilled labor stocks ($L2_t \equiv FS_t(LAB2)$), while the labor supply of workers who have completed the skill accumulation from skilled (*s*) to high-skilled labor (*h*) is added into the pre-existing high-skilled labor stocks ($L3_t \equiv FS_t(LAB3)$), as expressed by equation Eq.(4.38). In addition, it is possible to derive the residual Δ through comparing the dynamically changing total labor stock value LS_t at the time *t*, subtracted by the skilled labor stocks ($L2_t \equiv FS_t(LAB2)$) and the high-skilled labor stocks ($L3_t \equiv FS_t(LAB3)$) with the value of the low-skilled labor stocks ($L1_t \equiv FS_t(LAB1)$) to capture the labor supply of newly added low-skilled labor, and associated changes in the low-skilled labor stocks. Dynamic changes in the human capital compositions within the economy through endogenous human capital accumulation process can be expressed by Eq.(4.42).

$$LS_{t+1} = (1 + gl_t) \cdot LS_t$$
$$\text{where } LS_t = L1_t + L2_t + L3_t \qquad \text{... Eq. (4.41)}$$

$$L1_{t+1} = (1 - labdep) \cdot L1_t - LS_{s,t}$$
$$L2_{t+1} = (1 - labdep) \cdot L2_t + LS_{s,t} - LS_{h,t} \qquad \text{... Eq. (4.42)}$$
$$L3_{t+1} = (1 - labdep) \cdot L3_t + LS_{h,t}$$

In addition, in the process of determining the evolution of the labor stocks, this study has introduced the concept of the depreciation rate of human capital (see Eq.(4.42)), and reflected the value for the human capital depreciation rate (*labdep* = 0.015, 1.5%) estimated by Ban (2017). The human capital depreciation can be divided into internal obsolescence and external obsolescence. In the former case, it is associated with the loss of physical and mental ability/capacity caused by the human capital itself. In the latter case, it is related with the fact that the knowledge and skills learned from formal and on-site training possessed by workers gradually become obsolete due to changes in the external environments, which can be called as vintage effects (Neuman & Weiss, 1995; De Grip & van Loo, 2002). For example, if rapid technological progress may lead to the depreciation of skills accumulated in individuals by providing limited opportunity to utilize the cognitive skills held by individuals. On the other hand, absence in the labor market due to career interruption or long-term unemployment can also lead to the human capital obsolescence. Based on this concept, the obsolescence of human capital which is considered in this study is the external obsolescence affected by the external conditions including technological progress and institutional conditions of the labor market. It is highlighted that the external obsolescence of human capital can be determined by the economic, social, and cultural conditions surrounding the learning process of economic actors (Salthouse, 2009; Hanushek et al., 2013). Ban (2017) has tried to estimate the human capital depreciation rates for OECD countries, and found out that Korea has relatively higher human capital depreciation rate compared to other countries. A higher level of the human capital depreciation rate implies that it cannot guarantee a higher return on education investment. Based on this concept of human capital obsolescence, this study has introduced the concept of the depreciation rate of human capital to describe the process of determining the evolution of the labor stocks, and changes in the human capital compositions.

The labor stocks $(L1: low-skilled, L2: skilled, L3: high-skilled)$ in each period are allocated to final goods producing sectors and R&D sectors within the model in accordance with the levels of labor demands induced by those sectors. Accordingly, the relationship between the changes in labor supply through the human capital accumulation of workers and the production function of final goods producing sector can be depicted as Figure 27. In this regard, this study has endogenized the skill accumulation process of workers (affected by the level of educational investments and relative wages among workers) within the CGE model, thereby enabling to capture the dynamic evolution of the human capital compositions.

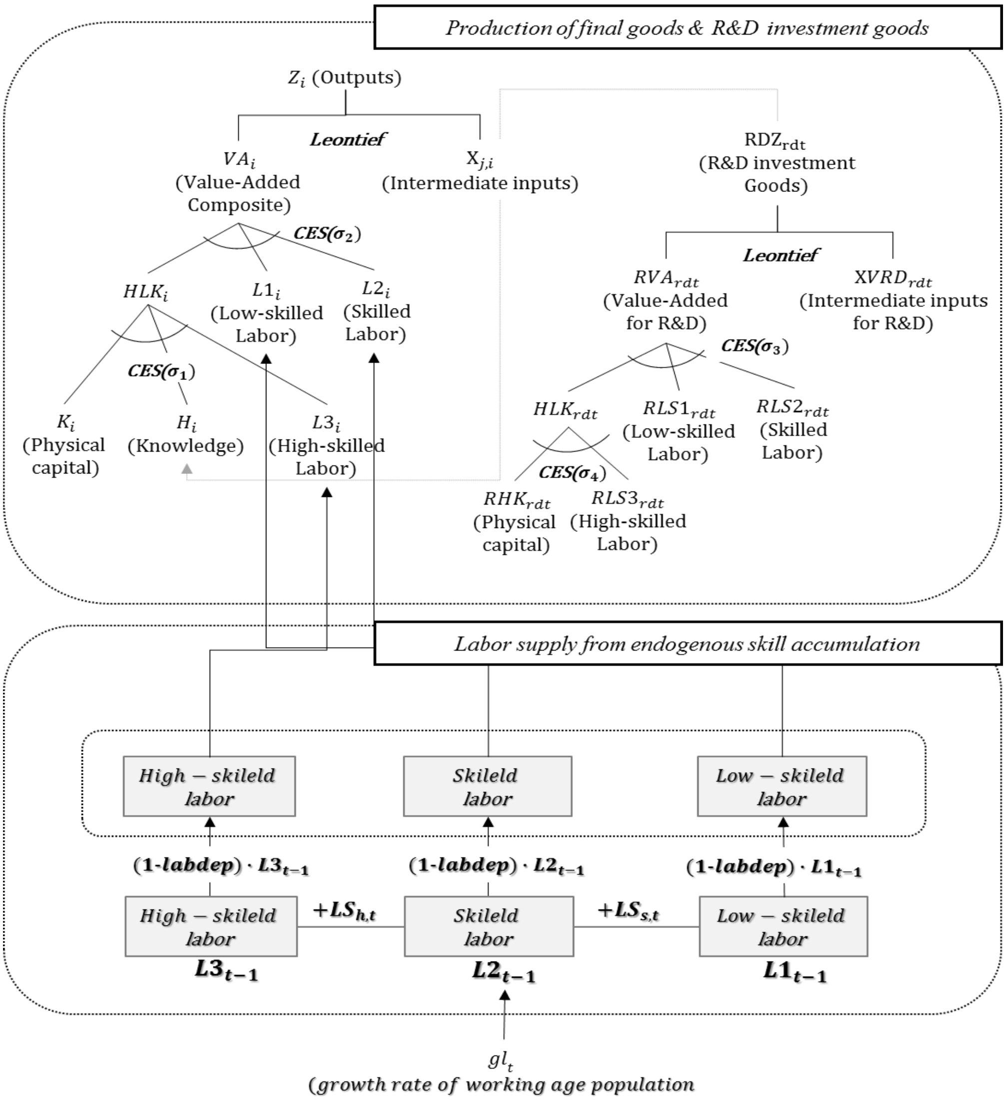


Figure 27. Relationships between changes in labor supply from human capital accumulation and production function within the CGE model

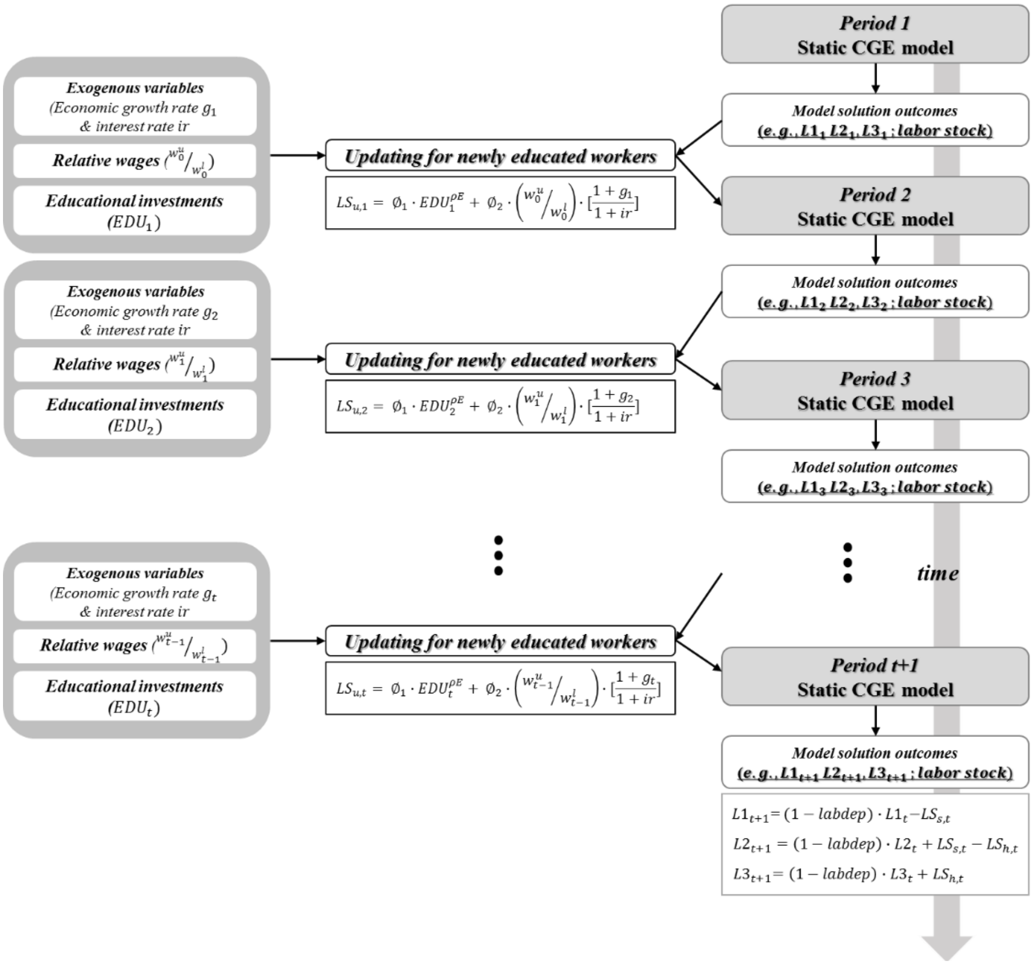


Figure 28. Dynamics of the CGE model in terms of the evolution of labor stocks through skill accumulation from the recursive dynamics perspective

In addition, the knowledge-based CGE model proposed in this study is a recursive dynamic model. In the case of the recursive dynamic model, the amounts the investments depend on the values of savings, as in the static model. These investments will form the next-period's capital stock through the capital accumulation process being added into the capital stocks in the previous period, and this nest-period's capital stock affects the production volumes of industrial sectors in the corresponding period. Likewise, it is also designed within the CGE model that the changes of labor stocks affect the production functions of individual sectors through the labor stocks' accumulation process. Under the time-recursive dynamic model, economic agents in the model make decisions on their economic activities every periods, in which the conditions on the factor inputs markets (including labor stocks and capital stocks) are pre-determined for each period. In this regard, the dynamic process of changes in labor stocks within the CGE model can be described as Figure 28.

We will briefly provide explanations on how the labor stock for each labor type is determined in next period of *(t+1)* with the information on the labor stocks for low-skilled, skilled, and high-skilled $(L1_t, L2_t, L3_t)$ in period of time *(t)* from the dynamic perspective with considerations of relevant variables within the CGE model. The labor stocks of skilled and high-skilled labor for next period of *(t+1)* can be generated through adding newly educated workers $LS_{s,t}$ (from low-skilled to skilled labor) and $LS_{h,t}$ (from skilled to high-skilled labor) to the pre-existing labor stocks $(L2_t, L3_t)$. The amounts of newly educated workers $LS_{s,t}$ (from low-skilled to skilled labor) and $LS_{h,t}$ (from skilled to high-skilled labor) in the period of *(t)* are endogenously derived by the values of relative wages $\left({w_{t-1}^u}/{w_{t-1}^l}\right)$ generated form the optimization process of the CGE model for the period of *(t-1)* which can be specified as $(\frac{PL3_{t-1}}{PL2_{t-1}})$ and $(\frac{PL2_{t-1}}{PL1_{t-1}})$ within the model, and the values of educational investment level EDU_t, exogenously assumed economic growth rate

g_t, and interest rate ir in the period of *(t).*

To be specific, the total labor stock (LS_t) in the economic system is assumed to be evolved in accordance with exogenously determined growth rate of labor force (gl_t) (see Eq.(4.37)). The labor supply of workers ($LS_{s,t}$) who have completed the skill accumulation from low-skilled labor (*l*) to skilled labor (*s*) in the period of *(t)* is endogenously determined by the ratio of the wage rate of skilled labor relative to that of low-skilled labor ($\frac{PL2_{t-1}}{PL1_{t-1}}$), generated form the optimization process of the CGE model for the period of *(t-1), and* the values of educational investment level EDU_t as policy shocks (i.e., policy variables), exogenously assumed economic growth rate g_t, and interest rate ir in the period of *(t).* The labor supply of workers ($LS_{s,t}$) who have completed the skill accumulation from low-skilled labor (*l*) to skilled labor (*s*) in the period of *(t)* is incorporated into the pre-existing skilled labor stocks ($L2_t \equiv FS_t(LAB2)$), thereby forming the labor stock $L2_{t+1}$ for the next period of *(t+1).*

In addition, the labor supply of workers ($LS_{h,t}$) who have completed the skill accumulation from skilled (*s*) to high-skilled labor (*h*) in the period of *(t)* is endogenously determined by the ratio of the wage rate of high-skilled labor relative to that of skilled labor ($\frac{PL3_{t-1}}{PL2_{t-1}}$), generated form the optimization process of the CGE model for the period of *(t-1), and* the values of educational investment level EDU_t as policy shocks (i.e., policy variables), exogenously assumed economic growth rate g_t, and interest rate ir in the period of *(t).* The labor supply of workers ($LS_{h,t}$) who have completed the skill accumulation from skilled (*s*) to high-skilled labor (*h*) in the period of *(t)* is incorporated into the pre-existing skilled labor stocks ($L3_t \equiv FS_t(LAB3)$), thereby forming the labor stock $L3_{t+1}$ for the next period of *(t+1)*.

The number of newly educated workers ($LS_{s,t}$) who have completed the skill accumulation from low-skilled (*l*) to skilled labor (*s*) in the period of *(t)* is deducted from the low-skilled labor stock, while the same amount is added into the skilled labor stock. In addition, the labor supply of workers ($LS_{h,t}$) who have completed the skill accumulation from skilled (*s*) to high-skilled labor (*h*) in the period of *(t)* is subtracted from the skilled labor stock, while this same amount is added into the high-skilled labor stock. In addition, it is possible to derive the residual Δ through comparing the dynamically changing total labor stock value LS_t at the time *t*, subtracted by the skilled labor stocks ($L2_t \equiv FS_t(LAB2)$) and the high-skilled labor stocks ($L3_t \equiv FS_t(LAB3)$) with the value of the low-skilled labor stocks ($L1_t \equiv FS_t(LAB1)$) to capture the labor supply of newly added low-skilled labor, and associated changes in the low-skilled labor stocks. As mentioned above, as a dynamic element within the CGE model, we have explicitly described the dynamics of endogenously determined labor stocks, thereby affecting the production function every periods.

Furthermore, we will investigate how endogenous interactions between technological innovation and human capital are modeled within the CGE framework. As described in Figure 29, in the case of exogenous shocks in the form of an increase in human capital investment, the increase in the spending on education investment (EDU_t) will directly affect the skill accumulation process of workers, thereby increasing the supply of workers with higher skills ($L2_t,\ L3_t$). This change in labor supply resulting from the accumulation of human capital can indirectly increase the rate of return on the knowledge capital investments ($PH_{i,t}$) based on the complementary relationship between knowledge and high-skilled labor within the production function, leading to indirectly promote the sector-specific R&D investments ($IR_{i,t}$) for knowledge accumulation.

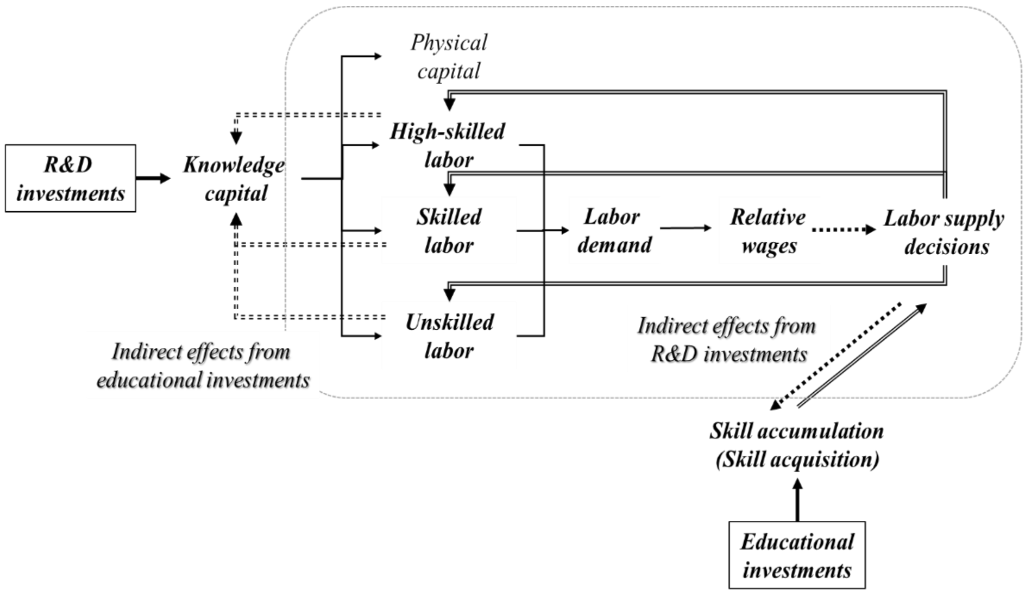


Figure 29. Endogenous interaction between innovation and human capital accumulation within the CGE model

On the other hand, if the exogenous policy shock in the form of the increase in knowledge capital investment (i.e., R&D investment) is introduced in the model, the increase in the knowledge capital investment level ($RDZ_{rdt} \cdot (1+\tau_{rdt}) \cdot PRDZ_{rdt}$) will directly increase the rate of return on the knowledge capital investment ($PH_{i,t}$), leading to spur the industry-specific R&D investments ($IR_{i,t}$). The accumulation of knowledge capital stock ($H_{i,t}$) by industry, on the basis of the complementary relationship with the high-skilled labor in the production function, increases the relative wage of high-skilled labor ($PL3_{t-1}/PL2_{t-1}$). It can indirectly affect the endogenous skill accumulation process of workers. In this way, this study has explicitly described and reflected the endogenous interaction between the technological progress driven by the R&D investments and human capital accumulation and associated changes in the human capital compositions within the CGE model. Figure 29 represents the main channels within the production function describing the interactions between innovation and human capital accumulation.

4.7 Institutions (households and government)

In this CGE model, we have considered heterogeneous households classified into 20 quantiles based on income levels. Each household by income quantile forms total earnings consisting of wage income, physical capital income, and knowledge capital earnings. Total wage incomes for each type of skill ($HLINC_{type}$), physical capital income ($HKINC$), and knowledge capital earnings ($HHINC$) earned by households can be expressed as Eq.(4.43), Eq.(4.44), and Eq.(4.45). This aggregated earnings for each factor input earned by households are distributed to 20 types of households, based on the share of each income quantile within the gross income from each production factor $ffhh0_{hh}$ derived from the calibration process of the model to characterize the heterogeneous income structures of households. Accordingly, as shown in Eq.(4.46) $FHL1_{hh}, FHL2_{hh}, FHL3_{hh}$ respectively indicate the proportion of each income quantile (*hh*) within the labor incomes from low-skilled labor, skilled labor, and high-skilled labor). On the other hand, FHK_{hh}, FHH_{hh} respectively represent the proportion of each income quantile (*hh*) within the capital earnings and knowledge capital earnings as shown in Eq.(4.47) and Eq.(4.48). Total net incomes for each income quantile (see Eq.(4.49)) subtracted by the transfer payments (TG_{hh}) are allocated to consumption (XP_{hh}), savings (SP_{hh}), and payments of income taxes ($TINC_{hh}$). Heterogeneous consumption expenditures of households among 20 income quantiles are identified by the consumption structure, based on the values for the relative shares of consumption expenditures by industry for each income quantile ($\alpha0_{i,hh}$) drawn from the base year SAM data, which can be expressed by Eq.(4.50).

$$HLINC_{type} = \sum_{i}\left(L_{i,type} \cdot PL_{type}\right) + \sum_{rdt}\left(RLS_{rdt,type} \cdot PL_{type}\right)$$

where $L_{i,type}$*: Labor inputs for sector i by skill type;* ... Eq. (4.43)

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

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

$$HKINC = \sum_{i}(K_i \cdot PK) + \sum_{rdt}(RK_{rdt} \cdot PK)$$

where K_i*: Physical capital inputs for sector i;* ... Eq. (4.44)

RK_{rdt}*: Physical capital inputs for R&D investments;*

PK*: Returns of capital*

$$HHINC = \sum_i (H_i \cdot PH_i)$$

... Eq. (4.45)

$where\ H$: *Knowledge capital inputs for sector i;*

PH_i: *Factor price of knowledge capital*

$$FHL1_{hh} = ffhh0_{hh,LAB1} \cdot HLINC_{LAB1}$$

$$FHL2_{hh} = ffhh0_{hh,LAB2} \cdot HLINC_{LAB2}$$

... Eq. (4.46)

$$FHL3_{hh} = ffhh0_{hh,LAB3} \cdot HLINC_{LAB3}$$

$$FHK_{hh} = ffhh0_{hh,CAP} \cdot HKINC$$

... Eq. (4.47)

$$FHH_{hh} = ffhh0_{hh,KNOW} \cdot HHINC$$

... Eq. (4.48)

$$HINC_{hh} = FHL1_{hh} + FHL2_{hh} + FHL3_{hh} + FHK_{hh} + FHH_{hh}$$

... Eq. (4.49)

$$XP_{i,hh} = \alpha 0_{i,hh} \cdot (HINC_{hh} - TG_{hh} - SP_{hh} - Tinc_{hh})/PQ_i$$

... Eq. (4.50)

In the model, the government forms its income through levying taxes in the form of indirect taxes, income taxes, corporate taxes and import tariffs. In the case of indirect tax (Tz), it represents the production tax imposed on the production outputs of the final goods producing industries, and R&D sectors, while the income tax ($Tinc$) is the tax imposed on the households' incomes. The corporate tax ($Tcor$) represents the taxation on capital incomes imposed on the industrial and R&D sectors, while the import tariffs ($Ttar$) are imposed to the imported goods. Here, we consider the ad-valorem tax to represent those types of taxation. Different types of taxes collected by the government can be expressed as

Eq.(4.51), Eq.(4.52), Eq.(4.53), and Eq.(4.54). Tax rates for those taxation $(\tau_{Z,i}, \tau_{inc,hh}, \tau_{cap,i}, \tau_{tar,i})$ are assumed to be constant as the levels for the base year when there is no policy shocks. Net incomes of the government ($Ginc$) consisting of tax revenues, government debt, and household transfers (see Eq.(4.55)) are used for savings (SG) and consumption expenditure for the government (Xg). At this time, the government's consumption structure is reflected within the model, based on the relative share of each industrial sector within the gross government's consumption expenditures ($\mu 0_i$), drawn from the base year SAM data, which can be expressed by Eq.(4.56).

$$Tz_i = \tau_{Z,i} \cdot Z_i \cdot PZ_i \text{ where } \tau_{Z,i} = Tz0_i / Z0_i$$
$$\text{Total}_{TZ} = \sum_i Tz_i \qquad \text{... Eq. (4.51)}$$

$$Tinc_{hh} = \tau_{inc,hh} \cdot HINC_{hh} \text{ where } \tau_{inc,hh} = Tinc0_{hh} / HINC0_{hh}$$
$$\text{Total}_{Tinc} = \sum_{hh} Tinc_{hh} \qquad \text{... Eq. (4.52)}$$

$$Tcor_i = \tau_{cap,i} \cdot K_i \cdot PK \text{ where } \tau_{cap,i} = Tcor0_i / K0_i$$
$$\text{Total}_{Tcor} = \sum_i Tcor_i \qquad \text{... Eq. (4.53)}$$

$$Ttar_i = \tau_{tar,i} \cdot M_i \cdot PWM_i \text{ where } \tau_{tar,i} = Ttar0_i / M0_i$$
$$\text{Total}_{Ttar} = \sum_i Ttar_i \qquad \text{... Eq. (4.54)}$$

$$Ginc = Total_{TZ} + Total_{Tinc} + Total_{Tcor} + Total_{Ttar} + Bg + \sum_{hh} TG_{hh} \qquad \text{... Eq. (4.55)}$$

$$XG_i = \mu 0_i \cdot (Ginc - SG)/PQ_i \qquad \text{... Eq. (4.56)}$$

4.8 International trade (exports and imports)

This model assumes a small open economy, implying that the economy of the target country is so small that the economic activities of a country do not have any impacts on foreign countries. These assumptions are reflected in the model with exogenously given prices of goods exported or imported. In case of the export price of goods (PE_i), it is determined by multiplying the world price of exported goods (PWE_i) by the exchange rate ε as expressed by Eq.(4.57), while the price of imported goods (PM_i) is determined by multiplying the world price of imported goods (PWM_i) by the exchange rate ε and the import tariff tax rate $\tau_{tar,i}$, as expressed by Eq.(4.58).

$$PE_i = \varepsilon \cdot PWE_i \qquad \text{... Eq. (4.57)}$$

$$PM_i = \varepsilon \cdot (1 + \tau_{tar,i}) \cdot PWM_i \qquad \text{... Eq. (4.58)}$$

In addition, Armington composite Q utilized for the production and consumption activities represents an artificial composite combined with domestic goods *D* and imported goods *M* (see Eq.(4.59) below). Accordingly, as shown in Eq.(4.59), it is assumed that domestic goods and imported goods have imperfect substitutional relationships under the Armington's assumption. Based on this equation, the relative demand relation of imported and domestic goods can be derived as shown in Eq.(4.60).

$$\mathrm{Q}_i = \gamma \cdot (\varphi \cdot M_i^{v} + (1 - \varphi) \cdot D_i^{v})^{1/v} \qquad \text{... Eq. (4.59)}$$

$$\mathrm{M}_i/\mathrm{D}_i = [\frac{PD_i}{PM_i} \cdot \frac{\varphi}{(1 - \varphi)}]^{\,1/(1-v)}$$

... Eq. (4.60)

$$PQ_i \cdot Q_i = \; PM_i \cdot M_i + \; PD_i \cdot D_i$$

On the other hand, the goods produced domestically are consumed domestically or some exports to the rest of world. Individual industries engaged in production activities transform the produced industrial outputs into goods to be sold domestically, and to the rest of world. In this regard, in this model we introduce the Constant Elasticity of Transformation (CET) function as shown in Eq.(4.61). Accordingly, each industrial sector can determine the quantity of domestic and export goods based on Eq.(4.62).

$$Z_i = \vartheta \cdot (\theta \cdot E_i^{\beth} + (1 - \theta) \cdot D_i^{\beth})^{1/\beth} \qquad \text{... Eq. (4.61)}$$

$$E_i/\mathrm{D}_i = [\frac{PD_i}{PE_i} \cdot \frac{\theta}{(1 - \theta)}]^{\,1/(1-\beth)}$$

... Eq. (4.62)

$$PZ_i \cdot Z_i = \; PE_i \cdot E_i + \; PD_i \cdot D_i$$

4.9 Integrated structure of CGE model

The knowledge-based CGE model maintains the general equilibrium framework by imposing the market clearing conditions on the markets for commodities and production factors. The equation Eq.(4.63) below implies that the supply of the Armington composite is distributed across the economy to meet the demands for intermediate goods consumption,

consumption expenditures of households and government, physical capital investment, and knowledge capital investment. In addition, supply and demand also coincide in the production factor market, which includes low-skilled, skilled, high-skilled labor, physical capital, and knowledge capital, as expressed by Eq.(4.64), Eq.(4.65), and Eq.(4.66). In addition, the CGE model with these components finds the optimal equilibrium solution under the utility maximization condition for the households, and finds the equilibrium points for every periods in a dynamic process.

$$Q_i=\sum_j X_{i,j} + \sum_{hh} XP_{i,hh}+XG_i + Xv_i + \sum_{rdt} XVRD_{i,rdt} \qquad \text{... Eq. (4.63)}$$

$$L1 = \sum_i L1_i + \sum_{rdt} RLS1_{rdt}$$

$$L2 = \sum_i L2_i + \sum_{rdt} RLS2_{rdt} \qquad \text{... Eq. (4.64)}$$

$$L3 = \sum_i L3_i + \sum_{rdt} RLS3_{rdt}$$

$$K = \sum_i K_i + \sum_{rdt} RK_{rdt} \qquad \text{... Eq. (4.65)}$$

$$H_i = HS_i \qquad \text{... Eq. (4.66)}$$

In summary, the key features of the knowledge-based CGE model constructed for this study can be summarized as follows; 1) endogenizing the innovation-related elements considering the characteristics of innovation and knowledge (including, consideration of knowledge as a factor of production, endogenization of knowledge capital investments, and consideration of spillover effects coming from the knowledge accumulation via productivity improvements), 2) endogenizing the decision making process of labor on the human capital accumulation (i.e., up-skilling and re-training) affected by the relative wages of workers and educational investments within the economy, 3) designing the endogenous interaction between the knowledge capital accumulation (i.e., innovation) and human capital accumulation within the production function, 4) describing the intrinsic attributes of technological progress within the production structures, and 5) establishing the macroeconomic model to simultaneously estimate the growth and distribution effects with considerations of heterogeneous labor and households within the equational systems and datasets (i.e., SAM). It is expected that this study consisting of the development of the CGE model and quantitative analyses based on the constructed model can provide a theoretical and methodological basis for analyzing the effects of various policy options and alternatives in terms of growth and distribution within the knowledge-based economy. The overall structure of the proposed CGE model can be described as shown in Figure 30, which contains the information on the key equations related to each components and interactions among those components.

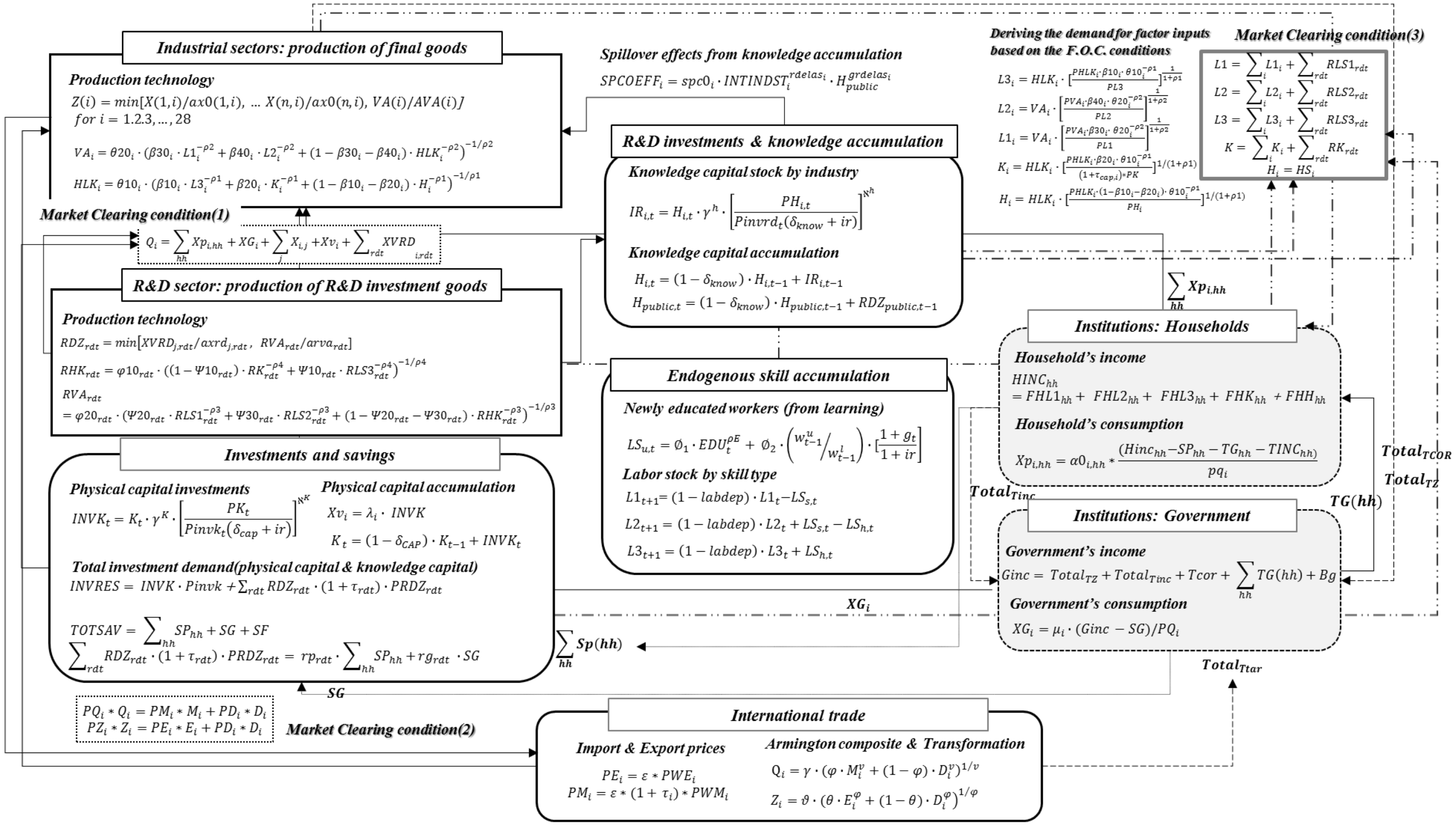


Figure 30. Overall structure of the knowledge-based CGE model and the relationships among components

Chapter 5. Quantitative analysis on Interaction between Innovation and Human Capital and its effects on Economic Growth

5.1 Research background and research objectives

In order to improve the productivity and expand its growth potential of Korea's economic system, investments in human capital and innovation activities is highly emphasized. In addition, in regard of human capital investment, there is a need to explore ways to increase productivity growth through qualitative improvements rather than quantitative expansion in human capital and efficient combination with investment in innovation activities. Therefore, it is required to elaborate policy implications on how to foster human capital in the Korean innovation system and to strengthen complementary relations with technological innovation investment in order to expand its future growth potential. In the knowledge-based economy, in which technological advances based on technological innovation serve as a major driver of long-term economic growth rather than accumulation of physical capital (Grossman & Helpman, 1991; Grossman & Helpman, 1994; Romer, 1986, 1990, 1994), it is important to accumulate and improve the quality of human capital that is practically applied to technology innovation activities. In particular, for long-term economic growth, several studies highlight that if there is no mismatch between ‘skill distribution’ due to human capital accumulation and ‘technology distribution’ due to investment in technological innovation, the economic growth effects may be greater

(Acemoglu & Zilibotti, 2001; Goldin & amp; Katz, 2008).

On the other hand, productivity improvement effects through technological innovation without appropriate human capital development can be limited. In addition, if demand for skilled labor is insufficient, the endogenous process of technology adoption and technological development through R&D investments may not be accelerated, which again hinders the promotion of skilled labor supply. Therefore, in order to promote economic growth based on technological innovation and human capital accumulation, it is necessary to secure and enhance interaction effects between sufficient human capital demand through technological innovation, and supply expansion through human capital accumulation. In this context, in order to increase the productivity of investment in the R&D sector for technological innovation, it is necessary to investigate in which policy directions to nurture human capital and how to strengthen complementarities between human capital investment and innovation activities investment for the innovation system.

Nowadays, Korea is facing challenges to expand its growth potential as the potential economic growth rate has been declining for a long time. Korea has achieved a remarkable achievement in technology level through quantitative expansion in R&D investment. In fact, the size of R&D investment in Korea has been steadily expanding, reaching the highest level of quantitative investment in the world. Korea's national R&D investment intensity (R&D investment-to-GDP ratio) in 2016 ranks the second (4.23%) in the world (OECD, 2018b). Expansion of innovation activities has been achieved by the expansion of the R&D investments, quantitative performance-oriented R&D systems and associated innovation policies. However, there has been limits to improve productivity growth with R&D investment, and secure long-term economic growth.

Furthermore, Korea’s enrollment rate for the tertiary education in 2016 is shown to be about 69.85%, ranking the top rank in the world (OECD, 2017b). Although the expansion of university education is a global trend, the rate or growth rate of enrollment in tertiary education in Korea is considered to be exceptional, considering the level of economic growth and income. However, quantitative expansion of the tertiary education, which is not accompanied by the quality management, can cause inefficient allocation of human capital such as increasing trends of youth unemployment and unemployment of highly educated people. On the other hand, educational investment level for the human capital accumulation of workers after entering the labor market is shown to be low compared to other developed countries. The participation rate of formal and informal lifelong learning in Korea is about 35.8% in 2016 (OECD, 2017b), which is very low compared to developed countries. Particularly, participation rate of vocational training (of 25-64 year old adult workers) directly related to the development and advancement of skills and knowledge of workers is found to be only 17.3%, which is less than half of OECD average and is the lowest among the major countries.

Thus, it is not an exaggeration to say that the educational investment for human capital accumulation in Korea is only limited to the education of adolescents (i.e., prior to engage in economic activities), and the human capital accumulation after the entry into labor market is stagnated. Low level of the educational investment for the human capital accumulation within the labor market makes workers have the difficulties in actively responding to the technological uncertainty and changes in external conditions during their life-cycles of working. Also, it can be deduced that stagnation of human capital accumulation after labor market entry leads to the acceleration of the human capital obsolescence and depreciation. Subsequently, it implies the possibility of the existence of the discrepancy between shifts in labor demand due to technological innovation and shifts of labor and skills supply within the Korean economy.

As such, even though Korea economy has achieved the quantitative expansions in R&D investments of technological innovation and educational investments for the human capital accumulation, their growth effects are shown to be limited. Accordingly, instead of simply focusing on the economic growth effects by simply increasing the investment levels for R&D and human capital accumulation, it is necessary to examine how to achieve the qualitative changes in R&D investment and educational investments, as well as how to enhance the complementary relationship between innovation and human capital accumulation to spur long-run economic growth and increase growth potentials through productivity improvement in the innovation system.

Therefore, this chapter applies the constructed knowledge-based CGE model to conduct policy experiments in order to draw policy implications to reinforce the complementarity of technological innovation and human capital, and to suggest an empirical evidence for the policy formulation and implementation in future. To be specific, through the quantitative analysis based on the CGE model, this study aims to investigate how the long-run economic growth can be achieved through the endogenous interaction between innovation and human capital accumulation via R&D investments and educational investments within the economy. Furthermore, this study aims to investigate and understand the direct and indirect paths within the national economy driven by the endogenous complementarity between the innovation (i.e., R&D investments) and human capital accumulation (i.e., educational investments) which shape the growth patterns of the economy. Based on the findings drawn from the analysis, this study expects to provide a new perspective on the role and scope of innovation policy for enhancing the mid- to long-term growth potential in the Korean innovation system.

5.2 Policy scenario settings

5.2.1 Business As Usual (BAU) scenario settings

The CGE model with the methodological features mentioned in the previous chapter, will describe Korea's economic situation by 2030, which is the target year for the analysis, based on external forecasts of Korea's economic situation. The scenario assuming that there is no exogenous policy shocks from the base year 2010 to 2030 is called as the Business As Usual (BAU) scenario. In the CGE model, the BAU scenario implies that the policy shock is not introduced into the model, that is, the economic situation of the base year is maintained constantly. This makes it possible to determine the policy impacts by comparing the changes in macroeconomic variables in the CGE model driven by the constructed policy scenarios with those values in the BAU scenario. We have used the projection data for the working age population from Statistics Korea to describe the change of the aggregate labor stocks, and reflected values for the economic growth rates from Bank of Korea's economic growth estimates in constructing the BAU scenario. In addition, for the BAU scenario, it is assumed that 4% of Korea's R&D investment intensity (measured as the ratio of knowledge capital investment to GDP level) in the base year 2010 will be maintained continuously until 2030, while it is assumed that investment expenditure on education relative to GDP also maintains as 8.6%, as of 2010, by 2030.

5.2.2 Policy scenario settings for analysis

The main purpose of this study is to analyze and investigate the interaction channels between innovation due to R&D investment, and human capital accumulation driven by the educational investment. More specifically, in order to draw some implications on how human capital investment and knowledge capital investment interact, and thereby affect long-term economic growth, the CGE model has been constructed to describe Korean economy (see Chapter 4) and has been utilized to analyze the economy-wide impacts of policy scenarios. For the analysis, three policy scenarios are constructed to understand macroeconomic effects of individual scenarios by imposing variants in the R&D intensity and the educational investment intensity. The constructed policy scenarios for the analysis can be described as follows.

The first scenario (SCN1) assumes that R&D intensity is set to be 1%p higher than that of BAU and education investment intensity remains same with BAU. Construction of this policy scenario is aimed at identifying the individual role of R&D investment, and its indirect impacts on the human capital accumulation. The second policy scenario SCN2 is assumed that education investment intensity is set be 1%p higher than that of BAU, and R&D intensity is set to be same with the level of BAU scenario. This SCN2 scenario is constructed to investigate the independent role of the human capital investments, and its indirect impacts on the R&D investments. The last scenario (SCN3) is assumed that R&D intensity is 0.5%p higher than that of the BAU scenario, and educational investment intensity is also 0.5%p higher than that of BAU. The construction of the SCN3 scenario enables us to analyze the complementarity between R&D and educational investments, and their interaction effects in the economy. The gross changes in exogenous R&D and educational investment intensities in SCN1, SCN2, and SCN3 are all same as 1%p increase relative to the BAU scenario. The absolute levels of changes in R&D and educational investment levels considered in constructed policy scenarios are all same, which can be understood in Figure 31 below.

With these constructed policy scenarios, this study aims to investigate and understand the direct and indirect paths within the national economy driven by the endogenous complementarity between the innovation (i.e., R&D investments) and human capital accumulation (i.e., educational investments) which shape the growth patterns of the economy. In addition, this study aims to draw policy implications in designing and formulating the innovation policy by identifying key paths and channels in which endogenous interactions of human capital and technological innovation affect economic growth within the economic system. For SCN1, SCN2, and SCN3, the total intensity of R&D and education investment is set be at 13.6%, which is 1%p higher than the level of BAU with 12.6%. Figure 31 and Table 17 provide brief descriptions and explanations on the constructed policy scenarios.

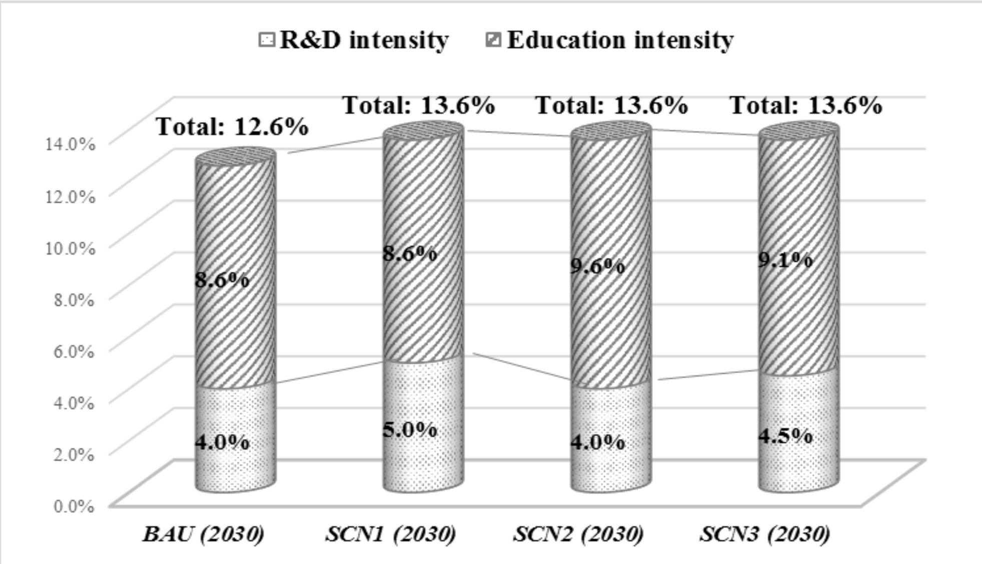


Figure 31. Constructed policy scenarios (BAU, SCN1, SCN2, SCN3)

Table 17. Descriptions on the constructed policy scenarios (BAU, SCN1, SCN2, SCN3)

Scenario	R&D intensity (2010-2030)	Educational investment intensity (2010-2030)
BAU	4.0%	8.6%
SCN1	5.0%	8.6%
SCN2	4.0%	9.6%
SCN3	4.5%	9.1%

5.3 Results analysis

5.3.1 Effects on economic growth

In this subsection, we present the main results generated by the constructed policy scenarios by comparing the changes in variables associated with the economic growth. It is shown that as represented by Table 18, the highest economic growth is found to be achieved under the SCN3 scenario where the R&D investment and education investment intensities are simultaneously increased by 0.5%p relative to the BAU level (% growth rate of GDP: 78.92%; annual average GDP growth rate: 2.95% from 2010 to 2030), followed by the SCN1 (% growth rate of GDP: 73.87%; annual average GDP growth rate: 2.80% from 2010 to 2030), and SCN2 (% growth rate of GDP: 60.76%; annual average GDP growth rate: 2.40% from 2010 to 2030) scenarios. It is found that the SCN2 scenario where the only the educational investment intensity is increased by 1%p compared to that of the BAU scenario has shown the lowest GDP growth rate.

Table 18. GDP growth rates from 2010 to 2030 under different scenarios (Unit: %)

Scenario	GDP growth rate	Average annual GDP growth rate
BAU	49.93%	2.05%
SCN1	73.87%	2.80%
SCN2	60.76%	2.40%
SCN3	78.92%	2.95%

As shown in Figure 32 which depicts the changes in GDP levels for constructed policy scenarios (i.e., SCN1, SCN2, and SCN3 scenarios) compared to the BAU level (focusing on the target year of 2030), same results can be found. Figure 32 reveals that the SCN3 scenario shows the highest GDP increase in 2030 with 19.33% higher than that of the BAU level, followed by the SCN1 (15.96% higher compared to the BAU level), and SCN2 (7.22% higher relative to the BAU level).

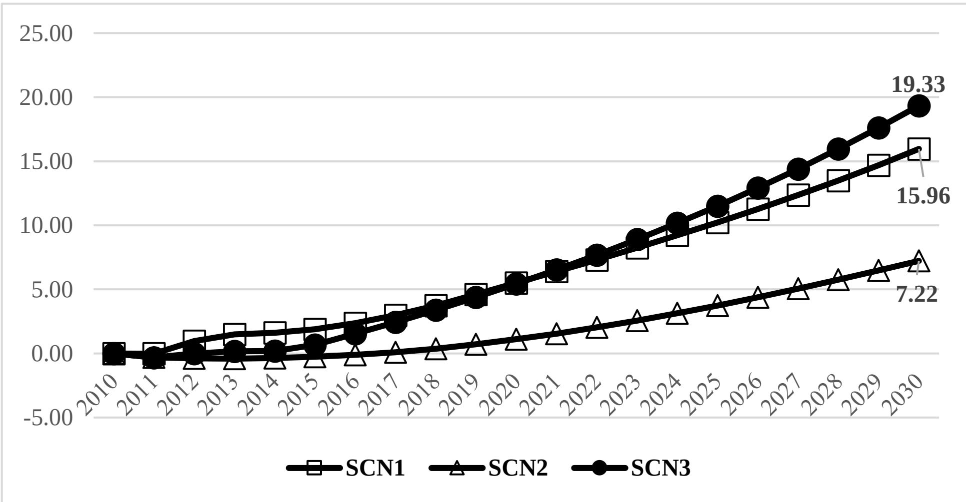


Figure 32. Changes of GDP level (Unit: % change relative to the BAU scenario in 2030)

Accordingly, it is noted that the GDP levels of all designed policy scenario show the higher GDP levels compared to the BAU scenario. Again, it implies that both R&D investment and human capital investment are important factors in the national economic growth. More specifically, we will examine the relevant channels which affect the different patterns of the economic growth generated by those policy scenarios. Firstly, the SCN1 scenario can be understood as the policy scenario with the exogenous shock on the R&D intensity solely applied, while the SCN2 scenario assumes the direct exogenous shock on the education investment applied within the CGE model. As in the case of SCN1, when the exogenous shock is applied to the R&D investment level (i.e., knowledge capital formation), as direct effects of the introduced policy shock the accumulation level of knowledge capital in the economic system increases, and positive external effects of knowledge capital accumulation are enhanced within the economic system. The increase in knowledge capital accumulation leads to additional demand for the production factors, based on the complementarity between knowledge, physical capital, and high skilled labor within the production technology, thereby promoting the scale effects within the economy via indirect impact channels.

On the other hand, as in the case of SCN2, when the policy shock is introduced only for the education investment intensity, the skill accumulation of the workers can be expanded with the increase of educational investment as direct effects of the policy shock. With the expansion of the newly educated workers, the proportions of high-skilled and skilled workers increases within the human capital composition, which indirectly leads to the expansion of innovation activities in the industrial sectors based on complementary relations between knowledge and high-skilled labor within the production structures. Accordingly, it can induce scale effects to drive economic growth. Thus, it is noted that the R&D and educational investments, respectively create different direct and indirect impact channels driving the different patterns of the economic system. In this context, the differences in the economic growth effects in SCN1 and SCN2 scenarios implies that the economic growth effect of technological progress led by exogenous shocks on R&D is relatively higher than that of human capital accumulation driven by exogenous shocks on educational investment.

Moreover, when the R&D and education investment intensities are increased together (SCN3), compared to SCN1 and SCN2 scenarios where the investment intensity increases individually for each R&D investment and education investment, it is found that SCN3 scenario achieves a higher level of economic growth than the SCN1 and SCN2 scenarios. Even though SCN3 scenario assumes that the investment levels of R&D and education investment are relatively low (i.e., R&D intensity: 0.5%p, and education investment intensity: 0.5%p higher than BAU) relative to SCN1 (i.e., R&D intensity: 1.0%p higher than BAU) and SCN2 scenarios (i.e., education investment intensity: 1.0%p higher than BAU), the highest economic growth effects generated by the SCN3 scenario suggest the strong complementary relationships between technological innovation and human capital accumulation, thereby promoting the productivity growth and scale effects within the economy. In addition, it suggests the importance of the contribution of efficient combination of the innovation and human capital to spur long-run economic growth, rather than stressing out the quantitative expansion of the factor accumulation for a single factor input.

Adopting the supply-demand framework, it can be also understood that in the case of the policy scenario SCN3, technological innovation triggered by additional R&D investments drive a higher demand for high-skilled labor, which increases the skill premium (i.e., wage rate) or profitability for the high-skilled labor. In addition, the improvement and advancement of workers' skills and knowledge through the expansion of education investment, and associated changes in labor supply through the human capital accumulation can facilitate the endogenous technological innovation as it enhances the complementarity between knowledge and high-skilled labor. Therefore, it can be understood that in the SCN3 scenario, the disparity between the demand of skills induced by the knowledge accumulation, and the supply of skills driven by the human capital accumulation is somewhat eased, thereby accelerating the endogenous interaction between innovation and human capital. The results shown in Table 18 and Figure 32 suggest that the acceleration of the endogenous interaction between knowledge capital and human capital investment can drive a higher level of equilibrium state in terms of the growth.

In addition, Figure 33 shows the changes in the utility of households by income quintile compared to the BAU scenario focusing on the target year 2030. As can be seen from the Figure 33, it is found that the SCN3 scenario shows the highest utility increase in 2030 compared to the BAU level, followed by the SCN1 and SCN2 scenarios. SCN1 results suggest that the increase in R&D investment intensity may lead to increases in the incomes and utility of households based on the scale effects driven by technological innovation. However, it can be seen that the income and utility growth effects in the SCN1 scenario are increased as the income level is higher. On the other hand, it is shown that in the case of the SCN2 scenario where the education investment intensity is increased by 1% p compared to the BAU, the increase in the household utility is relatively low among the designed policy scenarios.

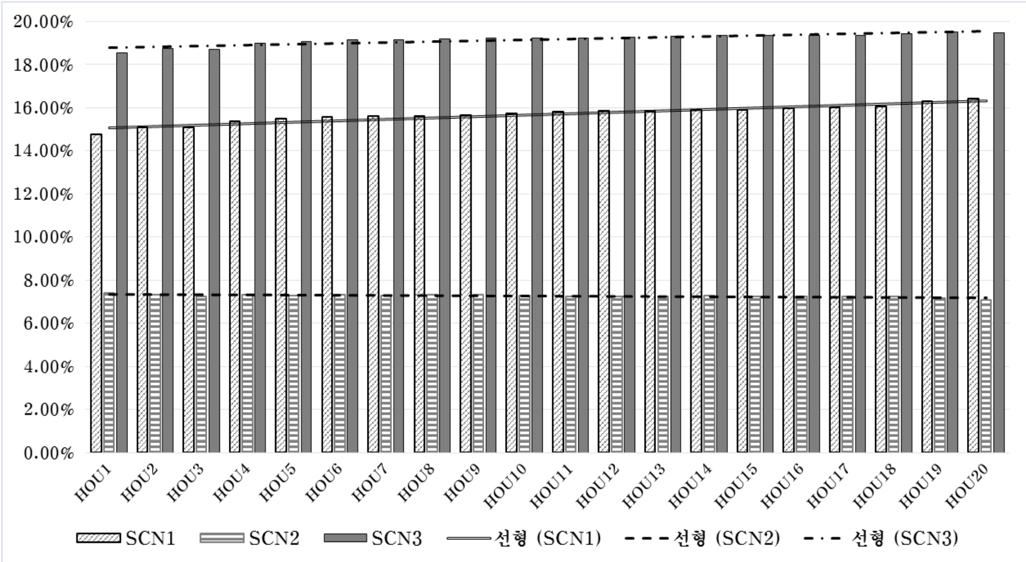


Figure 33. Changes in households' utility for scenarios relative to BAU (Unit: %)

5.3.2 Effects on employment and wage structure

This subsection provides key results on how changes in the employment and wage structures appear in in different scenarios, to understand key factors behind the economic growth. Table 19 below shows changes in employment levels by labor type, and by policy scenario (SCN1, SCN2, and SCN3 scenarios) versus BAU scenario. Table 19 illustrates the changes of aggregate employment levels by labor type in 2030 relative to the BAU scenario (for SCN1, SCN2 and SCN3 scenarios). As can be seen in Table 19, it is found that the aggregate employment grows the most (19.98% higher than the BAU level in 2030) under the SCN3 scenario, where additional investments in R&D and education are made simultaneously, followed by SCN1, and SCN2 scenarios (SCN1: 16.54% higher than the BAU level in 2030; SCN2: 7.63% higher than the BAU level in 2030). As can be seen in

Table 19, it is understood that all constructed policy scenarios from SCN1 to SCN3 show higher levels of total employment compared to the BAU level. However, direct and indirect paths (channels) affecting the expansions in the total employment levels for policy scenarios are found to be different.

Table 19. Changes of employment level by skill type relative to the BAU (Unit: %)

		2015	2020	2025	2030
Total employment	SCN1	1.80	5.37	10.41	16.54
	SCN2	0.24	1.52	4.14	7.63
	SCN3	0.61	5.47	11.77	19.98
Low-skilled labor	SCN1	1.16	3.75	8.32	13.82
	SCN2	0.44	1.96	4.73	8.29
	SCN3	0.12	4.99	11.14	19.01
Skilled labor	SCN1	1.59	4.84	9.58	15.28
	SCN2	0.40	1.92	4.71	8.30
	SCN3	0.59	5.55	11.83	19.87
High-skilled labor	SCN1	4.43	11.61	18.63	27.58
	SCN2	-0.94	-1.10	0.70	3.77
	SCN3	2.13	6.47	13.23	22.83

To be specific, when examining the changes of employment by skill type for policy scenarios compared to the BAU scenario, it is found that under the SCN1 scenario where the additional R&D investments are made, the highest level of employment growth in high-skilled labor is shown (27.58% higher than the BAU level in 2030) among three policy scenarios. From this result, it can be noticed that demand for high-skilled labor is more sensitive to changes in R&D intensity than for other types of labor. Higher sensitivity of high-skilled labor to variations in R&D intensity implies a strong linkage between the R&D investment level and the degree of skill-bias in technological progress, implying the presence of the SBTC. In Addition, it can be understood that a higher level of technological innovation has a tendency to favor high-skilled labor much more, and stimulates a greater 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. This argument can be confirmed from Figure 34 which illustrates the changes in labor demand and labor supply (i.e., low-skilled, skilled, and high-skilled labor) generated by policy scenarios relative to the BAU scenario in 2030.

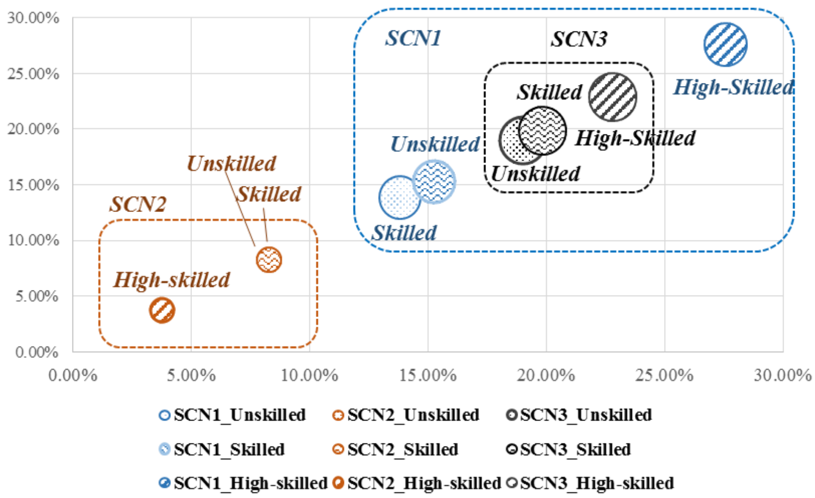


Figure 34. Comparison of labor demand and supply level by policy scenario compared to the BAU scenario in 2030 (Unit: %)

In addition, Figure 35 shows the changes of employment levels by industry. As shown in Figure 35 below, it is found that the higher employment inducement effect under the SCN1 scenario is mainly led by knowledge-intensive industries including R&D sector (52.31% higher than the BAU level in 2030), and high-tech manufacturing sector (28.12% higher than the BAU level in 2030). It suggests that industrial sectors with higher intensities of knowledge and innovation are sensitive to the changes in R&D intensity, having significant potentials for expanding employment levels with higher demands for labor than other industrial sectors. In addition, it implies that the knowledge and innovation-intensive industrial sectors' growth effects have the potentials to accelerate the degree of skill-bias of the technological progress in the economic system.

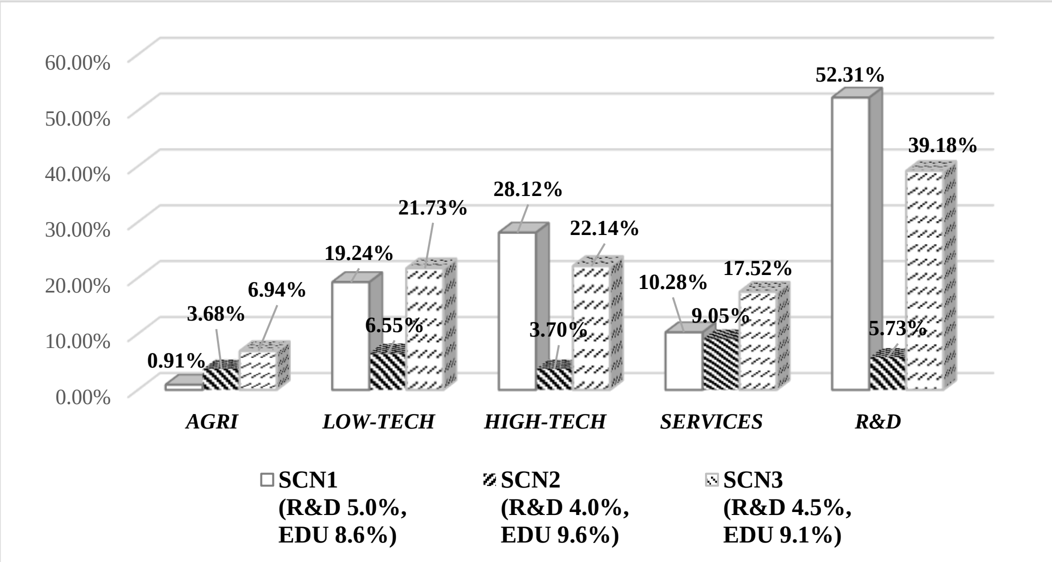


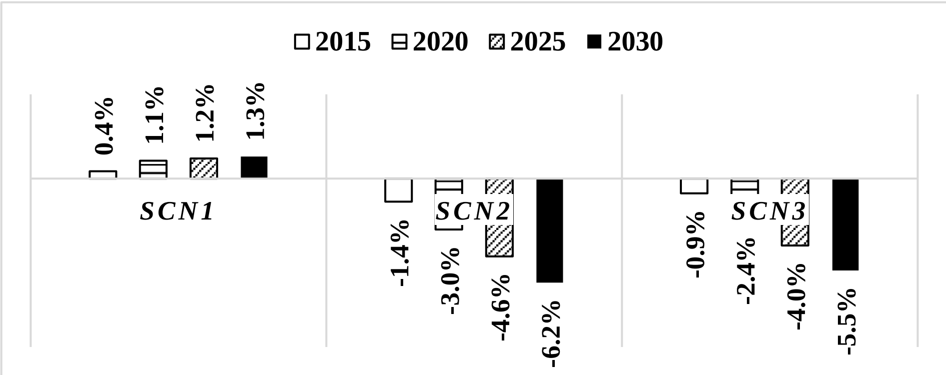
Figure 35. Comparison of employment level by industry type among policy scenarios compared to the BAU level in 2030 (Unit: %)

On the other hand, the SCN2 scenario shows the lowest level of employment growth (high-skilled labor: 3.77%, skilled labor: 8.30%, low-skilled labor: 8.29% higher than the BAU levels in 2030) among the constructed policy scenarios, among which the employment growth level of the high-skilled labor is shown to be the lowest. This suggests that there is a limitation to increase the profitability of the high-skilled labor in the form of the increase of wages when the human capital accumulation of workers through the increase of the educational investment is not accompanied with the R&D investment. Reduced profitability for the high-skilled labor is likely to constrain and limit the learning process of low-skilled and skilled labor. This limits the expansion of the labor supply of high-skilled labor through the endogenous human capital accumulation. Also, as shown in Figure 35, it can be seen that under SCN2, the growth of total employment level is found to be lower than other policy scenarios across industrial sectors. In particular, under the SCN2 scenario it is shown that the increases in labor demands (i.e., employment levels) from the high-tech manufacturing and R&D sectors are remarkably lower than other industries (high-tech manufacturing sector: 3.70%, R&D sector: 5.73% higher than the BAU levels in 2030).

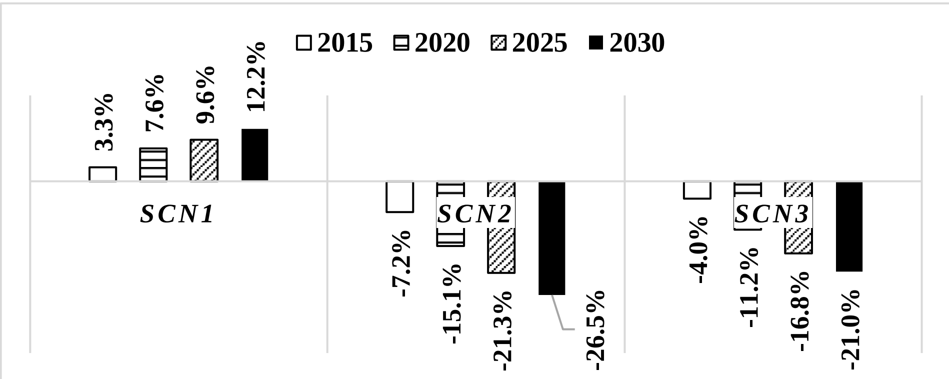
On the other hand, the SCN3 scenario shows a significant rise in demand for all kinds of labor, with the highest level of total employment growth. To be specific, it is also found that the SCN3 scenario induces greater increases in the employment of the high-skilled labor, followed by skilled, and low-skilled labor (high-skilled labor: 22.83%, skilled labor: 19.87%, low-skilled labor: 19.01% higher than the BAU levels in 2030). Even though the employment level for the high-skilled labor is relatively low compared to SCN1 scenario, the SCN3 shows that the employment growth is experienced over all types of labor as a whole, including high-skilled, skilled, and low-skilled labor compared to other scenarios, as shown in Figure 34. In addition, as represented by Figure 35, it shows that under the SCN3 scenario, there is significant increases in employment across industries, including low-tech manufacturing, and low-tech service sectors, as well as the R&D and high-tech manufacturing sectors. It is comparable to the results for the SCN1 scenario where the employment expansion is highly experienced by knowledge-intensive industries including R&D sector, and high-tech manufacturing sector due to the nature of skill-biased technological progress. This suggests the possibility of accelerating the polarization in the labor market in terms of employment (i.e., labor demand) driven by the increase of technological innovation. However, when additional investments for R&D and human capital accumulation are made together (SCN3 scenario), it is found that demand for skilled and low-skilled labor, as well as high-skilled labor has increased as a whole, implying that the polarization in the labor market across the economic system (as shown in the SCN1 scenario) can be mitigated.

The results of the SCN3 scenario address the importance of matching between the supply of skilled labor (through education), and the demand for skilled labor driven by the skill-biased technological progress. Increasing R&D investments and thus expanding innovation activities increasingly need for high-skilled labor, while advancing skills through the learning and human capital accumulation of workers with the increases of educational investments increases the supply of high-skilled labor. In this regard, it is noted that when additional investments for R&D and human capital accumulation are made together, the economic system can experience the advancement of skills across the economy, and achieve a higher level of economic growth, as shown by Figure 32 and Figure 34. As such, establishing the learning environments to support the skill accumulation process of workers through the educational investment can serve as an important policy instrument for expanding the growth potential in the knowledge-based economy. However, unless technological innovation which triggers the demand for high-skilled workers is accompanied, the growth effects of the human capital accumulation may be low as shown in the results of the SCN2 scenario (if this phenomenon continues, it may lead to oversupply of high-skilled workforce, leading to the skill mismatch in the economy). In addition, when the emphasis is only on technological innovation through the quantitative expansion in R&D investment to spur long-run economic growth, it has the possibility to facilitate the polarization of the labor market by disproportionately increasing the demand for high-skilled labor over skilled and unskilled labor, which can undermine the growth potential of the economy.

This can be understood from the change in the relative wages of workers by policy scenario compared to the BAU scenario as shown in Figure 36. The change in the relative wage of workers can be thought of as a result of the interaction between relative demand change and relative supply change. In other words, wage differentials among workers in the economic system change dynamically depending on changes in demand for workers their supply changes. In this regard, we will examine the changes of the relative wages among workers for constructed policy scenarios compared to the BAU scenario. Figure 36 illustrates changes of skill premium, which is calculated as the ratio of the wages of either skilled (PL2) to low-skilled labor (PL1) (Figure 36(a)), or high-skilled (PL3) to low-skilled labor (PL1) (Figure 36(b)), compared to those values in BAU scenario.



(a) Skill premium for skilled labor (ratio of the wages of skilled to low-skilled)



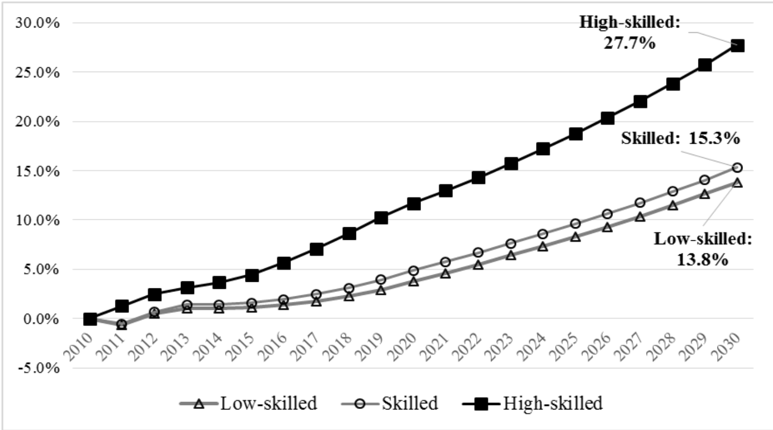
(b) Skill premium for high-skilled labor (ratio of the wages of high-skilled to low-skilled)

Figure 36. Changes of skill premium relative to the BAU scenario (Unit: %)

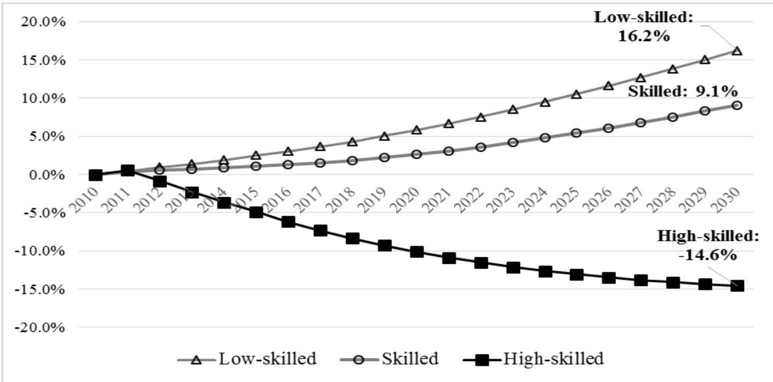
As can be seen in Figure 36, the SCN1 scenario where only the R&D intensity is increased by 1%p relative to the BAU level shows that the skill premiums for high-skilled and skilled labor increase over time with the highest levels among the policy scenarios (skill premium for skilled labor: 1.3% higher; skill premium for high-skilled labor: 12.2% higher than the BAU level in 2030). This is because, as described above, higher returns for workers with higher skills are formed due to the differential formation of labor demand induced by the skill-biased technical change. It can directly affect workers' endogenous decision-making process related to the skill accumulation. However, from the analysis results, it is found that the indirect effects of the quantitative expansions of R&D investments on the expansion of the labor supply of newly educated workers through the endogenous human capital accumulation are not significant in the SCN1 scenario.

On the other hand, under the scenario SCN2, in which only the education investment intensity is increased by 1%p compared to the BAU, it is found that the skill premiums for skilled and high-skilled labor decline with highest levels among policy scenarios (skill premium for skilled labor: -6.2% relative to the BAU level in 2030; skill premium for high-skilled labor: -26.5% relative to the BAU level in 2030). This can be interpreted that in the case of emphasizing only the quantitative expansion of the educational investments without accompanying the expansion of the R&D investments (SCN2 scenario), high premiums and returns for workers with higher skills are not formed with relatively lower levels of the demands for workers with higher skills and advanced knowledge to actually perform technological innovation. As the labor supply of newly educated workers increases with the quantitative expansion of the educational investments, the expected rate of returns on the R&D investments (for knowledge capital accumulation) can be increased indirectly. For the SCN2 scenario, however, it can be understood that the demand for skilled and high-skilled labor is relatively low than SCN1 scenario, as the R&D investment level induced by the human capital accumulation with quantitative expansion of the educational investment is relatively low than that of the SCN1 scenario.

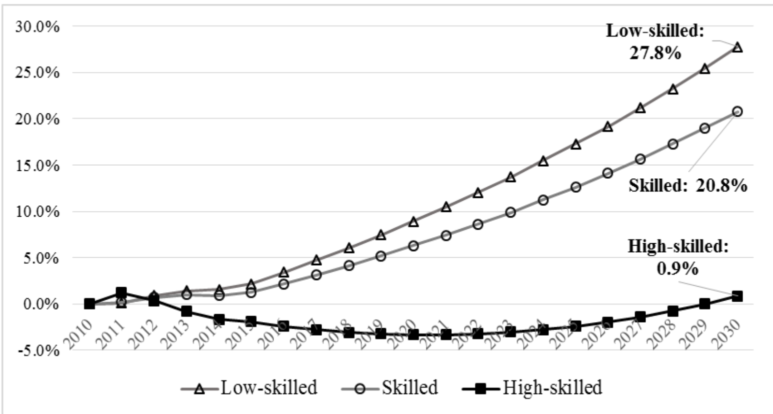
Moreover, in the case of SCN3 scenario where R&D intensity and education investment intensity are increased by 0.5%p compared to BAU, the relative wages of skilled and high-skilled workers are shown to be lower levels compared to the BAU scenario (skill premium for skilled labor: -5.5% relative to the BAU level in 2030; skill premium for high-skilled labor: -21.0% relative to the BAU level in 2030). However, it is found that the decreases in the skill premiums of skilled and high-skilled workers are relatively low, compared to the SCN2. It can be interpreted that there is a close relationship between the changes in labor demand due to technological progress driven by increased R&D investment, and the changes in labor supply induced by the human capital accumulation resulting from the quantitative expansion of educational investment. To be specific, higher demands for high-skilled and skilled workers triggered by skill-biased technological progress is linked with the increases of the skill premiums for them, while the higher levels of labor supply of high-skilled and skilled workers through the learning process is associated with the decreases of the relative wages of high-skilled and skilled workers. In this regard, we can understand the changes of skill premiums for high-skilled and skilled workers generated by the SCN3 scenario, in terms of the supply-demand framework.



(a) SCN1 scenario



(b) SCN2 scenario



(c) SCN3 scenario

Figure 37. Wage rates of different types of labor for scenarios relative to BAU (Unit: %)

The changes in the relative wages of workers by the policy scenario compared to the BAU scenario can also be understood from the results of changes in wage rates of different types of labor for policy scenarios relative to BAU as shown in Figure 37. Figure 37 depicts time series' trends in changes of wage by skill type for SCN1, SCN2, and SCN3 compared to the BAU scenario. As illustrated by Figure 37, it is shown that for the SCN1 scenario the growth rates of wages for high-skilled and skilled workers are relatively larger than that of low-skilled workers (high-skilled labor: 27.7% higher than the BAU level; skilled labor: 15.3% higher than the BAU level; low-skilled labor: 13.8% higher than the BAU level in 2030). It is strongly associated with the highest levels of skill premiums found in the SCN1 scenario (skill premium for skilled labor: 1.3% higher; skill premium for high-skilled labor: 12.2% higher than the BAU level in 2030). In SCN2 scenario, it is shown that the wages of high-skilled workers are about 14.6% lower than that of BAU in 2030, while the wages of low-skilled and skilled workers are about 16.2% and 9.1% higher than those of BAU. This explains the lowest decreases in the skill premiums for the high-skilled and skilled labor in the SCN2 scenario (skill premium for skilled labor: -6.2% relative to the BAU level in 2030; skill premium for high-skilled labor: -26.5% relative to the BAU level in 2030). In addition, under the SCN3 scenario, it is found that the wages of high-skilled workers are about 0.9% higher than that of BAU in 2030, while the wages of low-skilled and skilled workers are about 27.8% and 20.8% higher than those of BAU. This explains the decreases in the skill premiums for the high-skilled and skilled labor in the SCN3 scenario (skill premium for skilled labor: -5.5% relative to the BAU level in 2030; skill premium for high-skilled labor: -21.0% relative to the BAU level in 2030). The underlying reason for the result that wage increase of the high-skilled labor is lower than those of other labor types is strongly associated with the fact that the increase of the relative supply of high-skilled labor induced by indirect effects of R&D investments and direct effects of educational investments is higher than the increase of the relative demand for high-skilled labor induced by the skill-biased technological progress.

Based on the results of this analysis, it can be understood that the quantitative expansion of the R&D investments leads to the polarization of the labor market, thereby undermining the growth potentials of the economy. This is due to the mismatch between the changes in labor demand driven by technological progress and the changes in labor supply through the human capital accumulation. However, when the R&D investment and the education investment are combined with each other as in SCN3, we can understand that the discrepancy between the changes of labor and skill demand, and the changes of supply of labor and human capital can be alleviated. It also suggests the possibility of offsetting the increase of skill premiums of skilled and high-skilled labor, and solving the wage gaps between workers.

5.3.3 Effects on industrial outputs

In this section, we will investigate changes in industrial outputs for each scenario designed in this study. Table 20 and Figure 38 presented below depict time series' trends in changes of industrial outputs for SCN1, SCN2, and SCN3, compared to the BAU scenario.

For the analysis, we reclassify 28 industries into four types of industries; 1) primary industries, which contain agriculture, forestry, and fisheries; 2) low-tech manufacturing industries; 3) high-tech manufacturing industries; and 4) service industries. As shown in Table 20 which represents the changes in industrial outputs by policy scenario compared to BAU, it is found that the SCN3 scenario reveals the highest level of industrial outputs (total industrial outputs: 18.51% higher relative to the BAU level in 2030), followed by the SCN1 and SCN2 scenarios (SCN1: 16.79% higher relative to the BAU level in 2030; SCN2: 5.84% higher relative to the BAU level in 2030).

Table 20. Changes of industrial outputs in policy scenarios relative to BAU (Unit: %)

		2015	2020	2025	2030
Total industry	SCN1	2.69	7.10	11.48	16.79
	SCN2	-0.99	0.23	2.63	5.84
	SCN3	1.35	5.71	11.31	18.51
Primary industry	SCN1	-1.75	-4.53	-2.66	-1.03
	SCN2	-0.78	0.09	1.79	3.90
	SCN3	-4.01	-0.94	2.34	5.86
Low-tech manufact.	SCN1	3.69	8.44	10.79	12.83
	SCN2	-1.69	-0.68	1.11	3.24
	SCN3	2.08	5.70	9.45	13.44
High-tech manufact.	SCN1	6.93	18.66	27.28	39.82
	SCN2	-1.90	-0.44	2.95	8.23
	SCN3	6.27	12.07	21.21	35.00
Service	SCN1	-0.62	-0.91	2.52	6.38

	SCN2	0.16	1.41	3.70	6.55
	SCN3	-2.11	1.93	6.87	12.89

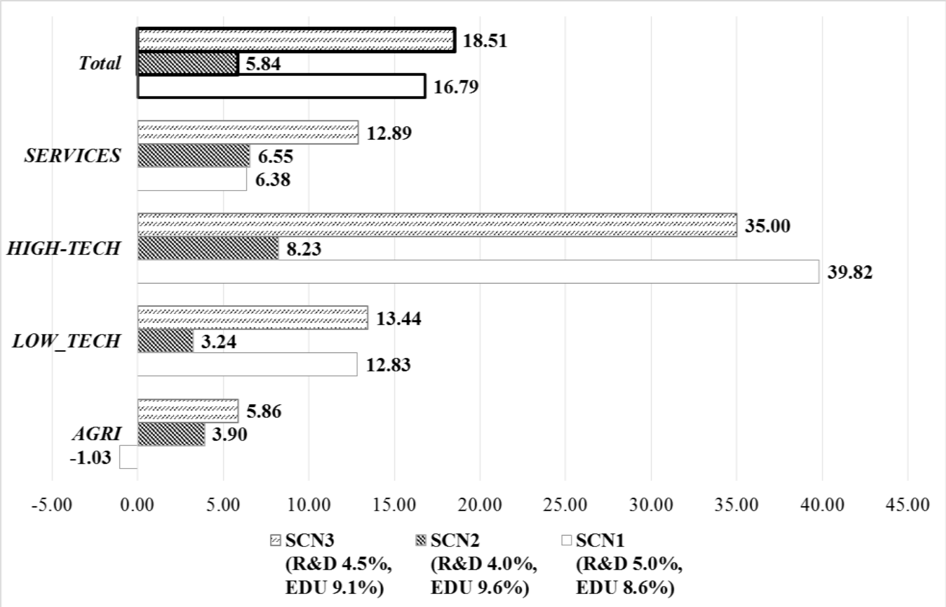


Figure 38. Changes of industrial outputs in policy scenarios relative to BAU (target year 2030) (Unit: %)

As shown in Table 20 and Figure 38, it can be seen that under SCN1, the growth effect of industrial outputs in the high-tech manufacturing sector is the highest level compared to other scenarios (39.82% higher relative to BAU in 2030), followed by low-tech manufacturing (12.83% higher relative to BAU in 2030), and service sectors (6.38% higher relative to BAU in 2030). Accordingly, we can understand that in the SCN1 scenario where the R&D intensity is increased as the policy shock, the growth of the manufacturing sectors including high-tech manufacturing and low-tech manufacturing sectors is most prominent. In other words, it suggest that policy intervention through the increase of R&D investment can drive long-run economic growth through facilitating a transition of the economy toward knowledge- and innovation-intensive industries. On the other hand, it is found that under SCN2, the growth effects of industrial outputs are relatively low compared to other scenarios (high-tech manufacturing sector: 8.23% higher relative to the BAU; service sector: 6.55% higher relative to the BAU; primary sector: 3.90% higher relative to the BAU; low-tech manufacturing sector: 3.24% higher relative to the BAU in 2030).

On the other hand, the SCN3 scenario where the R&D intensity and educational investment intensity are increased by 0.5%p, respectively compared to the BAU level shows relatively higher industrial output growth effects across the industrial sectors, including the primary sectors (i.e., agriculture, forestry, and fisheries sectors), low-tech manufacturing sectors, service sectors, as well as the high-tech manufacturing sectors (high-tech manufacturing sector: 35.00% higher relative to the BAU; low-tech manufacturing sector: 13.44% higher relative to the BAU; service sector: 12.89% higher relative to the BAU; primary sector: 5.86% higher relative to the BAU in 2030). In the case of the high-tech manufacturing sector, the increase in the industrial outputs is found to be 35.00% higher than the BAU level, however it can be seen that this is relatively low compared to the SCN1 scenario (4.82%p lower relative to the SCN1 scenario). It can be interpreted that the highest level of economic growth effect in the SCN3 scenario among the designed scenarios is driven by the industrial outputs growth across industrial sectors. On the other hand, the economic growth effect in the SCN1 scenario can be interpreted as the expansion of the industrial outputs in manufacturing sectors including the knowledge-and innovation-intensive high-tech manufacturing sectors.

To support this argument, this study has calculated the values of 'National Average Index (NAI)' for SCN1, SCN2, and SCN3 scenarios to measure the distribution of the industrial outputs. The NAI is an index used to measure the diversity and concentration of industries in the local economy, which summarizes the distribution of production activities across the industries (Oh et al., 2015; Wagner, 2000; Wagner & Deller, 1993). Based on this concept, the relative share of each industry within the total industrial outputs (P_i) in the target year of 2030 for each scenario has been calculated to derive the value for the NAI index. When the relative share of each industry within the total industrial outputs is found to be M_i in the target year of 2030 for the BAU scenario, the NAI index for each scenario can be calculated as $NAI = \sum_i [\frac{(P_i - M_i)^2}{M_i}]$. The closer the NAI index is to zero, the less industrial concentration and imbalance are (Oh et al., 2015).

In addition, in this study, we have tried to compare the industrial concentration by policy scenario using the entropy index. This concept is also used to measure the concentration of the industrial structure within the economic system, based on the information on the number of industries and their market shares in the economic system, which can be calculated as $E = \sum_{i=1}^{N} S_i \cdot log\, S_i$. In this equation, S_i indicates the relative share of each industry within the total industrial outputs in the target year of 2030 for each scenario. Based on this concept, the entropy index for each scenario has been calculated. The smaller the entropy index, the higher the degree of monopoly and concentration. In the case of pure monopoly, the entropy index has a value of zero.

Accordingly, the values for the NAI index and the entropy index for the SCN1, SCN2, and SCN3 scenarios are shown in Table 21 and Table 22 below. As shown in these tables, the SCN1 scenario shows the highest industrial concentration (NAI index: 0.03896; entropy index: 2.97246), while the SCN3 shows the lowest industrial concentration (NAI index: 0.02749; entropy index: 2.99676). Through these results, it can be understood that the policy intervention limited to the quantitative expansion of the R&D investment (as SCN1 scenario) spurs the economic growth by increasing the concentration of the industrial structures with greater expansions of high-tech manufacturing sectors. On the other hand, it can be seen that policy intervention, such as SCN3, which combines R&D investment and education investment, achieves the highest level of economic growth based on the diversified industrial structure with growth effects being spread evenly across industries.

This study suggests that the policy intervention in the form of the SCN1 scenario can lead to unbalanced growth of the economic system, by enhancing the growth effects of the knowledge-intensive industries. In addition, it is possible to deduce that the economic growth driven by the expansions of the knowledge-intensive industries has a potential for weakening the foundations of the economic system by further accelerating the polarization of the labor market (i.e., disproportionately increasing demand for high-skilled labor over skilled and low-skilled labor, and providing higher skill premiums for them). On the other hand, it can be understood that the policy intervention, such as SCN3, which combines R&D investment and education investment, achieves the highest level of economic growth based on the diversified industrial structure with growth effects being spread evenly across industries, having the potential to solve the polarization of the labor market.

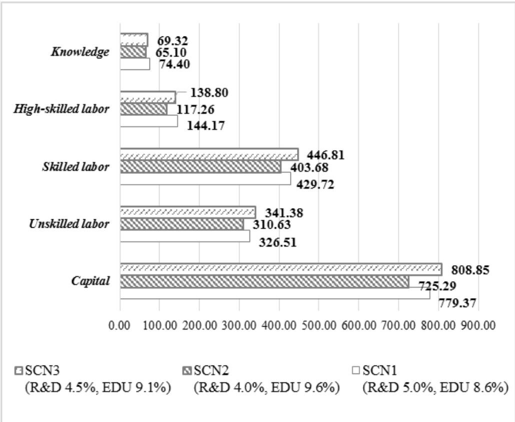
Table 21. Comparison of values for NAI index among policy scenarios in 2030

NAI	SCN1	SCN2	SCN3
(National Average Index)	0.03896	0.00369	0.02749

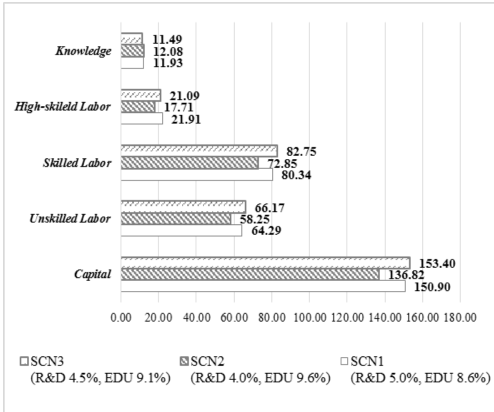
Table 22. Comparison of values for entropy index among policy scenarios in 2030

Entropy Index	SCN1	SCN2	SCN3
	2.97246	3.04789	2.99676

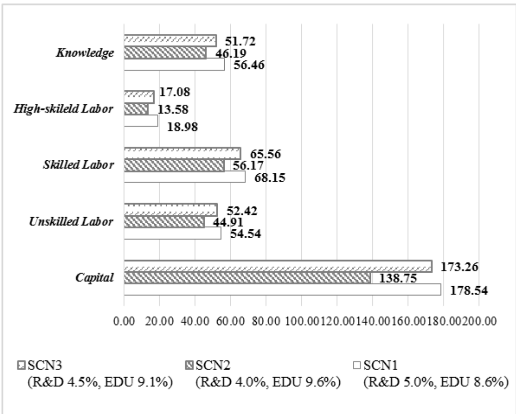
Figure 39 illustrates the comparison of the value-added compositions in industrial sectors for each scenario (SCN1, SCN2, and SCN3) in the target year 2030. As can be seen from the Figure 39, the SCN1 scenario shows the highest values for the value-added sourced from high-skilled labor and knowledge capital among policy scenarios (physical capital: 779.37 trillion KRW; low-skilled labor: 326.51 trillion KRW; skilled labor: 429.72 trillion KRW; high-skilled labor: 114.17 trillion KRW; knowledge capital: 74.40 trillion KRW in 2030 for the SCN1 scenario). In particular, under the SCN1 scenario, it is shown that the values of the gross value-added of high-skilled labor and knowledge capital are relatively high in the high-tech manufacturing and low-tech manufacturing sectors, compared to other scenarios. Accordingly, it can be understood that in the SCN1 scenario which assumes policy intervention through quantitative expansion of R&D investment, higher levels of demands for high-skilled labor and knowledge are largely led by the outputs growth of those industries, which can accelerate the degree of the skill biased of the technological progress.



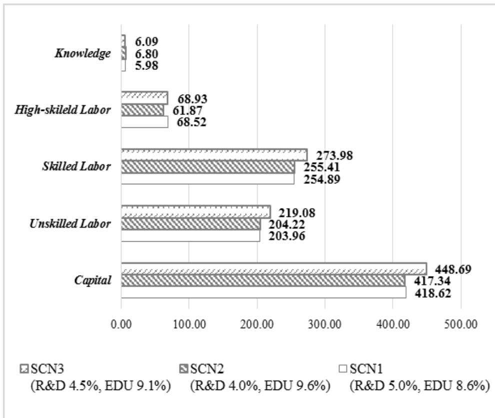
(a) Total industry



(b) Low-tech manufacturing



(c) High-tech manufacturing



(d) Service

Figure 39. Composition of gross value-added under different scenarios in 2030

(Unit: trillion KRW)

On the other hand, among the policy scenarios, it is shown that the SCN3 scenario has the highest values of the gross value-added of high-skilled labor and knowledge capital (physical capital: 808.85 trillion KRW; low-skilled labor: 341.38 trillion KRW; skilled labor: 446.81 trillion KRW; high-skilled labor: 138.80 trillion KRW; knowledge capital: 69.32 trillion KRW in 2030 for the SCN3 scenario). In SCN3 scenario, compared with SCN1 scenario, the values for the value-added of high-skilled labor and knowledge capital are relatively low, but the values for the gross value-added throughout the production factors (including, physical capital, knowledge capital, high-skilled, skilled, and low-skilled labor) are shown to be relatively high among constructed policy scenarios with the enhanced growth effects of industrial outputs across industries. On the other hand, under SCN2, it is shown to be reveal the lowest level of the gross value-added (physical capital: 725.29 trillion KRW; low-skilled labor: 326.51 trillion KRW; skilled labor: 429.72 trillion KRW; high-skilled labor: 144.17 trillion KRW; knowledge capital: 74.40 trillion KRW in 2030 for the SCN2 scenario). Through these results, it can be understood that the changes in the production activities in industrial sectors for policy scenarios affect the changes in demands for production factors, leading to differences in the value-added compositions among scenarios.

5.3.4 Effects on productivity growth from knowledge spillover effects

In this subsection, we will examine how the changes in R&D and education investments, which are assumed to be different for each scenario, affect the productivity growth and innovation-related variables. Firstly, we examine the R&D investment inducement effects by scenario. As shown in Figure 40, the SCN1 scenario induces the highest level of the

R&D investment from the private sector (43.02% higher relative to the BAU level in 2030), as the R&D intensity for this scenario is exogenously increased by 1%p relative to the BAU level, followed by the SCN3 scenario in which the R&D investment and education investment are increased by 0.5%p respectively relative to the BAU (34.25% higher relative to the BAU level in 2030). On the other hand, the SCN2 scenario (i.e., 1%p increase in education investment intensity compared to the BAU level) reveals the lowest R&D investment inducement effects (7.32% higher relative to the BAU level in 2030).

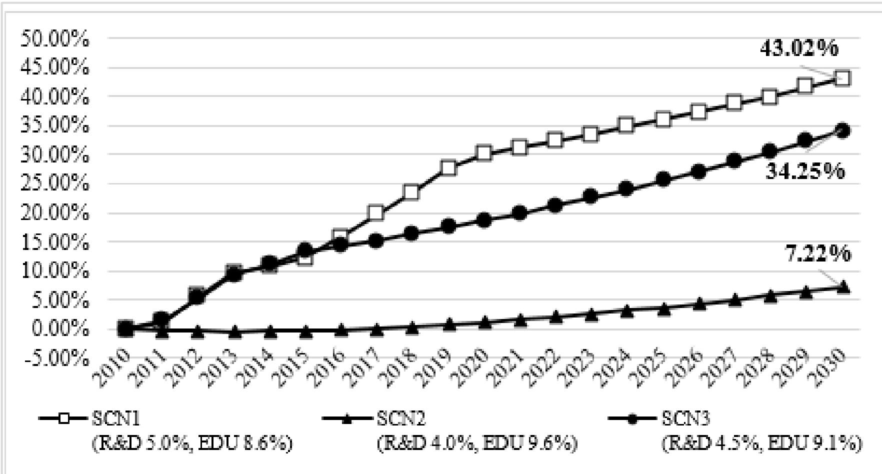


Figure 40. R&D investment level of the private sector in each scenario relative to the BAU scenario (Unit: %)

The R&D inducement effects of the private sector generated by policy scenarios can be interpreted as follows. In the case of SCN1, the R&D inducement effects has shown to be the highest among policy scenarios, as the increase of the exogenous R&D intensity applied in the model is the largest. In the SCN2 scenario, although the R&D intensity assumed in the SCN2 scenario is same as that of BAU, it is found that the SCN2 scenario reveals a higher level of R&D investment compared to the BAU scenario. This is because the accumulation of human capital, and skill upgrading of workers indirectly affect the knowledge accumulation based on the complementary relationship between high-skilled labor and knowledge capital within the production function. In other words, when the labor supply of the high-skilled labor is increased through promoting endogenous skill accumulation of workers, it can indirectly increase the rates of return on R&D investments and spur the knowledge capital accumulation. However, it can be understood that under the SCN2 scenario, the indirect effect of the human capital accumulation on inducing the R&D investments is shown to be the lowest among the policy scenarios.

In addition, the R&D inducement effect generated by the SCN3 scenario is the outcomes of the interaction of increased supply of workers who have improved skills through the learning process (via increase of educational investment intensity), and increased demand for high-skilled workers driven by the increased knowledge capital (via increase of R&D intensity) and associated skill-biased technological change. The SCN3 scenario reveals the R&D inducement effects which is 34.25 higher than that of BAU (8.77%p lower compared to SCN1 scenario), even though the level of R&D intensity is exogenously assumed to be half compared to SCN1 scenario. This implies a complementarity between the R&D investments and educational investments in terms of the R&D inducement effects.

Moreover, we examine the linkage between the R&D inducement effects and productivity growth (and associated knowledge spillover effects) for SCN1, SCN2, and

SCN3 scenarios. Table 23 and Figure 41 illustrate the changes of TFP for industrial sectors for each scenario compared to the BAU level. As mentioned in the previous Chapter 4, the change in total factor productivity (TFP) by industry is captured by comparing the value of the value-added composite input coefficients (AVA_i) for each scenario with that in BAU scenario. As can be seen in Table 23 below, it is found that the SCN3 scenario achieves the highest TFP growth in terms of the average TFP level (across industries) (SCN3: 10.95% higher relative to the BAU; SCN1: 8.44% higher relative to the BAU; SCN2: 4.88% higher relative to the BAU level in 2030).

Table 23. Changes of average TFP across industries relative to the BAU in 2030 (Unit: %)

		2015	2020	2025	2030
Average TFP level across industries	SCN1	1.48	3.82	6.16	8.44
	SCN2	0.19	1.33	2.96	4.83
	SCN3	0.96	4.31	7.43	10.95

In addition, as shown in Figure 41, which depicts the changes of industry-level TFP generated by policy scenarios relative to the BAU scenario, it is also found that under the SCN3 scenario, the highest level of productivity growth is seen in all industry sectors compared to other scenarios (SCN3: 10.94% higher relative to the BAU level in the low-tech industry, 14.27% higher relative to the BAU level in the high-tech industry, 8.11% higher relative to the BAU level in the service industry; SCN1: 8.35% higher relative to the BAU level in the low-tech industry, 11.49% higher relative to the BAU level in the high-tech industry, 5.93% higher relative to the BAU level in the service industry; SCN2: 4.88% higher relative to the BAU level in the low-tech industry, 5.99% higher relative to the BAU level in the high-tech industry, 3.84% higher relative to the BAU level in the service industry).

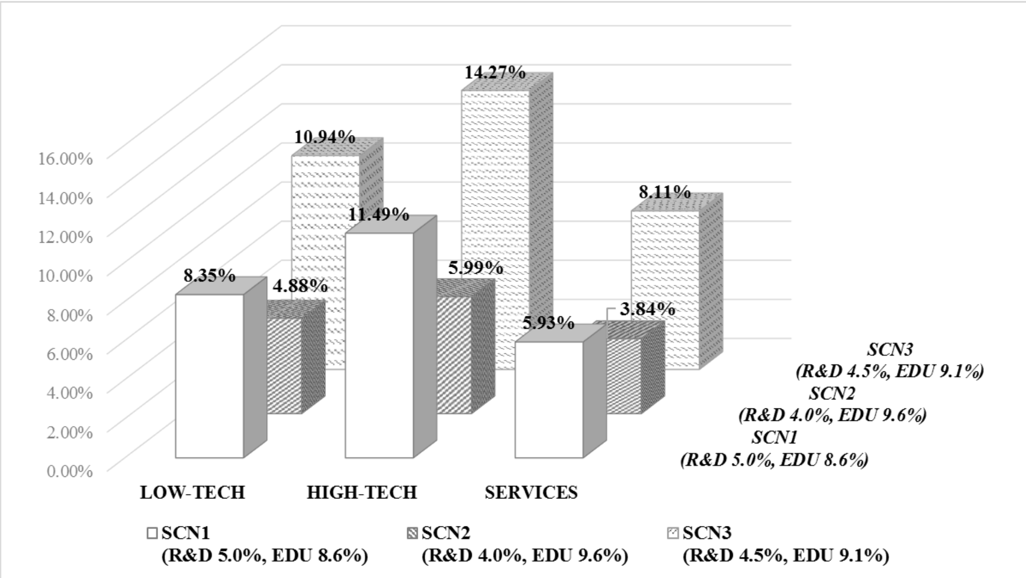


Figure 41. Changes of TFP in industries relative to the BAU in 2030 (Unit: %)

Through these results, it is found that the highest R&D inducement effects in the SCN1 scenario does not directly lead to the highest productivity growth effects. Despite of a lower level of R&D inducement effects compared to the SCN1, the SCN3 scenario has revealed the highest productivity growth in industrial sectors. This is because, when the interaction between technological innovation and human capital accumulation is facilitated through increasing R&D investments and human capital investments together, it leads to greater knowledge spillover effects with expansions of production activities across industries with the diversified industrial structure (i.e., more evenly spread output growth effects across industries). This argument is supported by Figure 42 which illustrates the comparison of the variable $INTINDST_i$ representing the level of knowledge spillover effects from other industries to individual sectors. From those results, it is noted that the holistic innovation policy taken into account the inter-linkages between R&D investment and educational investment should be prepared to facilitate the long-run economic growth, not merely focusing on the quantitative expansion of the R&D investments. In other words, this study's findings suggest that policy measures to increase the efficiency of the R&D investments should be proposed with the considerations of the endogenous interaction between innovation and human capital.

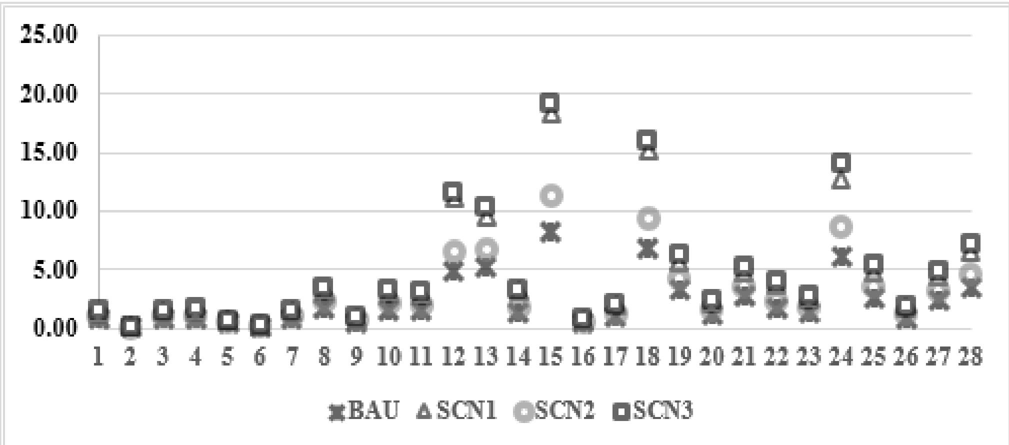


Figure 42. Comparison of $INTINDST$ values for individual sectors for policy scenarios

5.4 Sub-conclusion

In this study, an empirical analysis has been conducted based on the constructed CGE model focusing on Korean economy, to examine how long–term economic growth rates are achieved through the combination of R&D investment and human capital investment. Specifically, we have designed the knowledge-based CGE model to describe the endogenous interaction between innovation and human capital accumulation. Based on this CGE model, this study has constructed policy scenarios by differing the R&D intensity and educational investment intensity to conduct policy experiments. With these policy scenarios, this study has tried to investigate the key impact channels and direct/indirect paths that determine the complementarity effects driven by the endogenous interaction between innovation and human capital accumulation. Through the CGE analysis, this study aims to suggest a new perspective on the role and scope of the innovation policy for enhancing Korea economy's mid- to long-term growth potentials.

The results show that the interaction between R&D investment and human capital investment occurs through the following paths. Firstly, with the SCN1 scenario in which the R&D intensity is set to be 1%p higher than that of the BAU, it is shown that direct effects of the increase in R&D investment intensity increase the knowledge capital accumulation level, which further expands the degree of skill biased technological progress, leading to the disproportionate increases in the demand for the high-skilled labor over skilled, and low-skilled labor. Our results analysis has also suggested that the higher degree of the skill-biased technological progress ensures higher returns (i.e., skill premium) for high-skilled workers, resulting in the polarization of the labor market. To be specific, under the SCN1 scenario, the skill premiums for skilled and high-skilled workers are shown to be the highest levels among the policy scenarios. The increases in relative wages for the high-skilled and skilled workers imply that additional R&D investment can increase the expected returns of the human capital accumulation, which indirectly affects workers' endogenous decision-making to improve their skills and advance knowledge (See Figure 43 for the path of the "Indirect effects from R&D investments"). However, the indirect effect of the additional R&D investments on human capital accumulation is found to be not remarkable. It is because, given that the relative wages of workers are the outcomes of the interaction between changes in relative demand and supply of workers, the SCN1 scenario reveals a steady increase in the skill premiums for skilled and high-skilled workers during the analysis period, offsetting the decrease of the relative wages for those workers induced by the expansion of the labor supply with the human capital accumulation.

Secondly, the main impact channels of the human capital investment on R&D investment in the economic system can be explained as follows. As shown in the SCN2 scenario, where the education investment intensity is set to be 1.0%p higher than that of BAU, the increase in the intensity of education investment forms direct impacts on the supply of high-skilled workers, as the endogenous skill accumulation process is partly determined by the changes in the educational investment level within the economy. Further, the changes in the labor supply driven by the workers' human capital accumulation process indirectly increases the expected rates of return on the R&D investments on the basis of the complementary relationship between the knowledge capital stock and high-skilled labor within the production function, thereby indirectly inducing the R&D investment for knowledge accumulation (See Figure 43 for the path of "Indirect effects from educational investments"). However, in SCN2, it is shown that the extent to human capital accumulation indirectly affects (induces) the R&D investment is lower than that of SCN1. This implies that the indirect effect of human capital accumulation on inducing R&D investment (i.e., SCN2 scenario) is relatively low compared to the level of R&D inducement investment effect triggered by the direct effect of expanding R&D investment (i.e., SCN1 scenario). The key channels related to the endogenous interaction between the R&D investments and human capital investments can be depicted as Figure 43.

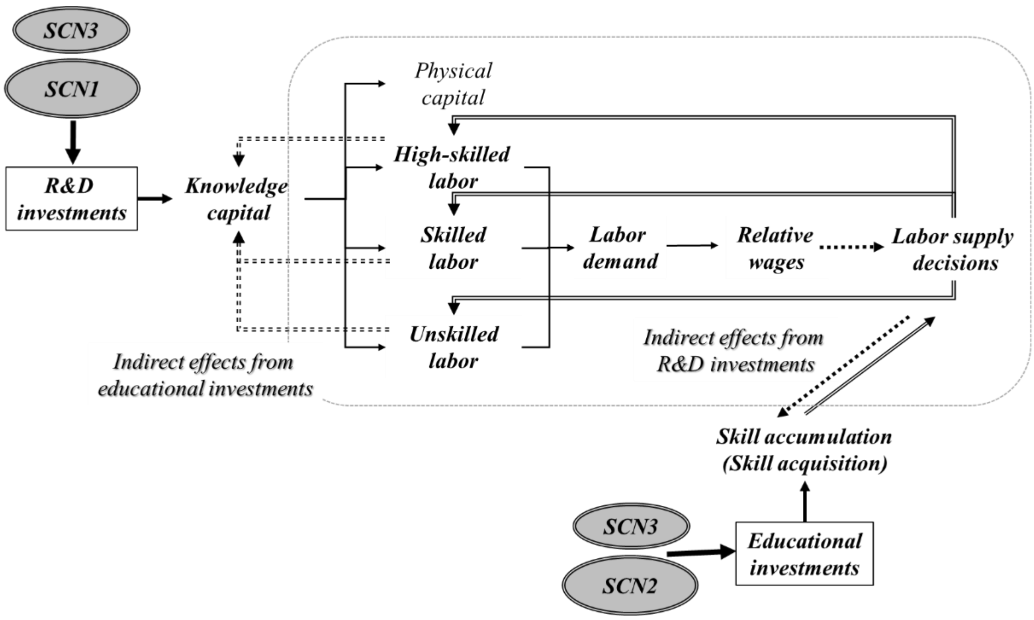


Figure 43. Endogenous interaction between R&D and human capital investments

Lastly, in SCN3 where R&D investment and education investment intensity are increased by 0.5%p respectively compared to BAU, it is shown that the complementary relationship between innovation and human capital accumulation is further enhanced. As mentioned earlier, technological innovation from the expansion of R&D investment triggers higher demands for workers with higher skills, and increases their profitability. The increase of the higher expected returns (i.e., wages) for high-skilled labor can indirectly affect the endogenous skill accumulation process of workers. In addition, the improvement of workers' skills through the expansion of educational investments and associated labor supply due to the human capital accumulation can indirectly accelerate technological innovation. In SCN3, we have found that the discrepancy between the skills demand and skills supply distributions is mitigated, which facilitates the endogenous skill-biased technological change within the production function, and associated scale effects.

For example, in the case of SCN1, it is found that the labor market may be polarized due to the increased mismatch between the skills demand and skill supply. On the other hand, under the SCN3 scenario, it is shown that the disparity of the labor market (in terms of employment and wage structures) is solved, on the basis of the decreased discrepancy between changes in labor and skills demand induced by the variants in R&D intensity, and changes in labor (skills) supply driven by the variants in the education investment intensity. Moreover, in the case of SCN3 scenario, the relative wages of skilled and high-skilled workers are shown to be lower levels compared to the BAU scenario. However, it is found that the decreases in the skill premiums of skilled and high-skilled workers are relatively low, compared to the SCN2. It can be interpreted that there is a close relationship between the changes in labor demand due to technological progress driven by increased R&D investment, and the changes in labor supply induced by the human capital accumulation resulting from the quantitative expansion of educational investment. To be specific, higher demands for high-skilled and skilled workers triggered by skill-biased technological progress is linked with the increases of the skill premiums for them, while the higher levels of labor supply of high-skilled and skilled workers through the learning process is associated with the decreases of the relative wages of high-skilled and skilled workers. In this regard, we can understand the changes of skill premiums for high-skilled and skilled workers generated by the SCN3 scenario, in terms of the supply-demand framework.

Based on the key findings drawn from the CGE analysis, this study shows that there is a limitation to drive productivity growth, and enhance the growth potentials when solely focusing on the quantitative expansion of R&D investment. From the analysis of the SCN1 scenario, we have found that the increase of the R&D intensity leads to the accumulation of knowledge capital in the economic system, thereby promoting the knowledge spillover effects via productivity growth. Also, it is found that the complementarity among production factors such as knowledge, physical capital, and high-skilled labor within the production technology leads to the expansion of scale effects, promoting economic growth in SCN1 scenario. However, from the analysis we have found that policies limited to the quantitative expansion of R&D investment can have some limitations as follows; 1) Firstly, it can accelerate the polarization and disparity of the labor market; 2) Secondly, it can further increase the concentration of knowledge- and innovation- intensive industries in the economic system, leading to unbalanced economic growth; 3) Thirdly, the intensification of the concentration of knowledge- and innovation-intensive industries can facilitate the polarization and disparity of the labor market. Deepening of the polarization and concentration in the industrial and wage/employment structures may hinder development of a sound industrial ecosystem, and undermine the growth potentials of the economy.

Accordingly, this study suggests that the design and implementation of the innovation policy should take into account to how to facilitate the efficient combination of R&D and human capital investments. The highest level of productivity growth and long-term economic growth shown in the SCN3 scenario can be explained by the fact that when the endogenous interaction between demand-side skills distribution formed by technological innovation and supply-side skills distribution through the human capital investments is promoted, the positive externality of knowledge accumulation within the economy is facilitated, which leads to a higher equilibrium state of economic growth. It suggest that productivity growth driven by the endogenous interaction (i.e., complementarity) between innovation and skill accumulation can serve a major growth engine to secure the long-term growth potential of Korea. In summary, it is noted that the design of innovation policy, which consists of a combination of R&D and educational investment, can alleviate the labor market polarization, and wage disparity trend, promoting the balanced-growth among industrial sectors with higher productivity improvement and scale effects. The main conclusions drawn from the study mentioned above can be illustrated as Figure 44.

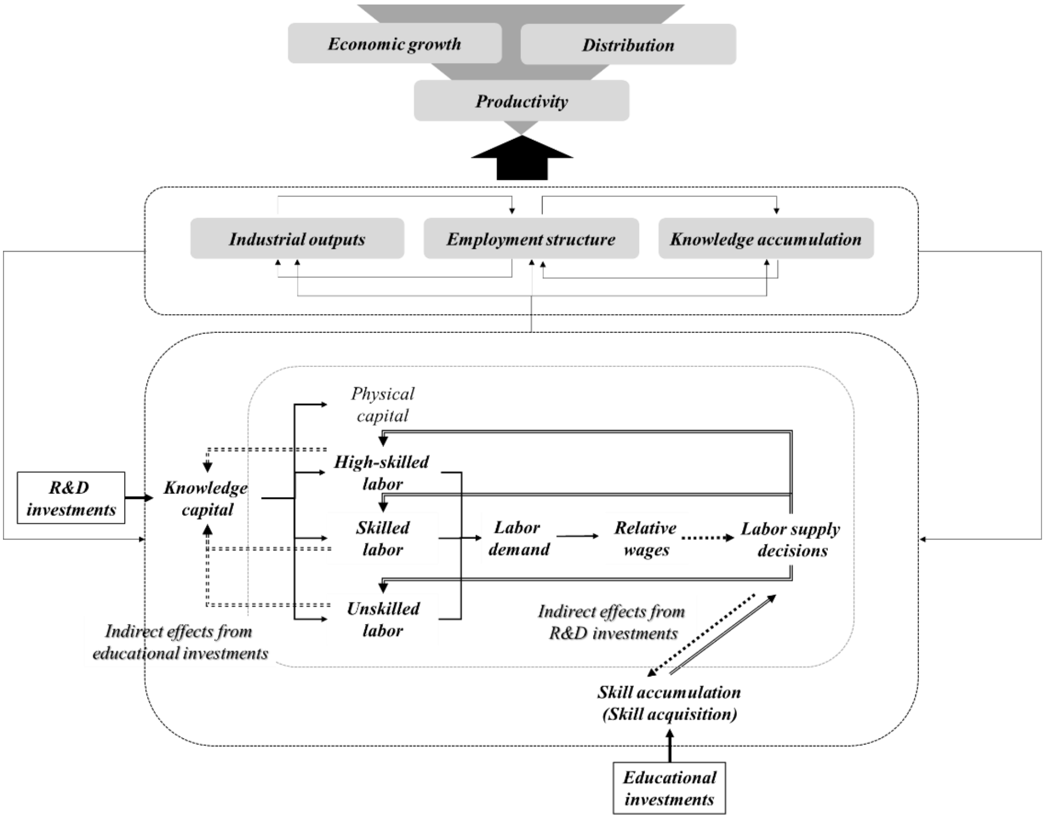


Figure 44. Key findings drawn from the study in terms of the endogenous interaction between innovation and human capital accumulation

In order to increase the growth potentials of the economy, productivity improvement is indispensable, and it is important to combine R&D investment and human capital investment to spur the productivity growth. Through CGE analysis, this study suggests that strengthening a complementary relationship between innovation and human capital accumulation is crucial to raise the national economy's competitiveness. Therefore, efficient combination of R&D investment and associated qualitative improvements of human capital should be taken into account for designing and formulating the innovation policy, instead of only stressing out the quantitative expansion of R&D investment. To promote the endogenous interaction between innovation and human capital accumulation, the human capital investment should include the establishment of life-long learning system for workers which help them improve their skills and knowledge to cope with rapid changing technological change. 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 learning process. 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 summary, in order to reinforce the interrelationship between innovation and human capital accumulation, it is necessary to accompany qualitative improvements of education and learning systems within the economy, which can enhance the flexibility and adaptability in the labor supply of workers in line with changing labor market demand. Also, since there is a time lag from the accumulation of human capital to the actual labor supply, consideration of various policy alternatives are needed to enhance the linkage between education system and labor market.

Chapter 6. Quantitative analysis on Role of Policy-mixes to drive Inclusive Growth in a Knowledge-based Economy

6.1 Research background and research objectives

Recently, many empirical studies have emphasized that decoupling of economic growth from employment expansion in the knowledge-based economy is not just a cyclical phenomenon, but also a structural problem driven by technological progress. In recent years, the jobless growth, widening of the income polarization and income inequality have become major problems faced by Korean economy. The jobless growth in the national growth is the economic phenomenon that the unemployment rates show high level for a prolonged period, despite of economic growth, as the economic growth largely is achieved by the higher productivities of employed workers, rather than from the employment expansion. This economic phenomenon is experienced by many advanced countries, including Korea economy.

In addition, the wage inequality in Korea is shown to be the highest among the OECD countries, having shown the increasing trends so far (OECD, 2018c). The higher the wage inequality and income inequality in the labor market, the lower the performance of economic growth with the greater number of low wage workers. It would be a bigger problem if high levels of income and wage inequality occur in the economic societies with the high levels of labor market rigidities. However, empirical studies address that Korean economy has the high level of the labor market rigidity, which stabilizes the inter-sectoral movements of labor (Ahn & Cheon, 2008; Yang, 2012; Choi, 2012).

In this context, previous studies have attempted to investigate stylized facts on the relationships between technological innovation and employment structure addressing that intrinsic properties of technological innovation are attributable to the jobless growth and structural employment which are emerging in advanced economies in recent years. In addition, those studies argue that technological innovation can expand the losses for workers in terms of jobs, skills, wages, and widen income inequality in the economy (Acemoglu, 1998; Acemoglu & Autor, 2012; Autor et al., 2017; Brynjolfsson & McAfee, 2012a, 2012b, 2014; Card & DiNardo, 2002; Fernald & Jones, 2014; Goos et al., 2014; Karabarbounis & Neiman, 2013; Stiglitz, 2014).

The intrinsic attributes of technological innovation highlighted in previous studies can be summarized as “factor-biased technological progress”. Firstly, technological innovation accompanies skill-biased technological change, which can be descried as a shift in the production technology that favors skilled over unskilled labor by increasing its productivity and therefore, its relative demand. Skill-biased technological change can be strongly associated with the capital-skill complementarity where capital goods (such as, machines with new technologies) become relatively more complementary with skilled labor than unskilled labor. The workers with higher skills (or, more educated) can deal better with technological change. It is less costly for them to learn the additional knowledge needed to adopt a new technology, and they are less adversely affected by the turmoil created by major technological change. Accordingly, the nature of the complementarity between capital and skills (or, between technology and skills) leads to an increase in the wage gap between high skilled workers and relatively low skilled workers.

Secondly, recent studies on the relationship between technological innovation and employment structure address that technological progress from innovation causes not only SBTC, but also capital-biased technological change. Technological progress driven by innovation can unevenly affect the marginal productivity of capital and labor. In this regard, the concept of the capital-biased technological change can be defined as a kind of change that makes the economy more flourishing, but workers poorer. 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. As technological change increases the productivity of the machines, it consequently triggers a fall in wages relative to the costs of capital, which could later cause wages to diminish and even redundancies. In addition, there can be a deepening of income inequality as capital ownership tends to be concentrated. This capital-biased (or, labor-saving) technological change from innovation can result in higher level of technological unemployment. Consequently, wages fall relative to the cost of capital, and the proportion of labor wages in GDP decreases.

As noted above, intrinsic properties of technological progress can be summarized as labor-saving and skill-biased, which has the potentials to deepen social inequalities and polarization by increasing economic returns to high-skilled workers and capitalists in the economic system. Thus, economic growth accompanied by factor-biased technological change can generate higher inequality and income polarization. As a result, policy makers are faced with the question of how to intervene in the market in order to deal with the deepening of job polarization, income disparities in the knowledge-based economy where technological innovation is a main source of growth. In this regard, countries are increasingly showing interests in implementing “inclusive innovation policies” – a specific set of innovation policies that aim to boost the innovation capacities and opportunities of individuals and social groups that are underrepresented in innovation activities. Therefore, in the design and implementation of innovative policies to promote the inclusive growth in the knowledge-based economy, a broader range of innovation policy dimensions should be considered, taking into account interactions of the technological innovation with various institutional conditions within the economic system (de Mello & Dutz, 2012; Heeks, Foster, & Nugroho, 2014; OECD, 2018a; Ostry et al., 2014).

Under this background, there is a growing demand for policy design and related research seeking to the policy suggestions to spur the inclusive growth in the knowledge-based economy, by considering the conflicts between inclusiveness and the intrinsic characteristics of innovation. In the existing framework of economic growth theory, the effect of technological innovation on economic growth is associated with the growth effects based on the externality and scale effects through productivity growth. However, the presence of the factor-biased technological progress implies the possibility to deepen social inequalities and polarization by increasing economic returns to high-skilled workers and capitalists in the economic system. Accordingly, it is necessary to search for the role and direction of innovation policy in the framework of inclusive growth.

However, a variety of policy suggestions proposed by previous studies are rather fragmented, and mostly limited to a specific (single) policy instrument. In this regard, the policy options to facilitate inclusive growth having been proposed so far largely are found to focus on how to mitigate the “direct impacts of technological innovation” on employment structure and income distribution. In addition, there has been a lack of quantitative analysis of those policy suggestions to draw upon policy implications to mitigate the negative impacts of technological innovation. 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 a single policy instrument. In this spirit, we advocate that technological policies should be accompanied by other complementary policies in order to counterbalance the negative impacts of skill-biased and labor-saving technological progress in the knowledge-based economy. The structural problems caused by the factor-biased technological change should be solved through a wide range of policy instruments, rather than a single policy instrument. The question is then how to formulate and coordinate policy options from various dimensions to achieve an inclusive growth in the knowledge-based economy. Existing studies, however, often fall short of reflecting the concept of policy mixes. Although there are indeed existing useful frameworks and policy suggestions for examining the impacts of factor-biased technological change, they seem insufficient to draw policy implications in practical senses. In this regard, the present study intends to bridge this gap in the literature.

Considering these limitations of previous studies, this study firstly aims to propose a conceptual framework to investigate the economy-wide impacts of factor-biased technological change and the role of policy packages to deal with this issue, by addressing the limitations of previous studies' approaches. Secondly, this study aims to quantitatively assess the macroeconomic impacts of policy packages consisting of innovation, education, and taxation policies to mitigate the structural problems caused by the factor-biased technological change. Through this, we intend to identify the potential role of policy packages from several different dimensions (i.e., innovation, education, and tax policies) by investigating the impacts of the different types of policy mixes on the economic system using a CGE model so as to inform and advise policymakers in designing an appropriate policy package for inclusive growth. Our study is significant, in that it is devoted to a macroeconomic analysis in investigating the impacts of different types of policy mixes, and drawing upon policy implications addressing the complementarity of policy instruments. Ultimately, this study expects to shed light on the importance of the policy packages in resolving the side effects of factor-biased technological progress and spur the inclusive growth in the knowledge-based economy.

6.2 Conceptual framework and policy scenario settings

6.2.1 Development of a conceptual framework

The policy options to facilitate inclusive growth having been proposed so far largely focus on how to mitigate the “direct impacts of technological innovation” on employment structure and income distribution. Policy options for reducing job displacement effects experienced by lower skilled workers, and promoting reabsorption of workers into the labor market are considered as a main body of those policy options as a response to concerns about the structural unemployment and widening income disparities among workers (Brynjolfsson and McAfee, 2014, 2012; Piketty, 2014). Policy options proposed from this perspective, however, have not deeply considered compensation mechanisms which could counterbalance direct employment impacts of technological change. Accordingly, those policy suggestions are lack of considerations on how this substitution effects of workers interact with scale effects generated by technological innovation (e.g., productivity improvements, and production expansions effects). In other words, policy suggestions are limited mainly to the discussion on how to minimize the substitution effects of labor due to technological innovation, focusing only on the direct employment impacts of technological change (i.e., technological unemployment). These policy options include such as, job creation policies for quantitative expansion of jobs, unconditional basic income (UBI), reforms of education and vocational training systems, and regulatory reforms for labor markets.

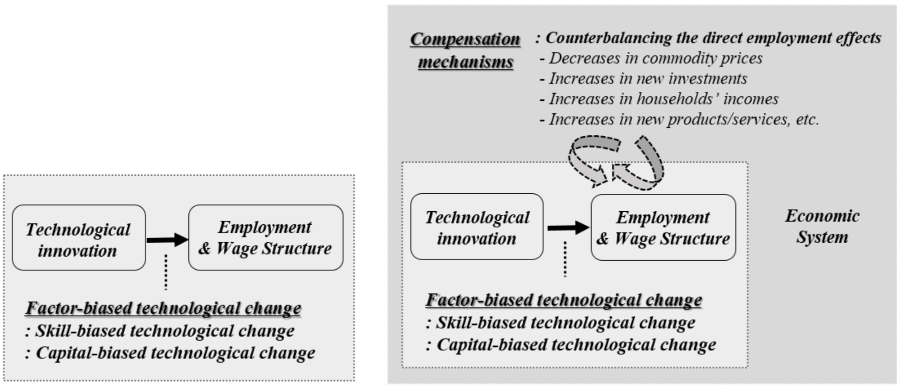
Such approaches and associated policy options are likely to have limitations in solving structural problems in the knowledge-based economy. For example, job creation policies for the quantitative expansion of jobs include directly creating large number of jobs in public sector (i.e., government agencies, public companies, and state-funded firms), subsidizing the formation of typical start-ups, and making transitions of temporary workers to full-time workers to boost welfare benefits and raise the number and quality of jobs (Hohmeyer & Wolff, 2010; Shane, 2009). Their goals include enhancing the employability of (potential) workers and their well-being, furthermore achieving the inclusive growth of the economy. While these government-led policies for quantitative expansion of jobs may bring about increases in employment levels in the short run, however in the long run it can lead to increases in labor costs for companies, which may result in decreases in innovation activities in firms (Hohmeyer & Wolff, 2010; Shane, 2009).

As Shane (2009) points out, typical start-ups and public sectors are typically not highly innovative, and have the potential to create few jobs and generate little wealth in the long-run. In other words, those are not knowledge- and high skill-intensive segments in terms of skill distribution, which cannot promote the economic growth driven by factor-biased technological change. On the other hand, it is highly possible to establish a virtuous cycle between innovation, industrial development, and job creation when the expansion of employment is endogenously determined by increases in innovation activities in firms/industries and associated increases in scale effects generated by technological innovation, not exogenously determined (Acemoglu & Autor, 2011b; Autor, 2010). When the outcomes of innovation are actively generated, and utilized in the economy, the economy will gain greater momentum for growth, and expansion of employment will be consequently followed. Attention to current workers may alienate future employment. Job creation policies based on the partial equilibrium perspective are likely to have limitations in taking into account the dynamic process in which jobs are endogenously created, and interactions among diverse agents and feedback loops between endogenous variables are occurred.

In addition, one of the policy measures that could address the issue of technological unemployment and income inequality is the introduction of universal basic income (UBI) (OECD, 2017a; Sage & Diamond, 2017; Standing, 2015; Van Parijs, 2004). This measure is defined as an unconditional payment of certain amount of cash provided by the government to individuals, regardless of their income, resources or employment status. The primary role of UBI is to maintain demand and consumption side of the economy by ensuring the minimum standards of living of individuals. In the short term this policy measure may be able to temporarily reduce income inequality by supporting the poor in the economy. In the long-run, however, UBI can discourage people from seeking employment, and significant costs of UBI can require higher taxes and burdens to individuals (De Wispelaere & Stirton, 2004; OECD, 2017a, 2018a; Woodbury, 2017). OECD (2017a) analyze the economic effects of UBI in selected countries (i.e., France, Italy, Finland), and find that UBI has limitations on solving the income disparities, but increasing the tax burdens of all groups of people in the economy. Furthermore, it is doubtful whether UBI can preserve well-functioning of markets and sustaining technological innovation, while ensuring the minimum standards of living of individuals from the long-run perspective.

As we have seen above, most of the policy suggestions proposed by previous studies largely depend on the partial static equilibrium framework. In this regard, there has been lack of considerations on diverse paths of compensation mechanisms in the market to offset the direct effect of technological progress (i.e., technological unemployment), and interaction effects between direct and indirect effects of technological innovation from the dynamic perspective under the general equilibrium framework. When focusing only on the direct employment impacts of technological innovation, it leads to discussions on how to minimize the substitution effects of workers. However, policy suggestions must be designed from a dynamic, and economy-wide perspective in order to fundamentally address the structural problems (i.e., technological unemployment and widening income inequality) of the knowledge-based economy. In other words, it is essential to consider how to accelerate the technological progress driven by factor-biased technological change, and reduce adverse effects caused by technological innovation by taking into account the process of endogenously determined technological innovation interacting with market- and policy-related variables. Policy suggestions derived from this perspective can provide an integrated framework on the issues of innovation, growth, and distribution. Hence, the limitations of underlying assumptions and perspectives of previous studies are presented in Figure 45, by highlighting our conceptual framework for this study.

Considering these limitations of previous studies, this study has proposed a conceptual framework to investigate the economy-wide impacts of factor-biased technological change and the role of policy packages to deal with this issue, by addressing the limitations of previous studies' approaches. Based on this conceptual framework, this study aims to quantitatively assess the macroeconomic impacts of policy packages consisting of innovation, education, and taxation policies to mitigate the structural problems caused by the factor-biased technological change. Through this, we intend to identify the potential role of policy packages from several different dimensions (i.e., innovation, education, and tax policies) by investigating the impacts of the different types of policy mixes on the economic system using a CGE model so as to inform and advise policymakers in designing an appropriate policy package for inclusive growth.



	Previous studies' framework	Our framework for this study
Main focus for the issue	• The direct employment effects of technological innovation (i.e., technological unemployment)	• The interaction between the direct technological unemployment effects & indirect effects driven by technological innovation (i.e., compensation mechanisms)
Policy responses (1)	• Policy suggestions based on static, and partial equilibrium perspectives	• Policy suggestions based on dynamic, and general equilibrium perspectives
Policy responses (2)	• Largely focus on a single policy instrument • Lack of considerations on interaction between policy instruments	• Focus on the policy package (mix) from various dimensions of policy instruments • Considerations on interaction between direct employment effects of technological innovation and indirect compensation effects

Figure 45. Conceptual framework for this study

Based on the discussions as presented above, this study aims to propose several types of policy mixes to ensure the inclusive growth in the knowledge-based economy which aim to mitigate the side effects driven by the factor-biased technological change. Among several types of policy options, this study focuses on the education investments from the government to promote skill upgrading of workers who are in jobs at risk of skill obsolescence, and the progressive income taxation to moderate the extent of income redistribution, along with the innovation policy which promote the innovation activities within the knowledge-based economy. Based on these settings, we are to examine the degree to which the interventions are complementary or competing in terms of this contribution to achieve the degree of inclusive growth in the economy by considering the interactions of policies. By looking at how those policies or instruments interact, this study aims to highlight the importance of deliberate design of policy mixes and portfolios of interventions.

As noted above in the previous chapter, 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 this regard, it is essential to establish the life-long learning systems and relevant training programs including the OJT and workplace-based vocational programs. In other words, the educational system should keep pace with technological change and evolving labor markets. In order for technological innovation to continue to function as a growth engine in the economy, human capital with the appropriate skills required by technological innovation must be continuously supplied.

Synergies between the evolution of labor demand triggered by innovation and the adaptability of labor supply resulting from education and learning should come together (Acemoglu, 2002; Alismail & McGuire, 2015; Cobo, 2013; Goldin & Katz, 2008; Goldin & Katz, 2007; Grossman et al., 2017; He & Liu, 2008; Pan, 2014). In this regard, the public sector's investments in education is highlighted, along with the investments in innovation activities

In addition, the income tax is considered as a representative policy option to address the problems of widening income disparities (Eissa & Liebman, 1996; Ojha et al., 2013; Piketty, 2014). In this study, we are to propose the progressive income taxation, and utilize tax revenues to finance the public expenditure on human capital formation. Several previous studies have highlighted the public expenditure on education to build learning capabilities to enhance skills of human capital, however those studies are lack of discussions on how to finance the expenditure on education. In this regard, we are to consider increased investments in human capital financed through the levying of progressive income tax as presented in Ojha et al. (2013)'s work. Furthermore, we are to consider the investments in research and development (R&D) as a representative policy instrument in innovation policy. Based on these settings, in this study we are to analyze the impacts of policy packages comprising of an enhancement in R&D investments, and tax-financed increases in public expenditure on human capital formation from the point of view of growth as well as equity.

Our logical framework for this study can be described as Figure 46. As shown in Figure 46, the improvement of workers' skills through education can alleviate the side effects of technological unemployment, and indirectly to some extent the income inequality caused by factor-biased technological progress. In addition, securing of education investment resources through introducing the progressive income taxation can ease budget constraints of government, and possibly reduce the deepening income equality of the society. However, increases in tax burdens faced by higher income earners could lead to the suppression of their participations in economic activities, which may have negative effects on the economic growth. Therefore, it is necessary to empirically investigate whether those policy instruments from innovation, education, and tax policies are complementary or substitutive under the form of policy package. Accordingly, we are to consider different types of policy options differing the levels of investments in R&D, education, and progressive income taxation so as to investigate the efficacies of policy options with the help of a CGE model of Korea.

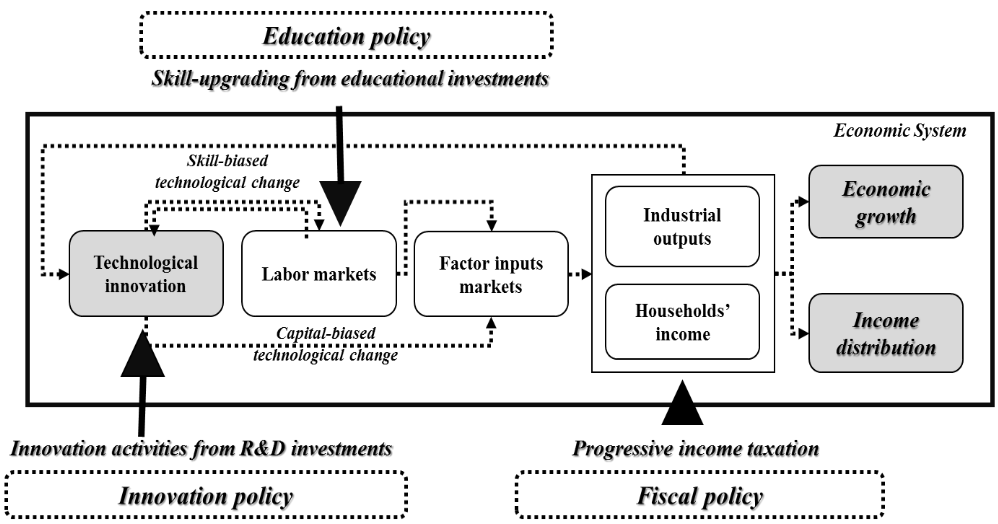


Figure 46. Logical framework for considerations of policy options in this study

6.2.2 Business As Usual (BAU) scenario settings

For the policy simulations based on the constructed CGE model, we firstly have designed the BAU scenario. Under the BAU scenario considered in this study, it is assumed that 4% of Korea's R&D intensity in the base year 2010 will continue to be maintained until 2030. In addition, investment in education by the Korean government (public sector) is also assumed to be maintained at 4% of GDP by 2030. Here, we do not consider the impacts of educational investment in the public sector on the endogenous skill accumulation of workers. For this, we set the BAU scenario by reflecting the EDU_t subtracted the public sector's expenditures on the educational investments, which affects the endogenous skill accumulation process of workers within the CGE model. The reason for this assumption is that the expenditures on the educational investments made by the government in Korea is mostly oriented towards the formal education including primary education, secondary education and tertiary education, which focus on the human capital accumulation before entering the labor market. Accordingly, the BAU scenario is designed to describe the current systematic characteristics of Korea's educational system are maintained continuously in which the educational investments from the public sector do not provide sufficient institutional environments for workers to participate in learning activities for workers' human capital accumulation after entry into the labor market (OECD, 2017b; Kang et al., 2011; Lim, 2006).

In addition, this study aims to draw policy implications for the public sector's policy design to spur the inclusive growth in the knowledge-based economy in terms of balancing the growth and distribution effects within the economic system. In this regard, this study assumes that the workers' endogenous skill accumulation process driven by the effects of the private sector's expenditures works efficiently within the CGE model. Furthermore, it is also assumed the optimal situation with smooth transitions of workers, either from low-skilled to skilled labor, or from skilled to high-skilled labor, affected by the private sector's spending on educational investments.

Based on this assumption for constructing the BAU scenario, we have only considered the volume of education investment expenditures of the private sector as the value for the variable of EDU_t which affects the endogenous skill accumulation process of workers within the CGE model. It can be said that those assumptions to design the BAU scenario have limitations to reflect the reality. However, it is again said that this study aims to draw policy implications for the public sector's policy design to spur the inclusive growth in the knowledge-based economy in terms of balancing the growth and distribution effects within the economic system. In this regard, we have attempted to reflect the current systematic characteristics of the public sector's investments on education, while assuming the optimal situation for the private sector's educational investments.

6.2.3 Policy scenario settings for analysis

This study aims to quantitatively assess the macroeconomic impacts of policy packages consisting of innovation, education, and taxation policies to mitigate the structural problems caused by the factor-biased technological change. Through this, we intend to identify the potential role of policy packages from several different dimensions (i.e., innovation, education, and tax policies) by investigating the impacts of the different types of policy mixes on the economic system using a CGE model so as to inform and advise policymakers in designing an appropriate policy package for inclusive growth. In this regard, policy seniors are constructed as represented by Table 24. In designing and reflecting the policy scenarios into the CGE model, the R&D intensity level is assumed to be a proxy variable to represent the innovation policy, while the educational investment intensity level is considered to be a policy variable related to the education policy. In addition, the progressive income taxation has been considered as the tax policy.

Table 24. Policy scenarios constructed for this study

Scenario	R&D intensity	Education investment intensity	Taxation
BAU	4.0%	4.0%	-
SCN1	5.0%	4.0%	-
SCN2	4.0%	4.0% (endogenous skill upgrading)	Progressive income taxation
SCN3	5.0%	4.0% (endogenous skill upgrading)	Progressive income taxation

The SCN1 scenario is assumed that the R&D intensity is increased by 1%p relative to the BAU. In the SCN1 scenario, it is assumed that the current systematic characteristics of Korea’s educational system are maintained continuously in which the educational investments from the public sector do not provide sufficient institutional environments for workers to participate in learning activities for workers' human capital accumulation after entry into the labor market. With this SCN1 scenario, we will quantitatively examine macroeconomic effects driven by the increase in the technological innovation in terms of the growth and distribution effects. Based on the simulation results generated by the SCN1 scenario, we will examine whether the stylized facts presented in the previous studies on the growth and distribution effects due to the factor-biased technological change appear in Korean economy.

The SCN2 scenario is assumed that the as in the case of the BAU scenario R&D intensity is maintained at 4% of GDP. In addition in the SCN2 scenario, the public sector's expenditures on educational investments are set to affect the endogenous skill accumulation of the workers, by assuming that the public sector's educational investments are not focusing on providing formal education, but also providing institutional conditions for human capital accumulation of the workers. Moreover, it is also assumed that the public expenditures on the education is maintained at 4% of GDP, which is financed by the progressive income taxation for households. Based on this SCN2 scenario, we will examine the complementarity between the education policy (i.e., encouraging workers to promote re-training or up-skilling enabling them to keep their competences in quickly adjusting to the rapid technological changes through increasing educational investments) and the tax policy (i.e., reforming the tax system by introducing progressive income taxation).

In addition, in case of the SCN3 scenario the R&D intensity is set to be 1%p higher than that of the SCN2, when comparing to the SCN2 scenario. Except for the R&D intensity level, other assumptions in the education and tax policy dimensions are the same. Based on this scenario, we will examine the complementarity between the policy instruments in the policy package including the three policy areas; 1) *innovation policy*: increasing R&D investments to spur innovation activities, 2) *education policy:* encouraging workers to promote re-training or up-skilling enabling them to keep their competences in quickly adjusting to the rapid technological changes through increasing educational investments, and 3) *tax policy*: reforming the tax system by introducing progressive income taxation can promote an inclusive growth in the knowledge- based economy. The potential impact channels induced by each policy instrument can be illustrated as Figure 47, which provides the basis for considering the policy scenarios of three different dimensions for the CGE-based analysis. The results of the policy scenarios designed for the analysis are analyzed in terms of economic growth, employment structure, and income distribution.

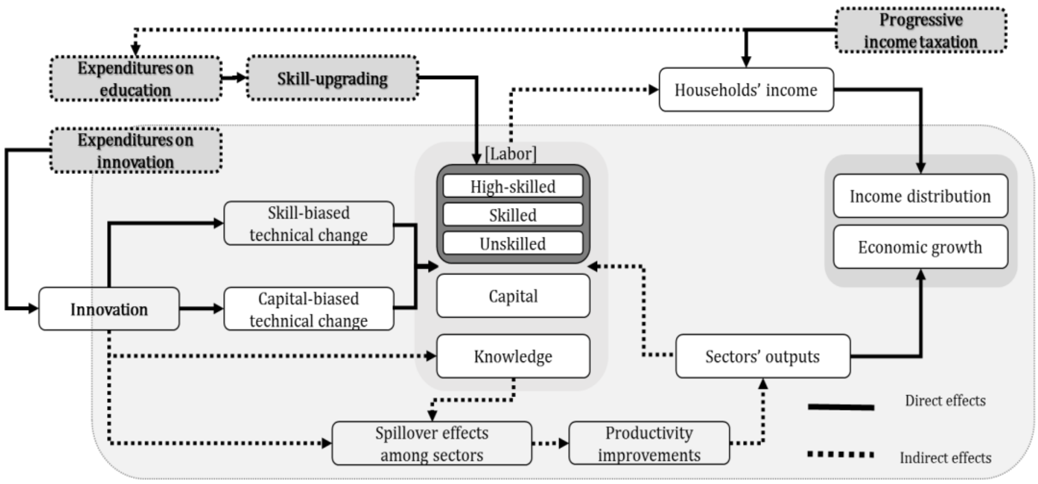


Figure 47. Impact channels of policy instruments in terms of the CGE model

6.3 Results analysis

6.3.1 Effects on economic growth

In this subsection, we present the main results generated by the constructed policy scenarios by comparing the changes in variables associated with the economic growth. . It is shown that as represented by Table 25 and Figure 48, the highest economic growth is found to be achieved under the SCN3 scenario (19.41% higher compared to the BAU level in 2030), while the SCN2 has shown to achieve the lowest economic growth among constructed policy scenarios (2.75% higher compared to the BAU level in 2030). Those results reaffirm that technological innovation is an important driver for the economic growth in the knowledge-based economy. A higher level of R&D investments leads to productivity improvements, which, in turn, lowers the production costs of industries in the economy via the knowledge spillover effects. Lower costs in producing final goods through the productivity improvements further promote price competitiveness of sectors. This forms the positive feedback loops to promote the expansion of the industrial outputs. As such, the increase in R&D investment spur the scale effects within the economy, and drive economic growth. In particular, the higher GDP level compared to BAU in the SCN1 scenario (15.61% higher compared to the BAU level in 2030), which considers only increasing knowledge capital investment for technological innovation, supports the effect of technological innovation on the economic growth based on the expansion of scale effects.

On the other hand, the GDP growth effects generated by the SCN2 scenario (compared to the BAU level) in which the efficient skill accumulation of workers is considered through the public sector's educational investments financed by the progressive income taxation imply the economic growth effects driven by the human capital accumulation through learning process of workers. In addition, this growth effects shown in the SCN2 scenario suggest the complementary relationship between the education policies which aims to provide sufficient institutional environments for workers to participate in learning activities (i.e., vocational training, informal lifelong learning, etc.) for workers' human capital accumulation after entry into the labor market, and the taxation policies which spur the income redistribution within the households.

Table 25. GDP growth rates from 2010 to 2030 under different scenarios (Unit: %)

Scenario	GDP growth rate	Average annual GDP growth rate
BAU	32.06%	1.40%
SCN1	52.67%	2.14%
SCN2	35.68%	1.54%
SCN3	57.69%	2.30%

In addition, it is shown that the highest economic growth is found to be achieved under the SCN3 scenario, which suggests the complementarity between the policy instruments in the policy package including the three policy areas; 1) *innovation policy*: increasing R&D investments to spur innovation activities, 2) *education policy:* encouraging workers to promote re-training or up-skilling enabling them to keep their competences in quickly adjusting to the rapid technological changes through increasing educational investments, and 3) *tax policy*: reforming the tax system by introducing progressive income taxation can promote an inclusive growth in the knowledge- based economy. Furthermore, the lower GDP growth effects generated by the SCN2 scenario compared to the SCN1, and SCN3 scenarios imply that the economic growth effects may be constrained when technological innovation is not accompanied with the human capital accumulation (through the learning process of workers), which limits the efficient interaction between innovation and human capital.

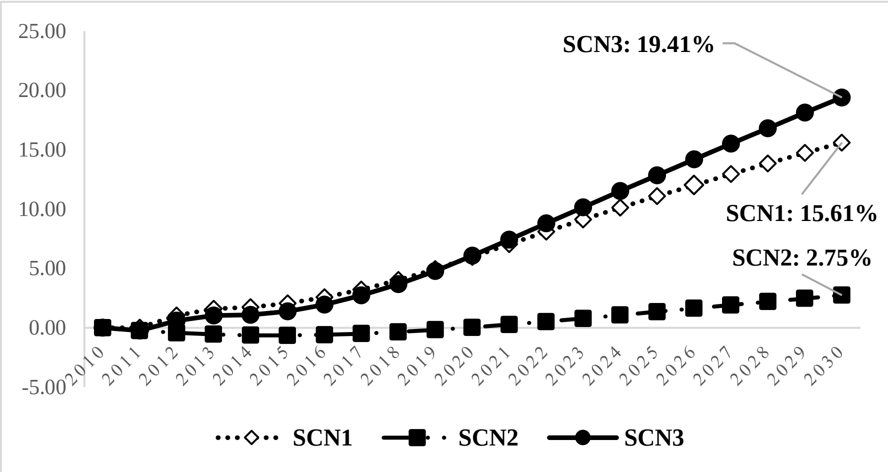


Figure 48. Changes of GDP level (Unit: % change relative to the BAU scenario in 2030)

In addition, Figure 49 shows the changes in the utility of households by income quintile compared to the BAU scenario focusing on the target year 2030. As can be seen from the Figure 49, it is found that the SCN3 scenario shows the highest utility increase in 2030 compared to the BAU level, followed by the SCN1 and SCN2 scenarios. SCN1 results suggest that the increase in R&D investment intensity may lead to increases in the incomes and utility of households based on the scale effects driven by technological innovation. However, it can be seen that the income and utility growth effects in the SCN1 scenario are increased as the income level is higher. On the other hand, it is shown that in the case of the SCN2 scenario, the increase in the household utility is relatively low among the designed policy scenarios.

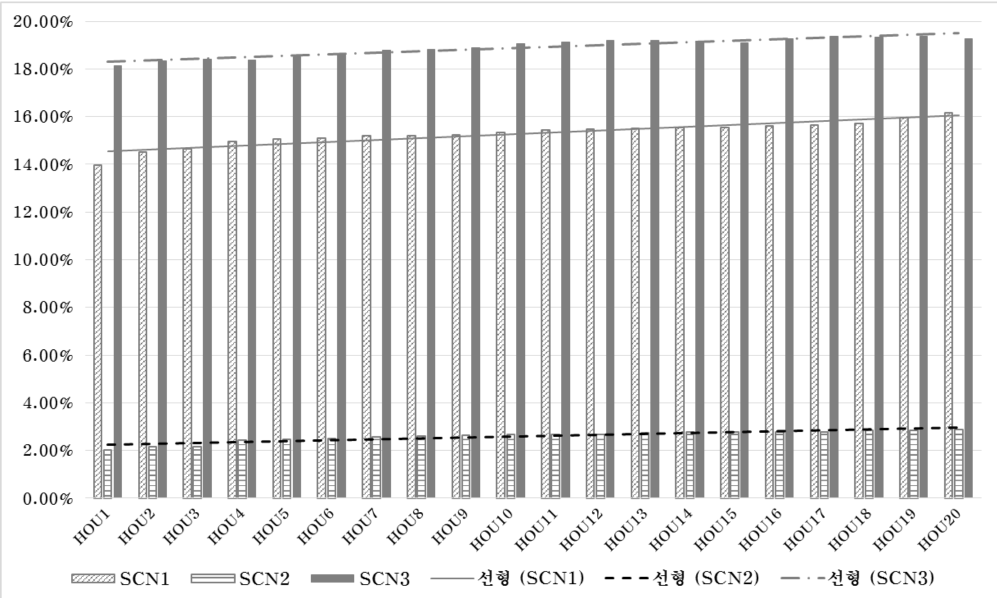
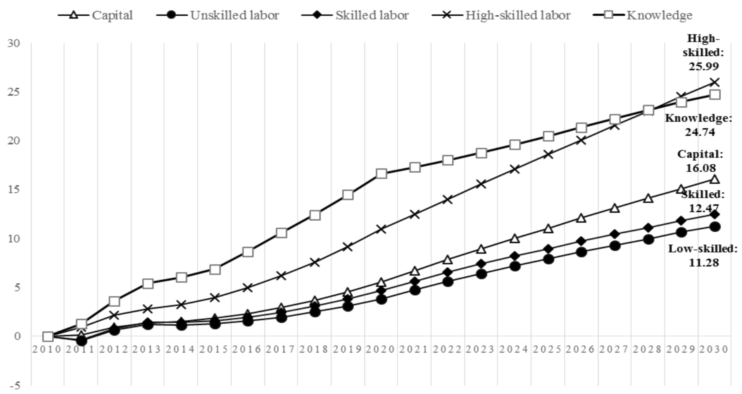


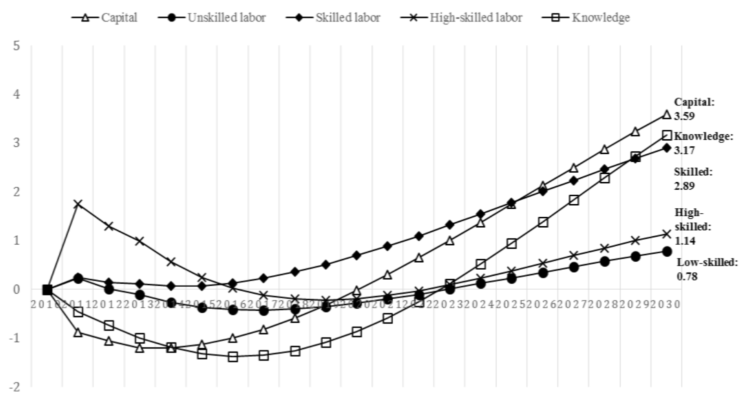
Figure 49. Changes in households' utility for scenarios relative to BAU (Unit: %)

To understand the key determinants and associated impact channels behind the economic growth, we have examined the changes in the composition of value-added appeared in different scenarios. Figure 50 illustrates the comparison of the value-added compositions in industrial sectors for each scenario (SCN1, SCN2, and SCN3) from the base year to the target year. As can be seen from the Figure 50, In the case of SCN2, it can be seen that the increases in the value-added over BAU shows slow trends compared to other scenarios (physical capital: 3.59%, knowledge capital: 3.17%, high-skilled labor: 1.14%, skilled labor: 2.89%, low-skilled labor: 0.78% higher relative to the BAU level in 2030). On the other hand, the dramatic growth effects in the value-added of high-skilled labor, knowledge capital, and physical capital are found in the SCN1 scenario, which can be explained by the complementary relationship among those factor inputs within the production function (physical capital: 16.08%, knowledge capital: 24.74%, high-skilled labor: 25.99%, skilled labor: 12.47%, low-skilled labor: 11.28% higher relative to the BAU level in 2030). The increase in knowledge capital accumulation leads to additional demand for the production factors, based on the complementarity between knowledge, physical capital, and high skilled labor within the production technology.

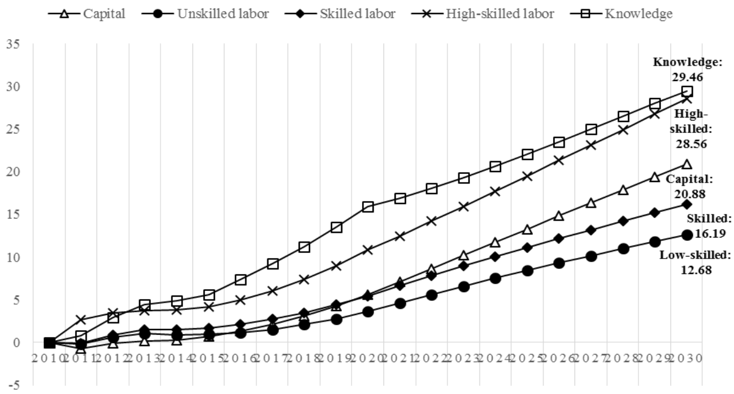
In addition, in the case of the SCN3 scenario, it shows a relatively higher value-added increase compared to the SCN1 scenario, showing the highest value-added growth among policy scenarios (physical capital: 20.88%, knowledge capital: 29.46%, high-skilled labor: 28.56%, skilled labor: 16.19%, low-skilled labor: 12.68% higher relative to the BAU level in 2030). To be specific, it is found that under the SCN3 scenario, the value-added growth effects for the high-skilled labor and knowledge capital are significant compared to other factor inputs. This implies that the improvement and advancement of workers' skills and knowledge through the public sector’s educational investments, and associated changes in labor supply through the human capital accumulation can facilitate the endogenous technological innovation as it enhances the complementarity between knowledge and high-skilled labor. Furthermore, it can be seen that under the SCN3 scenario, the value-added growth effects for the physical capital are also shown to be significant compared to other scenarios. It can be interpreted that as the complementary relation between knowledge and high-skilled labor is enhanced, the factor-biased technological progress (i.e., capital-biased technological change) is accelerated with higher demands for the physical capital.



(a) SCN1 scenario



(b) SCN2 scenario



(c) SCN3 scenario

Figure 50. Changes of the value-added composition compared to BAU level (Unit: %)

In addition, Figure 51 illustrates the growth rates of the value-added of factor inputs by each policy scenario. As can be seen from the Figure 51, it is found that that the growth rates (from 2010 to 2030) of the value-added of knowledge capital, high-skilled labor, and physical capital are the highest among production factors under the SCN3 scenario (value-added growth rates from 2010 to 2030 under the SCN3 scenario: 173.01% for knowledge capital; 107.28% for high-skilled labor; 58.34% for physical capital). Moreover, Figure 52 depicts the absolute level of the gross value-added by scenario type. As can be seen this Figure 52, it is also found that the SCN3 scenario shows the highest value among all scenarios, which is mainly led by value-added growth in knowledge capital, high-skilled labor, and physical capital. It implies the presence of the strong knowledge-capital-skill complementary within the production function under the SCN3 scenario. In this regard, we can understand that the provision of the institutional conditions to promote learning process of workers within the economy combined with the additional R&D investments leads to the enhancement of complementary relationships among knowledge capital, high-skilled labor, and physical capital.

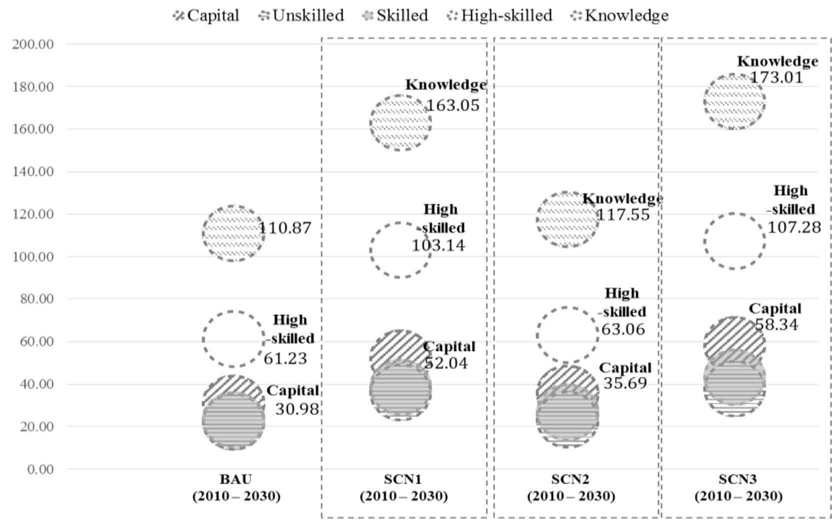


Figure 51. Growth rates of value-added under different scenarios (2010-2030, Unit: %)

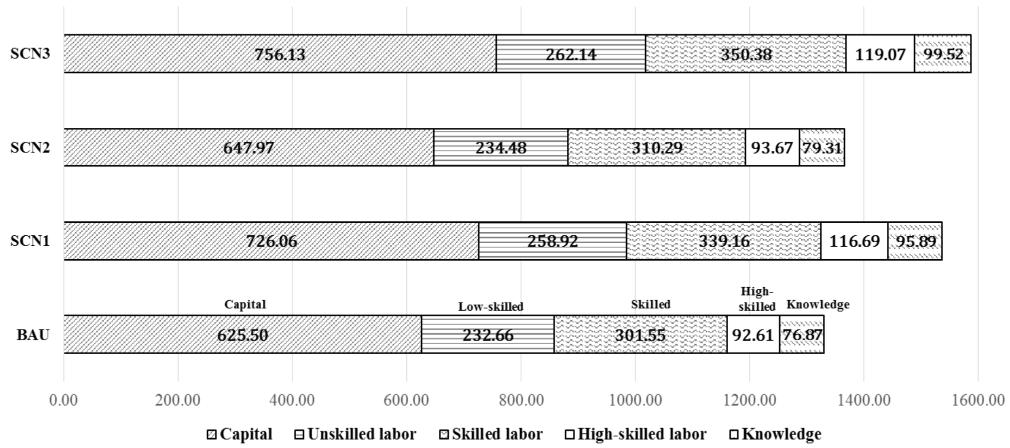


Figure 52. Composition of gross value-added under scenarios in 2030 (Unit: trillion KRW)

Accordingly, we can understand that to spur a higher level of economic growth in the knowledge-based economy, it is essential to consider policy options to facilitate this strong knowledge-capital-skill complementary within the economy. This result suggests that to sustain the long-run economic growth in the knowledge-based economy, with innovation as a key engine of growth, the government should take into considerations of the establishment and provision of sufficient institutional environments for workers to participate in learning activities for workers' human capital accumulation after entry into the labor market. It is noted that considering the intrinsic attributes of the technological progress (i.e., factor-biased technological change), the endogenous complementarity among knowledge capital, high-skilled labor, and physical capital can be accelerated when right and appropriate types of skills (or, knowledge) are built up through the learning process, to adjust to a shift in the skills demand distribution induced by the technological changes. In other words, the educational (and learning) systems provided by the public sector should keep pace with technological change and evolving labor markets. In other words, it is necessary to change the viewpoint that consider the effects of the factor-biased technological change on the labor market in the economic system as opportunities, rather than challenges.

As mentioned above, for the analysis we have considered the progressive income taxation as policy option to address the problems of widening income disparities. To be specific we consider the progressive income taxation, and utilize tax revenues to finance the public expenditure on human capital formation by designing the SCN2 and SCN3 scenarios. If income taxes with the form of progressive structure, which assumes that higher income households are to pay more taxes for education investment spending in the public sector, the tax burdens imposed to households will increase compared to BAU. As a result, the levels of disposable incomes earned by households will change according to the income tax burdens, which will affect the consumption activities of the private sector. In this regard, Figure 53 illustrates the changes of the disposable incomes earned by households under the different scenarios (SCN1, SCN2, and SCN3 scenarios) compared to the BAU scenario. As can be seen in Figure 53, the SCN1 scenario reveals the highest growth in the disposable incomes earned by households. In the case of the SCN3 scenario, on the other hand, the disposable incomes of the households are shown to be relatively low compared to those of SCN1 scenario. However, in the SCN2 scenario, relatively low disposable incomes are formed compared to the SCN1 and SCN3 scenarios.

Such a decrease in household disposable income can be attributed to a decline in consumption activities in the private sector. As depicted by Table 26 which represents the growth rates of private consumption under different scenarios (SCN1, SCN2, and SCN3 scenarios) over the period of analysis (from 2010 to 2030). Table 26 shows that in the case of BAU, the growth rate of private consumption is about 40.36% during the analysis period, while the growth rates of the private consumption for SCN1, SCN2 and SCN3 scenarios are 43.24%, 35.51% and 37.86%, respectively. To be specific, it is found that under the SCN2 scenario, households' disposable incomes (see Figure 53) and private consumption growth rates (see Table 26) are relatively low compared to the BAU level. Nevertheless, the SCN2 scenario has relatively higher economic growth than BAU (see Table 25). This suggests that the expansion of the scale effects driven by the human capital accumulation of workers with the public sector's educational investments offset the effects of income reduction on households (i.e., the effects of private consumption reduction) resulting from the introduction of progressive income taxation.

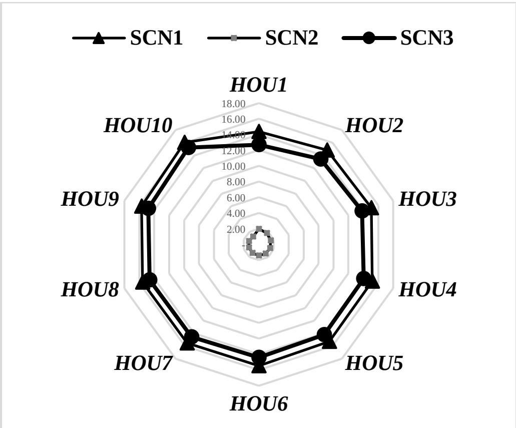


Figure 53. Changes of disposable incomes of households under different scenarios relative to the BAU level (Unit: %)

Table 26. Growth rates of private consumption under scenarios

(Unit: %)

Scenario	Growth rates of private consumption (2010-2030)
BAU	40.36%
SCN1	43.24%
SCN2	35.51%
SCN3	37.86%

This interpretation is also possible for the results of SCN3 scenario. In case of the SCN3 scenario the R&D intensity is set to be 1%p higher than that of the SCN2, while other assumptions in the education and tax policy dimensions are the same. Under the SCN3 scenario, it is found that disposable incomes and consumption levels of households for the SCN3 scenario are relatively low compared to those of SCN1 scenario, in which only R&D intensity is increased by 1%p compared to the BAU scenario. However, in terms of the

GDP growth effects, we can see that SCN3 scenario has a relatively higher growth effects than SCN1. It also suggests that the scale effects through facilitating the knowledge-capital-skill complementarity within the production function based on the endogenous interaction between human capital accumulation and innovation are larger than the income reduction effects of households (i.e., the effects of private consumption reduction) resulting from the introduction of progressive income taxation. Those interpretations can be understood with Figure 54 which contains key impact channels from interaction between innovation and human capital accumulation to the expansion of scale effects, and from progressive income taxation imposed to households to the depression of private consumption.

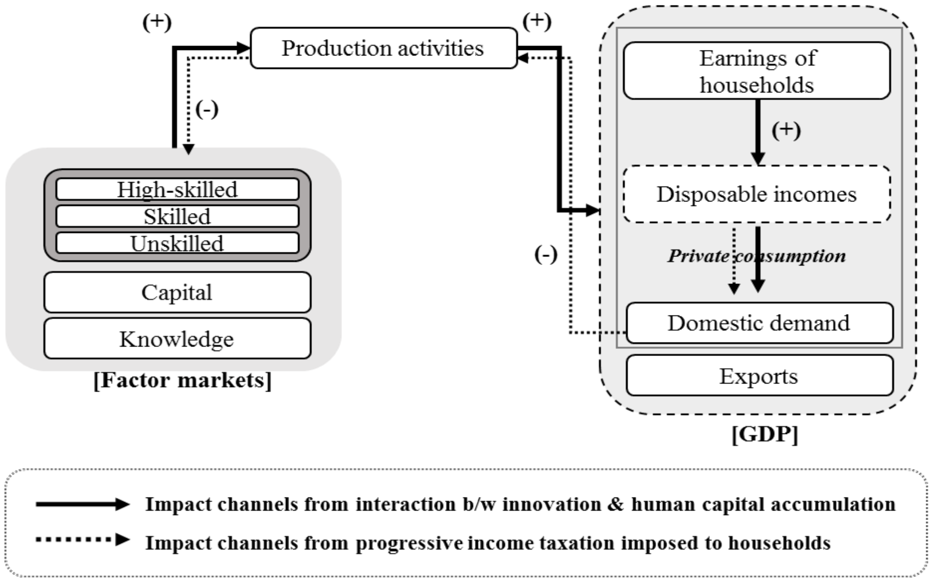


Figure 54. Key impact channels of interaction between innovation and human capital accumulation and progressive income taxation imposed to households

Moreover, we will investigate changes in industrial outputs for each scenario designed in this study. Figure 55 presented below depicts gross industrial outputs under different scenarios. As can be seen in Figure 55, the SCN3 scenario is shown to reveal the highest industrial outputs growth based on the enhanced endogenous interaction between innovation and human capital accumulation, and associated scale effects (gross industrial outputs under the SCN3 scenario: 83.6 trillion KRW for the primary sectors; 1909.1 trillion KRW for the low-tech manufacturing sectors; 1173.2 trillion KRW for the high-tech manufacturing sectors; 1840.8 trillion KRW for the service sectors). In addition, it can be seen that the scale effects (i.e., industrial output growth effects) in the SCN3 scenario are mainly come from the high-tech manufacturing and service sectors.

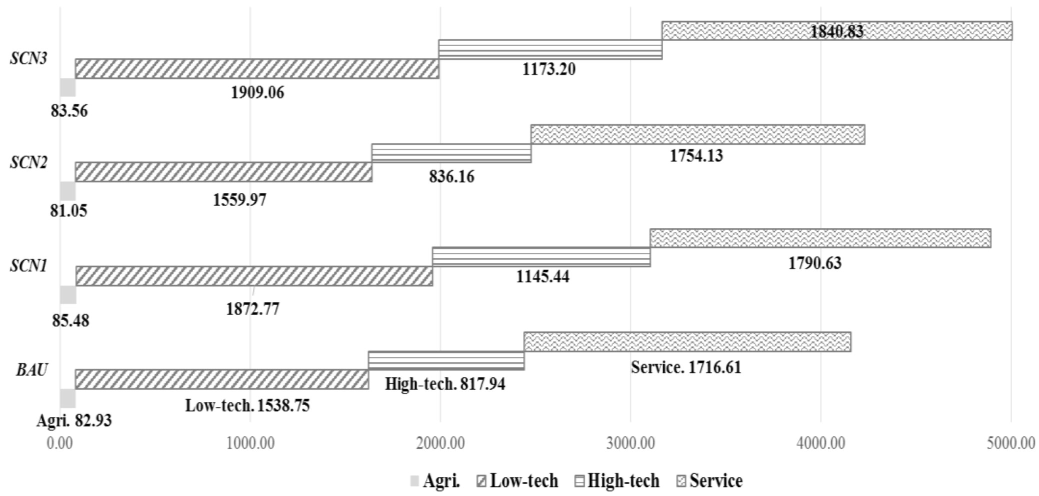


Figure 55. Gross industrial outputs under different scenarios in 2030 (Unit: trillion KRW)

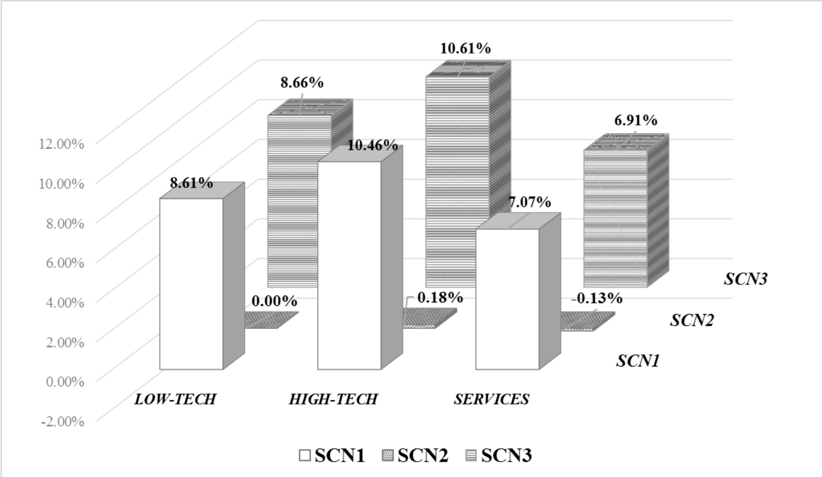


Figure 56. Changes of TFP in industries relative to the BAU in 2030 (Unit: %)

In order to understand the highest level of scale effects and economic growth effects shown in the SCN3 scenario, this study attempt to compare the changes of productivity by industrial sector under different scenarios compared to the BAU. Figure 56 depicts the changes of industry-level TFP generated by policy scenarios relative to the BAU scenario. As mentioned in previous Chapter 5, the change in total factor productivity (TFP) by industry is captured by comparing the value of the value-added composite input coefficients (AVA_i) for each scenario with that in BAU scenario. As shown in Figure 56, it is found that under the SCN3 scenario, the highest level of productivity growth is seen in all industry sectors compared to other scenarios (SCN3: 8.66% higher relative to the BAU level in the low-tech industry, 10.61% higher relative to the BAU level in the high-tech industry, 6.91% higher relative to the BAU level in the service industry; SCN1: 8.61% higher relative to the BAU level in the low-tech industry, 10.46% higher relative to the BAU level in the high-tech industry, 7.07% higher relative to the BAU level in the service industry; SCN2: 0.00% higher relative to the BAU level in the low-tech industry, 0.18% higher relative to the BAU level in the high-tech industry, -0.13% relative to the BAU level in the service industry).

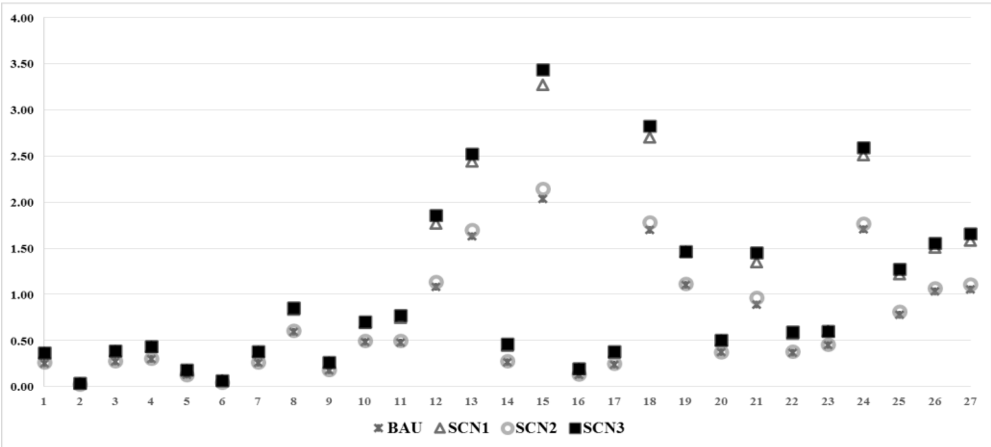


Figure 57. Comparison of $INTINDST$ values for individual sectors for policy scenarios

In particular, it is found that in the case of the SCN3 scenario, productivity increases are relatively higher in the low-tech and high-tech manufacturing industries as compared to the SCN1 scenario. This supports the finding that the increases in the industrial outputs and the scale effects are relatively high in the SCN3 compared to the SCN1, while the private consumption levels of households are relatively low in the SCN3 scenario compared to the SCN1. In other words, it can be understood that the SCN3 scenario has relatively high productivity growth effects in the industry as a whole, thereby facilitating the industrial output growth effects compared to the SCN1 scenario. This argument is supported by

Figure 57 which illustrates the comparison of the variable $INTINDST_i$ representing the level of knowledge spillover effects from other industries to individual sectors. As can be seen in Figure 57, we can understand that under the SCN3 scenario, the knowledge spillover effects (i.e., positive externalities from the knowledge capital accumulation) appear to be higher than other policy scenarios (i.e., SCN1 and SCN2 scenarios).

6.3.2 Effects on employment structure

This subsection provides key results on how changes in the employment and wage structures appear in in different scenarios. Table 27 illustrates the rate of changes in the aggregate employment level 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. As can be seen in Table 27, it is understood that all constructed policy scenarios from SCN1 to SCN3 show higher levels of total employment compared to the BAU level. Table 27 also reveals that the total employment level grows the most (45.83% increase from 2010 to 2030; 21.04% higher relative to the BAU in 2030) under the SCN3 scenario, followed by SCN1 (18.26% higher relative to the BAU in 2030), and SCN2 (5.63% higher relative to the BAU in 2030) scenarios.

Table 27. Changes of the aggregate labor demand under different scenarios (Unit: %)

	BAU	SCN1	SCN2	SCN3
Total employment change (%) (between 2010 and 2030)	22.72%	45.12%	29.62%	48.53%

Total employment in 2030 (% change relative to the BAU)	-	18.26%	5.63%	21.04%

A higher employment level (18.26% higher relative to the BAU in 2030) found in the SCN1 scenario suggests that higher levels of innovation activities through the increases of the R&D investments can create more jobs, which can offset the destructive impacts of technological progress on the labor market via the factor-biased technological progress. In addition, it is found that the SCN2 scenario in which the efficient skill accumulation of workers is considered through the public sector's educational investments financed by the progressive income taxation reveals the lowest employment growth effects (5.63% higher relative to the BAU in 2030). Furthermore, the highest employment growth is found to be achieved by the SCN3 scenario, in which the policy package consisting of the innovation, education, and tax policies (21.04% higher relative to the BAU in 2030).

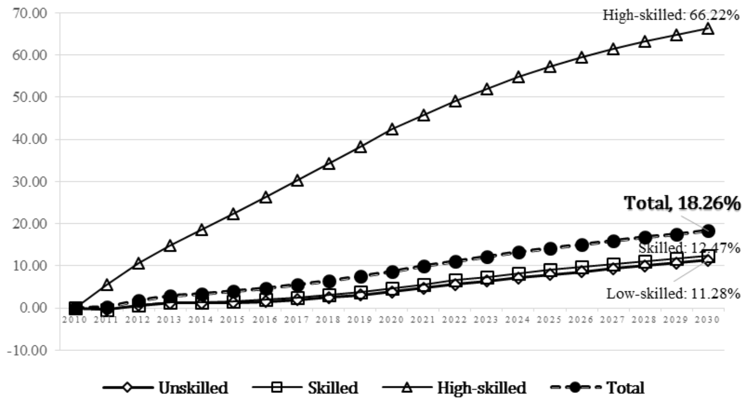
Table 28. Changes of employment level by skill type relative to the BAU in 2030 (Unit: %)

	SCN1	SCN2	SCN3
Low-skilled labor	11.28%	0.78%	12.67%
Skilled labor	12.47%	2.90%	16.19%
High-skilled labor	66.22%	33.43%	69.61%

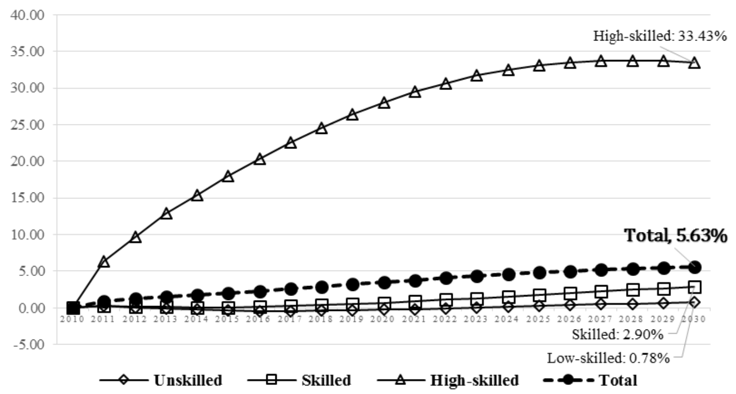
The difference in results between SCN2 and SCN3 suggests the importance of matching the supply of skilled labor (through education and learning process of workers) and the corresponding increase in demand for skilled labor with the increase of innovation activities (through additional R&D investments). Establishment and provision of sufficient institutional environments to promote workers' engagement in learning process (skill accumulation) through educational investments in the public sector serve as a crucial policy instrument to mitigate the destructive impacts of technological progress on the labor market via the factor-biased technological progress. However, unless technological innovation which triggers the demand for high-skilled workers is accompanied with the educational investments to facilitate the learning process of workers, the employment growth effects may be low as shown in the results of the SCN2 scenario. If this phenomenon continues, it may lead to oversupply of high-skilled workforce, leading to the skill mismatch in the economy. This argument can be confirmed by the employment level difference between SCN2 and SCN3 scenarios.

In addition, by comparing the employment growth effects found in SCN1 and SCN2 scenarios we can understand that to maximize the employment growth effects in the knowledge-based economy, it is essential to consider how to facilitate the endogenous interaction between skills demand through promoting the innovation activities with the increase of the R&D investments, and skills supply through providing sufficient institutional environments to promote workers' engagement in learning process. In this regard, it is highlighted that 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, these results address that the educational system should keep pace with technological change and evolving labor markets. In other words, synergies between the evolution of labor demand triggered by innovation and the adaptability of labor supply from education and learning should come together.

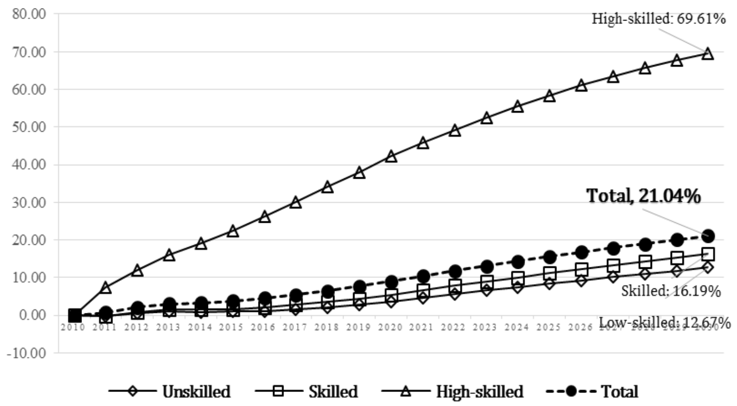
To be specific, when examining the changes of employment by skill type for policy scenarios compared to BAU as shown in Table 27 and Figure 58, we can see that the employment growth effects of high-skilled labor are relatively greater than those of skilled and low-skilled labor. It is found that under the SCN1 and SCN3 scenarios where the additional R&D investments are made (1%p higher R&D intensity relative to BAU), that employment growth effects for high-skilled workers are more sensitive to changes in R&D intensity than for other types of workers (SCN1: 66.22% higher employment level for high-skilled labor in 2030; SCN3: 69.61% higher employment level for high-skilled labor in 2030). Higher sensitivity of high-skilled labor to variations in R&D investments implies a strong linkage between the innovation and the degree of skill-bias in technological progress. In addition, the increase in innovation activities further requires a higher demand for high-skilled labor, and this skill-biased technological progress can be accelerated through the skill accumulation of workers and associated changes in labor supply. This can be understood from the fact that the employment level for high-skilled workers is higher in SCN3 compared to SCN1. On the other hand, under the SCN2 scenario, employment growth effects for all types of labor are found to be relatively low compared to others (high-skilled: 33.43%, skilled: 2.90%, low-skilled labor: 0.73% higher than BAU levels in 2030).



(a) SCN1 scenario

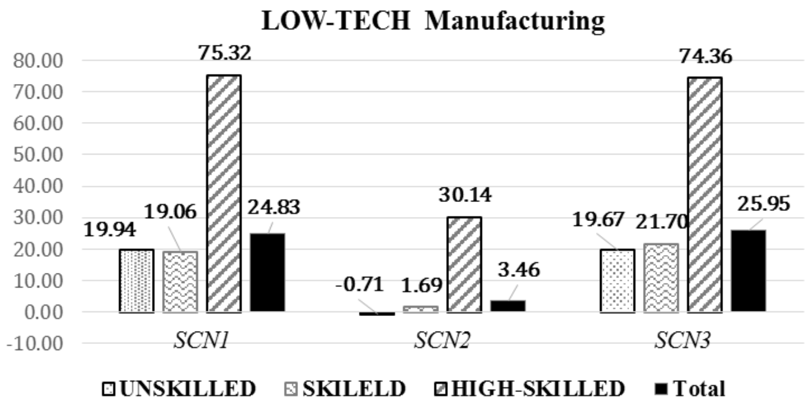


(b) SCN2 scenario

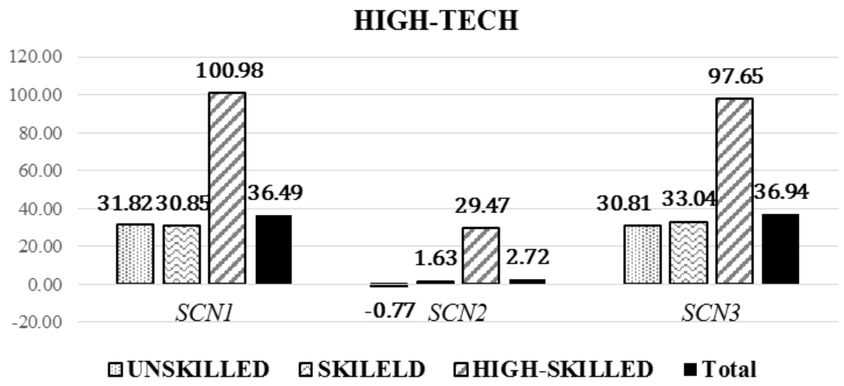


(c) SCN3 scenario

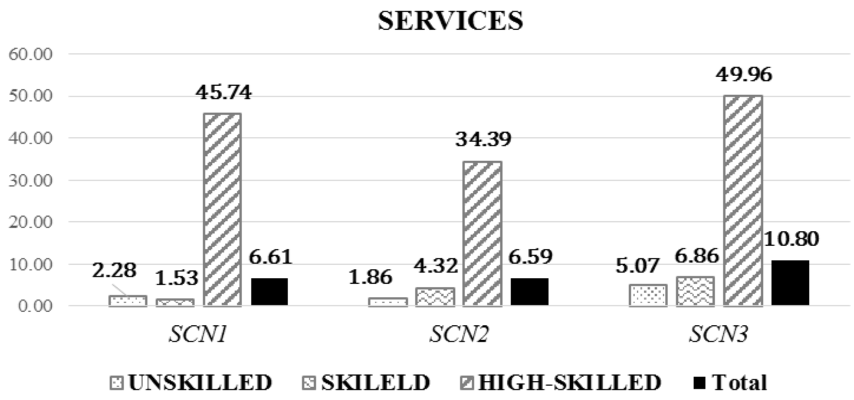
Figure 58. Changes of the employment level by skill type compared to BAU (Unit: %)



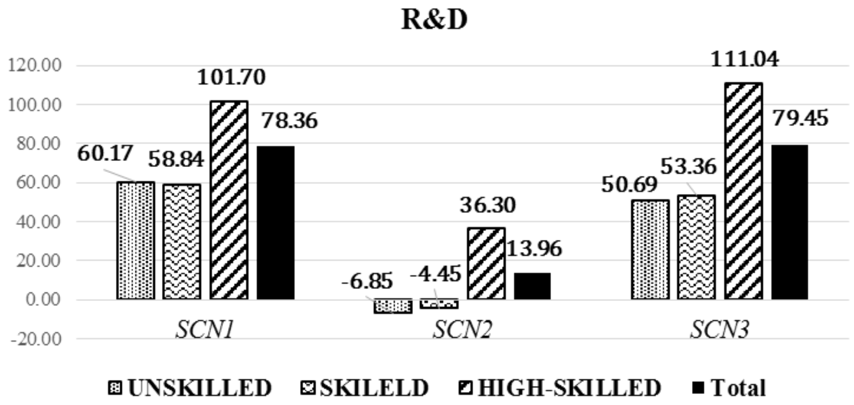
(a) Low-tech manufacturing industry



(b) High-tech manufacturing industry



(c) Service industry



(d) R&D industry

Figure 59. Changes of the employment level by industry compared to BAU (Unit: %)

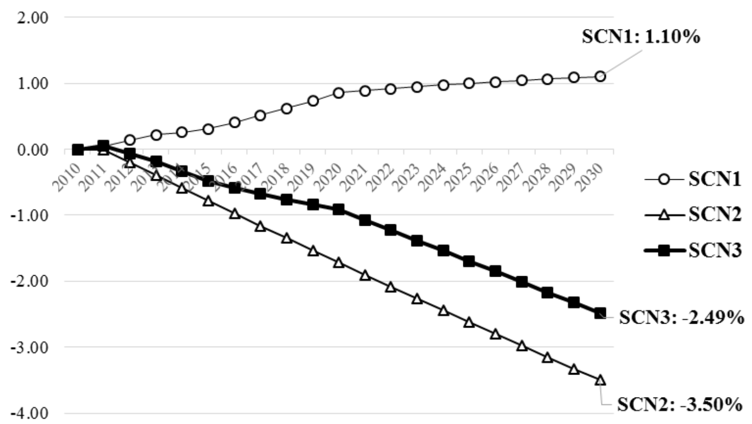
In addition, Figure 59 shows the changes of total employment levels by industry. As shown in Figure 59, it is found that under the SCN3 scenario, there are significant increases in total employment levels across industries (low tech manufacturing sector: 25.59%, high-tech manufacturing sector: 36.94%, service sector: 10.80%, R&D sector: 79.45% higher than the BAU levels in 2030). Especially, the SCN3 scenario shows the significant increases in the total employment levels of the knowledge- and innovation-intensive industries, such as high-tech manufacturing and R&D sectors. In addition, it is found that those industries triggers higher demands for high-skilled labor (the employment levels of the high-skilled labor under the SCN3 scenario: 97.65% higher relative to the BAU level in high-tech manufacturing sectors; 111.04% higher relative to the BAU level in R&D sectors). Accordingly, it can be understood that the highest employment growth effects under the SCN3 scenario are mainly led by knowledge-intensive industries. It also implies that the policy package consisting of innovation, education, and tax policy instruments with the consideration of the endogenous interaction between innovation and human capital accumulation can facilitate a transition of the economy toward knowledge- and innovation-intensive industries by expanding employment levels in high-tech and R&D industries.

6.3.3 Effects on income distribution

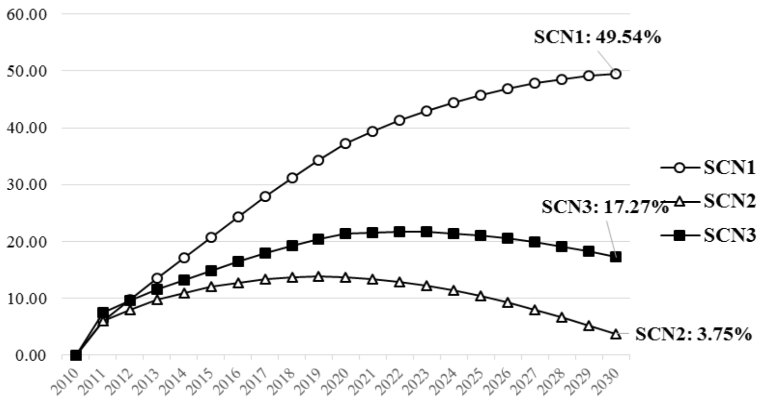
In this subsection, we will examine the changes in key indicators associated with income distribution under different policy scenarios. Based on this results analysis, we are to draw policy implications on the role of policy package to spur the inclusiveness of the economic growth. As mentioned above, the intrinsic properties of technological progress can be summarized as labor-saving and skill-biased, which has the potentials to deepen social inequalities and polarization by increasing economic returns to high-skilled workers and capitalists in the economic system. The concept of the skill-biased technological progress suggests that the complementarity between capital and skills (or, between technology and skills) leads to an increase in the wage gap between high skilled workers and relatively low skilled workers. On the other hand, the capital-biased (or, labor-saving) technological change from innovation implies the higher level of technological unemployment and declines in the labor incomes within the economy.

In this regard, we have examined the changes in the relative wages of workers by policy scenario compared to the BAU scenario as shown in Figure 60. Figure 60 illustrates changes of skill premium, which is calculated as the ratio of the wages of either skilled

(PL2) to low-skilled labor (PL1) (Figure 60(a)), or high-skilled (PL3) to low-skilled labor (PL1) (Figure 60(b)), compared to those values in BAU scenario. From the results analysis, it is found that the SCN1 scenario with the increase of the R&D intensity (not considering the education and tax policy within the policy scenario) shows steady increases in skill premiums for high-skilled and skilled labor.



(a) Skill premium for skilled labor (ratio of the wages of skilled to low-skilled)

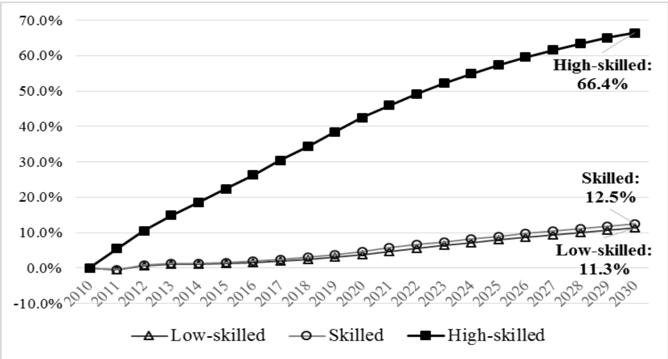


(b) Skill premium for high-skilled labor (ratio of the wages of high-skilled to low-skilled)

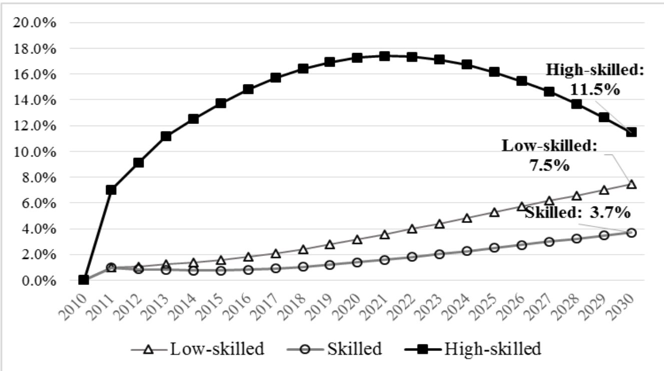
Figure 60. Changes of skill premium relative to the BAU scenario (Unit: %)

It is found that, under the SCN1 scenario, the skill premium for high-skilled labor dramatically increases (49.54% higher relative to the BAU level in 2030). This result suggests that technological innovation that lead to skill-biased technological progress further widen the wage gaps among workers, further supporting the widening of income inequality. However, it is shown that SCN2 and SCN3 scenarios have significantly reduced skill premiums compared to the SCN1 scenario. In particular, it is remarkable that skill premiums in the SCN3 scenario have decreased considerably compared to the SCN1 scenario, even though the exogenous variants in the R&D intensity are same as the SCN1 scenario (skill premiums for high skilled workers: SCN1 (49.54%) > SCN3 (17.27%)). Accordingly, those results imply that the policy-mix consisting of educational investments to spur the learning process of workers (i.e., education policy), and progressive income taxation (i.e., tax policy) can play a role in mitigating the structural problems caused by the factor-biased technological change.

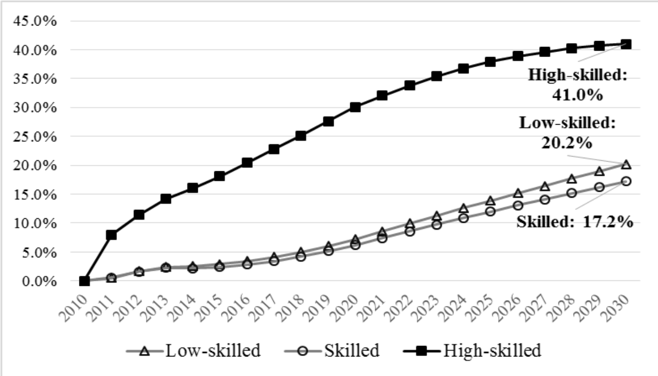
The changes in the relative wages of workers by the policy scenario compared to the BAU scenario can also be understood from the results of changes in wage rates of different types of labor for policy scenarios relative to BAU as shown in Figure 61. As illustrated by Figure 61, it is shown that for the SCN1 scenario the growth rates of wages for high-skilled and skilled workers are relatively larger than that of low-skilled workers (high-skilled labor: 66.4% higher than the BAU level; skilled labor: 12.5% higher than the BAU level; low-skilled labor: 11.3% higher than the BAU level in 2030). It is strongly associated with the highest levels of skill premiums found in the SCN1 scenario. In SCN2 scenario, it is shown that the wages of high-skilled workers are about 11.5% lower than that of BAU in 2030, while the wages of low-skilled and skilled workers are about 7.5% and 3.7% higher than those of BAU. This explains the lowest decreases in the skill premiums for the high-skilled and skilled labor in the SCN2 scenario. In addition, under the SCN3 scenario, it is found that the wages of high-skilled workers are about 41.0% higher than that of BAU in 2030, while the wages of low-skilled and skilled workers are about 20.2% and 17.2% higher than those of BAU. This explains the decreases in the skill premiums for the high-skilled and skilled labor in the SCN3 scenario.



(a) SCN1 scenario



(b) SCN2 scenario



(c) SCN3 scenario

Figure 61. Wage rates of different types of labor for scenarios relative to BAU (Unit: %)

Furthermore, the values for the standard deviation of personal incomes (SDPI) are calculated for constructed policy scenarios to examine the changes in income distribution, as shown in Table 29. As depicted by Table 29, the SCN1 scenario shows the highest level of the SDPI among policy scenarios (SCN1: 57.64 in terms of SDPI), which implies that the degree of the income inequality is the greatest with higher concentrations of incomes. It suggests that deepening of income inequalities and income polarization is resulted from the factor-biased technological change, as it allocates higher returns to high-skilled workers and capitalists in the economic system. However, as shown in Figure 60 and Table 29, it is found that the SCN3 scenario has the possibility to solve the widening of wage incomes, and the deepening of income polarization compared to the SCN1 scenario (SCN1: 57.64 in terms of SDPI; SCN3: 55.48 in terms of SDPI), while it achieves higher economic growth than SCN1 scenario.

Table 29. Comparison of standard deviation of personal incomes (SDPI) in 2030

	BAU	SCN1	SCN2	SCN3
SDPI	49.63	57.64	49.04	55.48

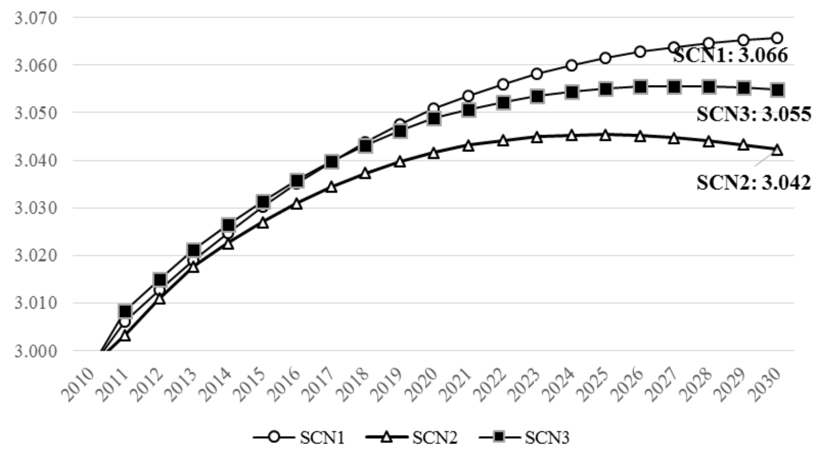


Figure 62. The decile distribution ratio under different scenarios

Furthermore, to analyze the income distribution structure across all households, the concept of the decile distribution ratio is utilized. The decile distribution ratio can be calculated as the relative share of the top 20% in relation to the share of the bottom 40% in terms of the income levels. Figure 62 illustrates the values of the decile distribution ratio for different policy scenarios. As depicted by Figure 62, the SCN1 scenario shows the highest level of the decile distribution ratio, while SCN3 scenario shows relatively low level compared to the SCN1 scenario (SCN1: 3.066 in terms of decile distribution ratio; SCN3: 3.055 in terms of decile distribution ratio). Those results suggest that the policy package proposed in the form of the SCN3 scenario has the potentials to serve as a policy option to achieve growth and distribution together to spur the inclusive growth in a knowledge-based economy. Furthermore, based on the CGE analysis, it is found that the progressive income taxation plays a role in moderating the degree of the income equality driven by the complementarity between knowledge and skills with the results of the SCN2 and SCN3 scenarios. Based on those results, it is found that the policy package proposed in this study can drive the inclusiveness of the economic growth in the knowledge-based economy, which consists of following three dimensions of policy areas; 1) *innovation policy*: increasing R&D investments to spur innovation activities, 2) *education policy:* encouraging workers to promote re-training or up-skilling enabling them to keep their competences in quickly adjusting to the rapid technological changes through increasing educational investments, and 3) *tax policy*: reforming the tax system by introducing progressive income taxation.

6.4 Sub-conclusion

Recently, advanced countries, including Korea, have proposed a wide range of policies, including job creation policies, to address negative impacts from technological innovation, noting that one of main underlying causes of jobless growth and the expansion of income inequality is factor-biased technological changes from innovation. Previous studies address that income inequalities are one of the most pressing challenges facing by developing and developed countries. Through policy interventions, each country intends to promote inclusive growth and sustainable growth of the knowledge-based economy. The concept of “inclusive growth” refers to sustained economic growth while at the same time improving access to opportunities for all population segments, and distributing the dividends of increased prosperity across (groups of) individuals. As a result, policy makers are faced with the question of how to intervene in the market in order to deal with the deepening of job polarization, income disparities in the knowledge-based economy where technological innovation is a main source of growth. In this regard, countries are increasingly showing interests in implementing “inclusive innovation policies” – a specific set of innovation policies that aim to boost the innovation capacities and opportunities of individuals and social groups that are underrepresented in innovation activities. 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 a single policy instrument. In this spirit, we advocate that innovation policies should be accompanied by other complementary policies in order to counterbalance the negative impacts of factor-biased technological progress. The question is then how to formulate and coordinate policy options from various dimensions to achieve inclusive growth in the knowledge-based economy.

Existing studies, however, often fall short of reflecting the concept of policy mixes, and seem insufficient to draw policy implications in practical senses. A variety of policy suggestions proposed by previous studies are rather fragmented, and mostly limited to a specific (single) policy instrument. In this regard, the policy options to facilitate inclusive growth having been proposed so far largely are found to focus on how to mitigate the “direct impacts of technological innovation” on employment structure and income distribution. In addition, there has been a lack of quantitative analysis of those policy suggestions to draw upon policy implications to mitigate the negative impacts of technological innovation. In other words, policy options proposed from this perspective have not deeply considered compensation mechanisms which could counterbalance direct employment impacts of technological change. Accordingly, those policy suggestions are lack of considerations on how this substitution effects of workers interact with scale effects generated by technological innovation.

Therefore, policy suggestions must be designed from a dynamic, and economy-wide perspective in order to fundamentally address the structural problems (i.e., technological unemployment and widening income inequality) of the knowledge-based economy. In other words, it is essential to consider how to accelerate the technological progress driven by factor-biased technological change, and reduce adverse effects caused by technological innovation by taking into account the process of endogenously determined technological innovation interacting with market- and policy-related variables. Policy suggestions derived from this perspective can provide an integrated framework on the issues of innovation, growth, and distribution. Considering these limitations of previous studies, this study has proposed a conceptual framework to investigate the economy-wide impacts of factor-biased technological change and the role of policy packages to deal with this issue, by addressing the limitations of previous studies’ approaches. Based on this conceptual framework, this study has conducted a CGE analysis to quantitatively assess the macroeconomic impacts of policy packages consisting of innovation, education, and taxation policies to mitigate the structural problems caused by the factor-biased technological change from a dynamic, and economy-wide perspective. For the analysis, we have utilized the constructed knowledge-based CGE model presented in Chapter 4, and examined the potential role of the policy packages consisting of three different policy areas based on the policy experiments; 1) *innovation policy*: increasing R&D investments to spur innovation activities, 2) *education policy:* encouraging workers to promote re-training or up-skilling enabling them to keep their competences in quickly adjusting to the rapid technological changes through increasing educational investments, and 3) *tax policy*: reforming the tax system by introducing progressive income taxation. The main findings and implications of this study can be summarized as follows.

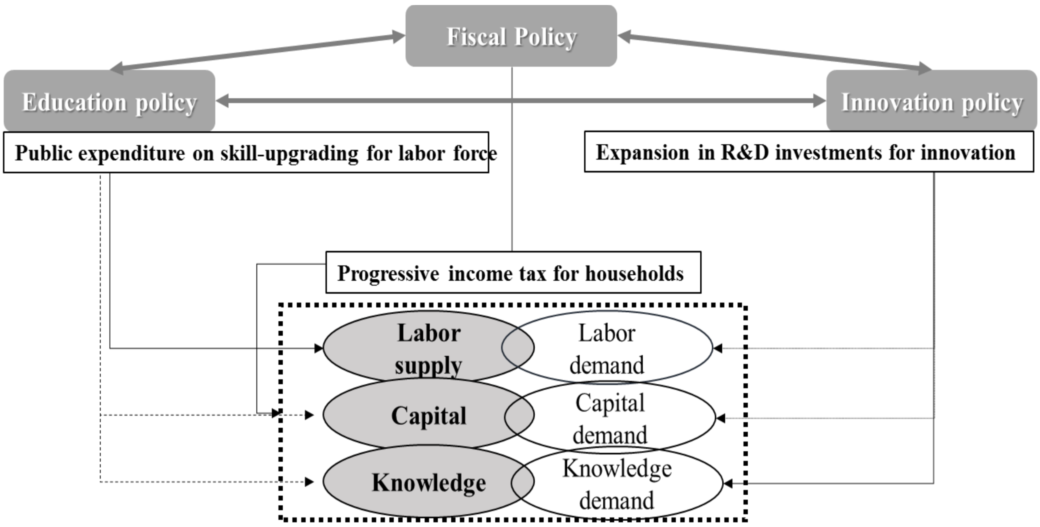


Figure 63. Main findings drawn from the study

In order for technology innovation to continue to function as a growth engine in the knowledge-based economy, it is necessary to accelerate the economic growth driven by the factor-biased technological change. Although the majority of studies regard element-oriented technological advances as challenges, it can be used as opportunities for growth if we understand the underlying principles of endogenous interaction between innovation and human capital accumulation. From this perspective, it is highlighted that the innovation policy should be designed and formulated oriented towards how to facilitate the endogenous interaction between innovation and human capital, and enhance the complementarity among knowledge, high-skilled labor, and physical capital within the production technology. In this regard, it is important for the public sector (government) to elaborate the education policy, not focusing on providing formal education, but also providing institutional conditions for human capital accumulation of the workers. 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 to facilitate the endogenous interaction between skills demand through promoting the innovation activities, and skills supply through providing sufficient institutional environments to promote workers' engagement in learning process. Our analysis results also suggest that synergies between the evolution of labor demand triggered by innovation and the adaptability of labor supply from education and learning should come together to solve the structural problems appeared in the knowledge-based economy (such as, skill mismatch and structural unemployment). Therefore, the government should take into account how to provide market signals to workers within the economy to promote their learning process (skill accumulation), and establish institutional conditions to facilitate skill accumulation.

In addition, this study has found that the introduction of the progressive income taxation affects the disposable incomes of households, and their consumption activities. Furthermore, based on the CGE analysis, it is found that the progressive income taxation plays a role in moderating the degree of the income equality driven by the complementarity between knowledge and skills. Those results suggest that careful consideration of how to design tax policies is needed so that tax policies do not undermine the complementarity between innovation and education policies. In summary, based on the CGE analysis we have found that the policy package proposed consisting of different policy areas (innovation, education, and tax policies) has the potentials to serve as a policy option to achieve growth and distribution together to spur the inclusive growth in a knowledge-based economy. Based on this empirical study, it is also highlighted that there should be policy design and implementation of the innovation policy, based on the understanding of the dynamically changing complementarity between technological innovation and human capital, and its linkages with other institutional components within the economy to achieve the inclusive and sustainable growth in the knowledge-based economy. Our study is significant, in that it is devoted to a macroeconomic analysis in investigating the impacts of different types of policy mixes, and drawing upon policy implications addressing the complementarity of policy instruments. Ultimately, this study expects to shed light on the importance of the policy packages in resolving the side effects of factor-biased technological progress and spur the inclusive growth in the knowledge-based economy.

Chapter 7. Conclusions and Discussions

7.1 Summary and policy implications

The focus on technological innovation and the role of human capital as the key determinants of the long-term growth of the economy began with the endogenous growth theory. Further, various studies that have attempted to explain the long-term growth of the economy emphasized the economic growth driven by an effective combination of human capital accumulation and innovation. These studies stressed that the changes in the dynamic complementarity between human capital accumulation and technological progress affect the economic growth trajectory, and highlighted that the contribution of human capital composition can vary according to the technological level of the economy (i.e., proximity to the technological frontier level). To analyze the growth effects driven by the combination of innovation and human capital under these perspectives, earlier studies have attempted to analyze the nexus between technological progress, human capital accumulation, and long-run economic growth focusing on the level effects of the human capital accumulation. In recent years the discussion moved towards the composition effects of human capital accumulation considering the heterogeneous human capital with different properties and marginal products is central. In discussing the role of human capital composition in the dynamic interaction between innovation and human capital accumulation, various studies emphasized the intrinsic characteristics of technological innovation, which can be described as factor-biased technological progress. These studies that focused on factor-biased technological progress expanded their scope of discussions towards the distribution effects, as well as the growth effects via productivity improvements through an endogenous interaction between technological innovation and human capital.

Skill-biased technological progress can be described as the intrinsic attribute of innovation provides implications for the dynamic changes in the distribution of technology and the demand for skills within the economy driven by innovation. In other words, changes in the demand for labor and skills induced by technological innovation emphasize the importance of labor supply and relevant human capital accumulation that can be adjusted appropriately according to the speed and direction of technological progress, addressing the co-evolution of the demand and supply of skills. In addition, recent studies have theoretically and empirically investigated that innovation not only causes skill-biased technological progress but also capital-biased (or, labor-saving) technological progress. This capital-biased technological progress concept suggests that innovation can possibly have uneven effects on the marginal productivity of capital and labor, leading to a decrease in the proportion of labor income in the economy. Recent studies have pointed out that the inherent nature of technological innovation is one of the underlying causes for structural unemployment and income inequality.

These interrelations between innovation and human capital shape the patterns of long-term economic growth and distribution. Further, as a result of the interrelationship between technological innovation and human capital, there is a potential conflict between growth and distribution within the economy when considering the intrinsic attributes of technological progress, which can be described as factor-biased technical change. Therefore, it is important to investigate what type of policy design and implementation can be used to achieve both objectives of growth and distribution within a knowledge-based economy. Furthermore, policy design needs to be pursued with comprehensive and structural approaches, given that economic growth and distribution are the outcomes of complex interactions among the many institutional sectors within the economic system. Thus, in the knowledge-based economy, where the dynamic interaction between technological innovation and human capital compositions defines growth and distribution patterns, evidence-based innovation policy design is required through empirically testing of the policy impact assessments considering the endogenous interaction between innovation and human capital accumulation and its economy-wide impacts through various direct and indirect paths.

Presuming that the dynamic interaction between innovation and human capital composition is an endogenous process in the economy, this study designed and proposed a macroeconomic CGE model where the interactions between innovation and human capital accumulation are determined endogenously. Through this methodology, this study tries to identify the effects of economic growth and distribution through various policy experiments that can possibly affect the interaction between technological innovation and human capital. The key findings and results of this study are summarized as follows.

In Chapter 2, we present the theoretical background of this study and try to summarize the key findings of relevant theoretical and empirical studies. Through this, this study aimed to promote understandings of the key concepts to be discussed in this study, by addressing that interaction between innovation and human capital is an important determinant of economic growth and distribution, and this interaction is an endogenous process within the national economy by providing key findings of relevant studies. To this end, this study conducted a comprehensive review on previous studies which focus on the contributions of innovation and human capital to economic growth, endogenous interaction between innovation and human capital composition, and impacts of dynamic interaction between the innovation and human capital composition on the labor market and income distribution. In addition, this study reviewed on the previous empirical studies which have utilized the CGE models and methodological approaches covered by those previous studies to highlight the contribution of this study in terms of the methodological development for the policy impact assessments.

In Chapter 3, we have conducted the SAM-based multiplier analysis based on the knowledge-based SAM constructed in this study. Based on the SAM multiplier analysis, this study has tried to investigate the relationship between innovation, labor market, and income distribution focusing on Korean economy to verify the stylized facts proposed in the previous studies. With this research objective, we have proposed methods and procedures to construct a knowledge-based SAM data used in this study, provided descriptions on the methodological principles of the SAM-based multiplier analysis. Based on these methodological settings, this study have conducted a SAM multiplier analysis to identify how the increased innovation activities in the economic system with additional R&D investments would affect the industrial outputs, value-added composition, and income distribution via multiplier effects and relevant direct and indirect paths within the national economy, by comparing with the scenario of increasing physical capital investment with the same amounts. Based on the key findings of the SAM multiplier analysis in this study, it is found that in the case of the Korean economy, technological innovation represented by R&D investment can lead to increases in output and gross income growth, but may could have a negative impacts on income distribution in the economic system by further inducing relative demand for high-skilled labor and physical capital. This study suggests that the Korean economic structure has an inherent possibility that leads to skill-biased and capital-biased technological progress by creating differential demand among the factors of production in the factor inputs market when there is an expansion of technological innovation through additional R&D investments.

In Chapter 4, we have presented the main characteristics of the CGE model constructed in this study including the descriptions on key components and structures of the model with the relevant key equations. In particular, as mentioned above this study has tried to embrace the economic intuition that dynamic endogenous interaction between innovation and human capital accumulation shape the patterns of growth and distribution of the national economy, and reflect this perspective into the development of CGE model. We have also put emphasis on the following key elements and components which are reflected in the developed CGE model when providing descriptions on the key features of the model in Chapter 4: 1) endogenizing the innovation-related elements considering the characteristics of innovation and knowledge (including, consideration of knowledge as a factor of production, endogenization of knowledge capital investments, and consideration of spillover effects coming from the knowledge accumulation via productivity improvements), 2) endogenizing the decision making process of labor on the human capital accumulation (i.e., up-skilling and re-training) affected by the relative wages of workers and educational investments within the economy, 3) designing the endogenous interaction between the knowledge capital accumulation (i.e., innovation) and human capital accumulation within the production function, 4) describing the intrinsic attributes of technological progress within the production structures, and 5) establishing the macroeconomic model to simultaneously estimate the growth and distribution effects with considerations of heterogeneous labor and households within the equational systems and datasets (i.e, SAM). Through this, we have tried to highlight that constructed CGE model in this study is a suitable model for analyzing growth and distribution effects induced by the endogenous interaction between the innovation and human capital accumulation, which can be used as a methodological tool for the innovation policy impact assessments.

In Chapter 5, we have conducted a quantitative analysis on how the long-run economic growth can be achieved through the endogenous interaction between innovation and human capital accumulation via R&D investments and educational investments within the economy based on the constructed knowledge-based CGE model. In particular, this study attempted to investigate and understand the direct and indirect paths within the national economy driven by the endogenous complementarity between the innovation (i.e., R&D

investments) and human capital accumulation (i.e., educational investments) which shape the growth patterns of the economy. To be specific, we have tried to analyze the effects of the human capital accumulation through the endogenous skill upgrading of workers on the innovation activities, as well as the effects of the knowledge capital accumulation through R&D investments on the human capital accumulation in quantitative manners. Based on the policy simulation of the CGE model, it is found that the policy limited to the quantitative expansion of R&D investment could have the possibility to constrain long-run productivity improvements through facilitating the polarization of the labor markets, and the concentration of the industrial structure and wage structure. We have found that long-run productivity growth is indispensable for long-run economic growth, and it is important to form efficient and effective complementarity between the R&D investments and human capital accumulation to drive long-run productivity improvements within the economy. In summary, based on this quantitative analysis, we confirm the complementary relationship between R&D and educational investments and conclude that increasing the inter-dependence between technological innovation through R&D investments and human capital accumulation through investments to facilitate learning in workers can be crucial in enhancing national competitiveness. In addition, we found out that to sustain the knowledge-based economy, with innovation as the 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 addition, in Chapter 6 we have presented the recent discussions on innovation and its impacts on the labor market and income distribution, including the polarization of the labor market and widening income inequality driven by the factor-biased technological progress. Based on those discussions addressed by previous literature, this study has proposed the form of policy-mix consisting of innovation, education, and tax policy, and conducted policy simulations with constructed policy scenarios to draw policy implications on policy design to mitigate the side-effects of technological progress (i.e., polarization of the labor market and widening income inequality). Through this, we have tried to quantitatively analyze the macroeconomic effects of policy options in terms of growth and distribution effects, considering the interaction mechanisms between innovation, education, and tax policy. Especially, based on the quantitative analysis we have tried to point out the limitations of previous studies' frameworks and approaches. From the analysis, it is found that a policy option consisting of different three dimensions: 1) increasing R&D investments to spur innovation activities, 2) encouraging workers to promote re-training or up-skilling enables them to be competent in quickly adjusting to the rapid technological changes through increasing educational investments, and 3) reforming the tax system by introducing progressive income taxation can promote an inclusive growth in the knowledge-based economy. Based on this empirical study, it is also highlighted that there should be policy design and implementation of the innovation policy, based on the understanding of the dynamically changing complementarity between technological innovation and human capital, and its linkages with other institutional components within the economy to achieve the inclusive and sustainable growth in the knowledge-based economy.

7.2 Significance and limitation of study, future research

To achieve an in-depth discussion on the growth and distribution patterns of the knowledge-based economy, there should be consideration of the dynamic interaction between changes in the composition of human capital (and associated labor supply) and changes in labor and skills demand induced by technological progress, and its effects on the wage and income structure in the economy. In addition, it is important to investigate what types of policy designs and practices can be used to balance growth and distribution goals within a knowledge-based economy. Policy design should be pursued under comprehensive and systematic approaches, taking into account the fact that economic growth and distribution are the results of complex interactions among many institutional elements within the economic system. In this sense, the CGE model is a useful tool for analyzing the impact of policy design alternatives.

However, in the case of the existing CGE models, the labor account as one of production factors is considered as a single account, without consideration of workers accumulated in heterogeneous human capital. The previous studies that considered heterogeneous labor within the CGE model were limited in capturing the endogenous process of human capital accumulation and dynamic changes in labor supply. The empirical studies based on the CGE model lack detailed descriptions of the characteristics of innovation and do not embrace the intrinsic characteristics of the technological innovation such as, the factor-biased technological progress within the production function. These limitations in methodological settings in the CGE framework provide a limited perspective in understanding the growth effects driven by the complementarity between innovation and human capital accumulation.

To overcome these methodological limitations of existing studies, this study has established and proposed a CGE model that reflects the endogenous interaction between the innovation and human capital accumulation within the production function with considerations of the heterogeneous labor and changes in labor supply induced by endogenous skill accumulation process and factor-biased technological progress driven by R&D investments. In addition, this study intended to integrate the discussions of CGE model-based studies by proposing the CGE model that can quantitatively measure both growth and distribution effects triggered by the policy shocks. To this end, a microscopic perspective has been reflected into the CGE model and SAM that facilitates the analysis of the differential effects on heterogeneous labor and households induced by the endogenous interaction between technological innovation and human capital accumulation. With considerations of heterogeneous labor and households within the SAM and CGE model, this study proposes a methodological base to quantitatively analyze the growth, efficiency, and distribution effects of policy options simultaneously.

It is expected that this study can provide a theoretical and methodological basis for analyzing the effects of various policy options in terms of growth and distribution within a knowledge-based economy. So far, previous studies using the CGE model that explicitly considered innovation and R&D activities within the model have focused on the direct support measures for innovation activities and their impact on the economy, including the subsidies and tax grants on the R&D investments. However, it is expected that the scope of the innovation policy impact assessments will be expanded by considering the various policy instruments such as human capital investment and tax policy. Furthermore, we also expect the proposed CGE model to be used as a tool for policy impact assessments to determine what types of policy options can achieve both growth and distribution goals in a knowledge-based economy. In addition, this study is also expected to contribute to expanding the academic discussions centered on keywords including innovation, human capital, growth, and distribution. In particular, the key findings of the empirical studies presented in this paper would provide the policy implications for redefining the scope (dimension) and role of the innovation policy.

However, this study also has limitations. Firstly, the values for the elasticities of substitution among production factors are reflected in the model by referring to previous studies. Substitution elasticities among production factors varies by country, by period, and by industry. Therefore, to perform an accurate analysis, it is necessary to estimate and reflect the values of elasticities of substitution among production factors by using Korean data. In addition, in the case of the CGE model as a macroeconomic model, there is a limitation to realistically reflect the heterogeneity of worker attributes within the model. The method of reflecting the heterogeneity of human capital based on the educational attainment level is limited to fully describe the heterogeneity of human capital possessed by workers. Accordingly, we have to improve the reliability of analysis results by using other methods to describe the heterogeneous characteristics of human capital.

In addition, the CGE model designed in this study assumes full employment in all industrial sectors of the economy. This assumption facilitates the model simulation, but the estimation results can lead to deviations (or gaps) from reality and there is a limitation in realistically describing the technological unemployment caused by innovation within the CGE model. Accordingly, future research direction should be oriented towards easing the assumption of full employment and explicitly considering the unemployment rate within the CGE model to increase the reliability of the model. In addition, there are limitations in describing the endogenous decision-making process of workers on skill upgrading and human capital accumulation within the CGE model designed in this study. As mentioned earlier, this study focuses on the expected returns of educational investment in describing the endogenous decision-making process undertaken by workers on human capital accumulation. Thus, the economic costs of skill accumulation (i.e., skill upgrading), including tuition fees, and opportunity costs due to absence from the labor market are not taken into consideration in describing the endogenous decision-making process of workers on skill upgrading and human capital accumulation within the CGE model. Accordingly, the effects of human capital accumulation drawn from the CGE analysis can be overestimated. Furthermore, the dimensions of formal and informal learning (or training) for employees are diverse and wide, which makes it difficult to identify relevant statistics and indicators containing the values for private and public sector investments levels on formal and informal learning for workers. For this reason, we use the total expenditure on education as the proxy variable to represent the institutional conditions that promote human capital accumulation of workers. This study also assumes an optimal situation with smooth transition of workers, from low-skilled to skilled labor or from skilled to high-skilled labor. Therefore, there may be some gaps in describing the education and training systems in the Korean economy. Accordingly, future research should include in-depth discussions on how to improve the reliability of the CGE model by elaborating the methodological features regarding the endogenous skill accumulation process and overcoming the limitations of the underlying assumptions made for the CGE model.

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Appendix 1: Lists of variables and parameters in CGE model

Sets and indices	
i, j	Sectors and goods
rdt	Type of R&D (public and private)
hh	Type of household
type	Type of skills (u: low-skilled(1); s: skilled(2); h: high-skilled(3))
f	Type of Production factors
t	Time (year)
Activity variables	
L1(i)	Low-skilled labor of sector *i*
L2(i)	Skilled labor of sector *i*
L3(i)	High skilled labor of sector *i*
K(i)	Physical capital of sector *i*
H(i)	Knowledge capital of sector *i*
X(j,i)	Intermediate goods for sector *i* produced in sector *j*
VA(i)	Value-added composite of sector *i*
HLK(j)	Composite factor from L3, K and H in sector *j*
Z(i)	Final output of sector *j*
D(i)	Domestic goods of sector *i*
E(i)	Export of sector *i*
M(i)	Import of sector *i*
Q(i)	Armington composite goods of sector *i*
XP(i,hh)	Household consumption of sector *i*
XG(i)	Government consumption of sector *i*
XV(i)	Investment demand of sector *i*
INVK	Demand for capital investment
RK(rdt)	Physical capital inputs in R&D investment of sector *rdt*
RLS1(rdt)	Low-skilled labor inputs in R&D investment of sector *rdt*
RLS2(rdt)	Skilled labor inputs in R&D investment of sector *rdt*

RLS3(rdt)	High-skilled labor inputs in R&D investment of sector *rdt*
RVA(rdt)	Composite factor from RHK, RLS1, and RLS2 in sector *rdt*
RHK(rdt)	Composite factor from RLS3 and RK in sector *rdt*
XVRD(rdt,i)	Intermediate inputs for R&D sector *rdt*
RDZ(rdt)	R&D investment goods produced by sector *rdt*
IR(i)	R&D investment demand by sector *i*
SPCOEFF(i)	Spillover coefficients in sector *i*
INTINDST(i)	Inter-industrial spillover in sector *i*
TOTSAV	Total savings in the economy
INVRES	Investment resource
SP(hh)	Household saving
SG	Government saving
SF	International trade balance
LS(s)	Newly educated workers from low-skilled to skilled labor
LS(h)	Newly educated workers from skilled to high-skilled labor
EDU	Total educational investments in time *t*
L1(t)	Low-skilled labor stock in time *t*
L2(t)	Skilled labor stock in time *t*
L3(t)	High-skilled labor stock in time *t*
LS(t)	Total labor stock in time t
KS(t)	Capital stock in time t
H(i,t)	Knowledge stock for industry *i* in time t
H(public,t)	Public knowledge stock in time t
Price variables	
PL1	Factor price(wage) of low-skilled labor
PL2	Factor price(wage) of skilled labor
PL3	Factor price(wage) of high skilled labor
PK	Factor price of physical capital
PH(i)	Factor price of knowledge capital in sector *i*
PVA(i)	Price of value-added composite in sector *i*
PHLK(i)	Price of composite factor from L3, K and H in sector *j*

PZ(i)	Price of final output in sector *i*
PD(i)	Price of domestic goods in sector *i*
PE(i))	Price of export in sector *i*
PM(i)	Price of import in sector *i*
PQ(i)	Price of Armington composite goods in sector *i*
PWE(i)	World price of export in sector *i*
PWM(i)	World price of import in sector *i*
Pinvk	Price of capital investment
Pinvrd	Price of R&D investment goods
PRDZ(rdt)	Price of R&D composite
PRVA(rdt)	Price of composite from RLS3 and RKS in sector *rdt*
PRHK(rdt)	Price of composite from RHK, RLS1, and RLS2 in sector *rdt*
Tax and income variables	
Tz(i)	Production tax (indirect tax) imposed to sector *i*
Total(Tz)	Total production tax collected from sectors
Tinc(hh)	Income tax imposed to household *hh*
Total(Tinc)	Total income tax collected from households
Tcor(i)	Corporate tax imposed to sector *i*
Total(Tcor)	Total corporate tax collected from sectors
Ttar(i)	Import tariffs imposed to imports of sector *i*
Total(Ttar)	Total import tariffs collected from imports
TG(hh)	Government transfer to household *hh*
Bg	Government debt
Ginc	Government income
HINC(hh)	Household income of household *hh*
HLINC1	Total household income from low-skilled labor
HLINC2	Total household income from skilled labor
HLINC3	Total household income from high-skilled labor
HKINC	Total household income from physical capital
HHINC	Total household income from knowledge capital
FHL1(hh)	Household *hh*'s income from unskilled labor

FHL2(hh)	Household *hh*'s income from skilled labor
FHL3(hh)	Household *hh*'s income from high skilledlabor
FHK(hh)	Household *hh*'s income from physical capital
FHH(hh)	Household *hh*'s income from knowledge capital
Parameters	
ax0(i,j)	Intermediate input requirement coefficients for sector *i*
ava0(i)	Value-added composite requirement coefficients for sector *i*
AVA(i)	Value-added requirement coefficient of sector *i*
arva0(rdt)	Value-added composite requirement coefficients for R&D sector *rdt*
axrd0(i,rdt)	Intermediate input requirement coefficients for R&D sector *rdt*
$\beta 10(i)$	Share parameter in CES production function for L3
$\beta 20(i)$	Share parameter in CES production function for K
$\beta 30(i)$	Share parameter in CES production function for L1
$\beta 40(i)$	Share parameter in CES production function for L2
$\theta 10(i)$	Scale parameter in CES production function for L3, K, and H
$\theta 20(i)$	Scale parameter in CES production function for L1, L2, and HLK
$\rho 1$	CES exponent for L3, K, and H in HLK production function
$\rho 2$	CES exponent for L1, L2, and HLK in VA production function
σ_1	Elasticity of substitution for L3, K, and H in HLK production function
σ_2	Elasticity of substitution for L1, L2, and HLK in VA production function
$\Psi 10(rdt)$	Share parameter in CES production function for RLS3
$\Psi 20(rdt)$	Share parameter in CES production function for RLS1
$\Psi 30(rdt)$	Share parameter in CES production function for RLS2
$\varphi 10(rdt)$	Scale parameter in CES production function for RL3 and RK
$\varphi 20(rdt)$	Scale parameter in CES production function for RHK, RLS1 and RLS2
$\rho 3$	CES exponent for RHK, RLS1 and RLS2 in RVA production function
$\rho 4$	CES exponent for RL3 and RK in RHK production function
σ_3	Elasticity of substitution for RHK, RLS1 and RLS2
σ_4	Elasticity of substitution for RL3 and RK
ffhh0(hh,n)	Income share parameter of household *hh* in each production factor *f*
$\alpha 0_{i,hh}$	Household *hh*'s consumption share parameter for sector *i*

$\tau_Z(i)$	Production tax rate for sector *i*
$\tau_Z(rdt)$	Production tax rate for R&D sector *rdt*
$\tau_{cap}(i)$	Corporate tax rate for household *i*
$\tau_{inc}(hh)$	Income tax rate for household *hh*
$\tau_{tar}(i)$	Rate of import tariffs in sector *i*
$\mu0(i)$	Government consumption share parameter for sector *i*
other0(j,i)	Interindustry spillover stock weight
spc0(i)	Scale parameter in interindustry spillover function
rdelas(i)	Interindustry R&D stock elasticity in interindustry spillover function
grdelas(i)	Public R&D stock elasticity in interindustry spillover function
γ^h	Scale parameter for industry-level R&D investment in Tobin's Q
$\aleph^h$	Industry-level R&D investments elasticity in Tobin's Q function
ir	Interest rate
γ^K	Scale parameter for physical capital investment in Tobin's Q
$\aleph^k$	Physical capital investments elasticity in Tobin's Q function
λ(i)	Share of sector *i* in physical capital investments
rp(rdt)	Share of private sector(households) in savings for R&D investments
rg(rdt)	Share of public sector(government) in savings for R&D investments
ρE	Labor supply elasticity from educational investments
$\emptyset_1$	Scale parameter for educational investments in labor supply function
$\emptyset_2$	Scale parameter for relative wages in labor supply function
$\mathcal{E}$	Exchange rate
g(t)	Economic growth rate
gl(t)	Population growth rate
δ_{cap}	Physical capital depreciation rate
δ_{know}	Knowledge capital depreciation rate
labdep	Human capital depreciation rate
rdi	R&D intensity(R&D investment level relative to GDP level)
φ	Share parameter for M in Armington's composite function
γ	Scale parameter for Armington's composite function
v	Substitution elasticity for domestic and import goods

θ	Share parameter for E in CET function
ϑ	Scale parameter for CET function
ב	Elasticity of transformation between domestic and export goods

Appendix 2: Lists of key parameters with references

Parameters	Value	Reference
***σ_1* (Elasticity of substitution for L3, K, and H in HLK production function)**		
All sectors	0.67	Krusell et al.(2000) and Jung et al.(2017)
***σ_2* (Elasticity of substitution for L1, L2, and HLK in VA production function)**		
All sectors	1.670	Křístková(2010, 2013) and Jung et al.(2017)
***σ_3* (Elasticity of substitution for RHK, RLS1 and RLS2 in RVA production function)**		
All R&D sectors	1.670	Křístková(2010, 2013) and Jung et al.(2017)
***σ_4* (Elasticity of substitution for RL3 and RK in RHK production function)**		
All R&D sectors	0.670	Krusell et al.(2000) and Jung et al.(2017)
rdelas(i) (Interindustry R&D stock elasticity in interindustry spillover function)		
S01	0.013	Hong et al.(2014, 2016), Jung et al.(2017), 이원기 and 김봉기(2004), 조윤애(2004)
S02	0.010	
S03	0.013	
S04	0.152	
S05	0.073	
S06	0.061	
S07	0.008	
S08	0.060	
S09	0.076	
S10	0.037	
S11	0.074	
S12	0.087	
S13	0.097	
S14	0.074	
S15	0.124	
S16	0.140	
S17	0.100	
S18	0.100	

S19	0.010	
S20	0.010	
S21	0.010	
S22	0.150	
S23	0.010	
S24	0.010	
S25	0.010	
S26	0.010	
S27	0.010	
S28	0.010	
grdelas(i) (Public R&D stock elasticity in interindustry spillover function)		
All R&D sectors	0.250	Hong et al.(2014, 2016), Jung et al.(2017) 이원기 and 김봉기(2004), 조윤애(2004)
$\aleph^k$ *(Physical capital investments elasticity in Tobin's Q function)*		
-	2.500	Křístková(2010), Hong et al.(2014)
$\aleph^h$ *(Industry-level R&D investments elasticity in Tobin's Q function)*		
All sectors	2.500	Křístková(2010), Hong et al.(2014)
ρE *(Labor supply elasticity from educational investments)*		
-	0.500	Ojha et al.(2013), Jung and Thorbecke(2003)
v *(Substitution elasticity for domestic and import goods)*		
All sectors	2.000	Yang et al.(2015), Hwang and Lee(2015), Oh et al.(2015), Sue Wing(2003)
ב *(Elasticity of transformation between domestic and export goods)*		
All sectors	2.250	Yang et al.(2015), Hwang and Lee(2015), Oh et al.(2015), Sue Wing(2003)

Abstract (Korean)

기술혁신과 인적자본의 동태적 보완성 변화는 국가 경제의 성장궤적에 영향을 미치게 되며, 국가의 기술적 수준에 따라 인적자본의 역할은 변화하게 된다. 이러한 관점 하 국가의 경제성장 궤적을 분석하고자 한 연구들은, 초기 경제체제 내 인적자본을 동질적인 것으로 파악하고, 인적자본의 수준 효과에 초점을 맞춰, 기술혁신과 인적자본, 성장 간 관계에 대해 설명하는 것을 넘어, 서로 다른 성질과 한계 생산을 가진 이질적인 인적자본에 대한 논의로 확장해왔다. 이러한 기술혁신과 인적자본의 상호작용에 따른 경제성장을 설명하는데 있어서 인적자본의 구성에 대한 논의는 기술혁신의 경제체제 내 노동시장(임금, 고용 등)에 대한 영향과 소득 분배 문제로 논의를 확장하고 있다.

이와 같은 배경 하, 본 연구는 기술혁신과 인적자본 간의 상호 관계가 경제체제의 장기 경제성장 및 분배의 패턴을 규정한다는 사실에 주목하고자 한다. 이를 바탕으로, 기술혁신 주도 경제성장을 바탕으로 한 지식기반 경제체제 내에서 어떤 형태의 정책설계 및 실행을 통해, 지식기반 경제체제 내 성장과 분배 문제를 양립할 수 있는지 판별할 수 있는 정책효과 분석도구로서 연산일반균형 모형을 설계 및 제안하고자 하였다. 그에 따라, 본 연구에서는 기존의 정책효과 분석 연구 및 연산일반균형 모형 기반 정량분석 연구들이 지닌 방법론적 한계를 극복하고자 모형 내 지식자본 투자에 따른 기술혁신과 인적자본 축적에 따른 두 부문 간 동태적 상호작용이 내생적으로 결정되는 구조를 제시하였다. 또한, 성장과 분배 측면의 정책 효과분석을 용이하게 하는 모형 및 기반

자료체계 제시를 위해 사회회계행렬 자료체계 내 노동 및 가계 계정의 세분화를 통해 정책 충격에 따른 성장, 효율성 및 분배 효과를 동시에 측정할 수 있는 모형 및 자료체계 제안을 이뤄냈다. 이를 바탕으로, 본 연구에서 제안하는 모형 및 자료의 특징은 1) 인적자본 투자에 따른 노동자의 숙련도 향상 의사결정의 내생화, 2) 기술혁신과 인적자본 간 상호작용의 내생화 통한 경제성장 및 분배구조 결정, 3) 자료체계 및 모형의 세분화 통한 성장 및 분배를 동시에 측정할 수 있는 거시 모형 수립으로 요약할 수 있다.

이처럼 설계 및 제안하는 연산일반균형 모형을 바탕으로, 본 연구는 실증연구를 통해, 기술혁신과 인적자본 간 상호작용이 파급되는 경제체제 내 경로를 식별하고자 하였다. 이를 바탕으로 R&D 및 교육 투자의 상호작용에 따른 상호 보완적 관계를 확인함으로써, R&D 투자를 통한 기술혁신과 교육 투자를 통한 인적자본 축적 간의 연계성을 높이는 것이 국가의 성장잠재력 제고에 있어서 핵심적인 중요성을 가질 수 있음을 파악할 수 있었다. 또한, 최근 활발하게 논의가 되고 있는 기술혁신 및 인적자본의 상호작용에 관련한 논의 중 기술혁신에 따른 노동시장 분화, 양극화 및 사회 불평등 해소를 위한 혁신, 교육, 세제정책 간 정책 조합의 형태를 제안하고, 제안하는 정책 조합의 역할을 규명하는, 정량적 정책효과 분석 연구를 진행하였다. 이를 통해, 혁신에 대한 투자 증대, 공공 부문의 교육투자에 있어서 이를 통한 노동자들의 재교육 및 평생학습 장려를 통한 숙련도 향상, 그리고 소득세 증세를 통한 세제정책 개편이라는 세 가지 정책 영역 내 정책 수단들이 하나의 정책 패키지로서 활용될 때 지식기반 경제체제 내 포용적 성장을 도모할 수 있음을 파악할 수 있었다.

해당 실증연구를 통해, 본 연구는 동태적으로 변동하는 기술혁신과 인적자본 간 상호작용에 대한 이해를 바탕으로, 해당 요소가 성장과 분배에 영향을 미칠 수 있는 다양한 경제체제 내 파급경로와 연관된 시장 내 제도적 부문 간의 상호작용을 고려한 정책설계가 이루어져야 함을 강조하고자 하였다. 더불어, 본 연구에서 다룬 기술혁신, 인적자본, 그리고 성장 및 분배라는 키워드가 중심이 된 학문적 논의에 있어서 본 연구는 거시경제 모형을 바탕으로 한 실증연구의 분석 결과를 바탕으로, 혁신정책의 범주에 대한 역할을 재정립하는 데 있어서 시사점을 도출하고자 하였다는 점에서 가치가 있다고 할 수 있다.

Keywords: Innovation, Human capital, Growth, Distribution, Computable general equilibrium model, Policy impact assessment
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주요어: 혁신, 인적자본, 경제성장, 소득분배, 연산일반균형모형, 정책 분석

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