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Winners and Losers in a Knowledge-based Economy : Investigating the Policy Packages for an Inclusive Growth based on a Computable General Equilibrium analysis of Korea

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Abstract: With factor-biased technical progress described as labor-saving and skill-biased technical changes, there are concerns that technological innovation leads to unemployment and widen inequality. Even though a growing body of studies proposes a wide range of policies to address negative impacts from innovation, they are rather fragmented, and mostly limited to a single policy instrument. In addition, there has been a lack of quantitative studies on policy impact assessments. With this background, this study propose a conceptual framework to investigate the economy-wide impacts of factor-biased technological change and the role of policy packages to spur inclusiveness of the economy, by addressing the limitations of previous studies. Based on this conceptual framework, this study explores the impacts of proposed policy-mixes on the economic system in terms of growth, employment, and distribution using a computable general equilibrium (CGE) model. The results show that the policy package consisting of different policy areas (i.e., innovation, education, and taxation 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. Our results suggest that policymakers should consider how to enhance complementarity between innovation and human capital accumulation to accelerate the innovation-driven growth, and how to design tax systems to balance growth and distribution effects within the economic system. 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.

Keywords: Innovation, Economic growth, Employment, Inequality, Computable General Equilibrium
JEL Classifications: C68, D58, O30, O40

1. Introduction

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 (Jung et al., 2017). 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 (Brynjolfsson and McAfee, 2014, 2012; Mallick and Sousa, 2017; Karabarbounis and Neiman, 2014; Goos et al., 2014; Acemoglu and Autor, 2012).

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 (SBTC), which can be descried as a shift in the production technology that favors skilled over low-skilled labor by increasing its productivity and therefore, its relative demand (Jung et al., 2017; Baccini and Cioni, 2010; Antonietti, 2007; Card and DiNardo, 2002; Krusell et al., 2000; Machin and Van Reenen, 1998). Skill-biased technological change is strongly associated with the capital-skill complementarity where capital goods (such as, machines with new technologies) become relatively more complementary with skilled labor than low-skilled labor (Raveh and Reshef, 2016; Chang and Hornsten, 2007; Acemoglu, 2002; Allen, 2001; Mortensen and Pissarides, 1999; David et al., 1997; Griliches, 1969). 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 (Brynjolfsson and McAfee, 2014, 2012a, 2012b; Piketty, 2014; Galor and Moav, 2000; Nelson and Phelps, 1966). 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 (Doraszelsk and Jaumandreu, 2018; Bridgman, 2017; Jung et al., 2017; Elsby et al., 2013; Karabarbounis and Neiman, 2014; Guerriero and Sen, 2012). 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

(Deskoska and Vlčková, 2018). In addition, there can be a deepening of income inequality as capital ownership tends to be concentrated (Bridgman, 2017; Acemoglu and Robinson, 2015). This capital-biased (or, labor-saving) technological change from innovation can result in higher level of technological unemployment (Stiglits, 2014; Piketty, 2014). Consequently, wages fall relative to the cost of capital, and the proportion of labor wages in Gross Domestic Product (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 income inequalities and polarization by increasing economic returns to high-skilled workers and capitalists in the economic system (Acemoglu and Restrepo, 2018; Brynjolfsson and McAfee, 2014, 2012a, 2012b; Autor, 2010; Karabarbounis and Neiman, 2013; Piketty, 2014). Thus, economic growth accompanied by factor-biased technological change can generate higher inequality and income polarization (Jung et al., 2017). A growing body of studies in recent years has expressed more concerns over the side effects caused by the factor-biased technological change. The world is now facing the rapid development and spread of new technologies led by wide deployment of information and communication technologies (ICT) that many scholars refer to as the ‘Fourth Industrial Revolution’ (WEF, 2016; Brynjolfsson and McAfee, 2014). This new age of technological innovation empowered by digital technologies could promote economic growth giving the economy the potential to flourish although if not managed wisely, many could also be left behind. A variety of literature argues that a widespread deployment and application of digital technologies such as artificial intelligence and robotics could accelerate the pace of factor-biased technological change, which has the potential to further promote job polarization and worsen the income distribution.

For example, Brynjolfsson and McAfee (2014) address that the growing role of the ICT technologies could reinforce the creation of winner-take-all markets, by providing higher rents to top superstar performers, and creating a large divide in the share of profits between workers. In addition, recent studies (Bárány and Siegel 2018; Aghion et al., 2017; WEF, 2016; Frey and Osborne, 2013; O'Mahony et al., 2008; Goos and Manning, 2007) have empirically found that technological progress led by ICT can substitute workers in occupations more intensive in routinized tasks, while complementing workers who perform abstract tasks at the top of the wage distribution. Brynjolfsson and McAfee (2012a) also note that as technological innovation is accelerated with more sophisticated software technologies, the pace of disruption of labor market is expected to be increased by making workers redundant. Furthermore, Frey and Osborne (2017) find that 47% of total U.S (United States of America) employment is in the high risk category, suggesting that relevant occupations are potentially automatable with wide diffusion of digital technologies.

Likewise, the main focus of the discussions on the relationship between technological innovation and jobs in recent years is oriented towards how much and what types of jobs (or workers) are to be displaced by factor-biased technological change driven by innovation. Those studies, however, generally describe the structural unemployment phenomenon led by technological innovation, taking into account only the direct effects of innovation on the employment structure. This approach can lead to over-interpretation of the phenomenon of technological unemployment, and associated income inequality which are accompanied by technological innovation in knowledge-based economy. As noted by several studies including Jung et al. (2017), Vivarelli (2014, 2013), and Edquist et al. (2001), to gain a better understanding of the net effects of technological innovation on the employment structure and income distribution of the national economic system, not only direct effects but also various compensation mechanisms and indirect effects should be taken into account. For example, Jung et al. (2017) find that higher level of innovation activities could create much more jobs via productivity improvements across industrial sectors and expansion of production activities in the national economy by offsetting the effects of capital-biased technical change, which lowers the employment level in the economy. Vivarelli (2014, 2013) also highlight that the initial labor saving impact of process innovation can be counterbalanced by compensation mechanisms via new machines, decreases in commodity prices, new investments, decreases in wages, and increases in households' incomes.

As noted by Bridgman (2017), investigating the underlying causes of the structural unemployment and widening income disparities is important to guiding policy responses. However, if we concentrate only on technological unemployment which is the direct effects of technological innovation on labor markets, the tools of public policy for problem-solving are also likely to be short-term, and localized prescriptions. One of policy options proposed with this approach include government-led job creation policies (or, programs). Along with job creation policies, a variety of policy prescriptions are also actually being proposed in several developed countries to address growing income disparities caused by the factor-biased technological change. Examples of policy suggestions include reforms in educational programs, reforms of regulations on labor markets, and budgetary policy instruments of the government, including taxation reforms, and implementation of universal basic income (UBI). However, a variety of policy suggestions are rather fragmented, and mostly limited to a specific (single) policy instrument. 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 (Jung et al., 2017). 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. Based on the empirical findings, we intend to identify the potential role of policy packages from several different dimensions (i.e., innovation, education, and fiscal policies) by investigating the impacts of the different types of policy mixes on the economic system using a computable general equilibrium (CGE) model, so as to inform and advise policymakers in designing an appropriate policy package for inclusive growth. We focus on the economy in Korea (South Korea), and simulation results for policy scenarios are analyzed in terms of employment structure, economic growth, and income inequality.

For the analysis, we reflect innovation-related activities (i.e., endogenously determined research and development (R&D) investments), characteristics of knowledge (i.e., spillover effects from knowledge accumulation), and factor-biased technological change in the model. In addition, we have modelled the endogenous interaction between innovation and human capital accumulation within the CGE framework. The economic intuition behind these methodological approaches is that factor-biased technological progress driven by innovation shape the employment structure and income distribution through interactions with market mechanisms. Another underlying assumption behind the methodological settings is strongly associated with the fact that interrelationship between factor-biased technological change and human capital accumulation shapes patterns of long-term economic growth and distribution within the 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.

The rest of the paper is structured as follows: Section 2 provides our conceptual framework utilized for the quantitative analysis; Section 3 presents contains general descriptions of the CGE model used for the analyses; Section 4 explains the scenario settings; the main results are presented in Section 5; and, lastly, the summary and concluding remarks are provided in Section 6.

2. Conceptual Framework

2.1. Systemic review on policy options for inclusive growth in knowledge-based economy

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. OECD (2017a) addresses 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 (OECD, 2017a; Ostry et al., 2014; de Mello and Dutz, 2012). 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 and Dutz, 2012; Heeks et al., 2014; Foster and Heeks, 2013; 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 solely 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 income 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, 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. In this context, a variety of policy suggestions proposed by previous studies are rather fragmented, and mostly limited to a specific (single) policy instrument. As a result, 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, 2012a, 2012b; 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 these 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 and Wolff, 2010; Shane, 2009). Policy goals of those interventions are involved with 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 (or, burdens) for companies, which may result in decreases in innovation activities in firms (Hohmeyer and Wolff, 2010; Shane, 2009).

As Shane (2009) points out, typical start-ups and public sectors are typically not highly innovative, and have the potentials 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 (or, industries) and associated increases in scale effects generated by technological innovation, not exogenously determined (Acemoglu and Autor, 2011; Autor, 2010). When the outcomes of innovation are actively generated, and utilized in the economy, the economy will gain greater momentums 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.

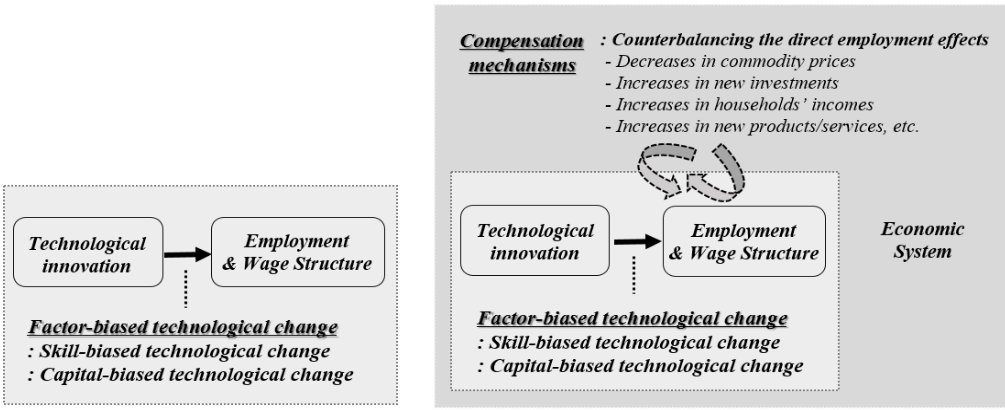
In addition, one of the policy measures that could address the issue of technological unemployment and income inequality is the introduction of universal basic income (UBI) (OECD, 2017a; Sage and Diamond, 2017; Standing, 2015; Van Parijs, 2004). This measure is defined as an unconditional payment of 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 (Sage and Diamond, 2017). In the short term, this policy instrument 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 and Stirton, 2004; OECD, 2017a, 2018; Woodbury, 2017). In addition, 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.

Furthermore, recent relevant studies have emphasized the role of education for skill accumulation of labor, focusing on the intrinsic properties of technological change from innovation (Grossman et al., 2017; Brynjolfsson and McAfee, 2014, 2012a; Pan, 2014; He and Liu, 2008). Assuming that technological progress is factor-biased, technological innovation will necessarily widen inequality among skill groups unless it is counted by increases in the supply of human capital (Acemoglu and Autor, 2012; Goldin and Katz, 2008, 20007). Therefore, from the supply-demand framework (Goldin and Katz, 2008), several studies put emphasis on the concepts of "up-skilling" and "skill-upgrading" through training, on-the-job learning, and schooling for the workers which enable human capital to keep their competencies in accordance to changes in the demand for skill triggered by factor-biased technological change (Acemoglu and Restrepo, 2018; Goldin and Katz 2008; Nelson and Phelps, 1966).

From this perspective, several studies including Grosman et al. (2017), Pan (2014), and He and Liu (2008) propose analytical frameworks and models to account for the relationship between skill accumulation and factor-biased technical change to draw implications for reducing wage inequality in terms of investments in education (or human capital). While those studies provide new insights on how investments in education affects the direction and pace of technological change, it is not straightforward to interpret main findings based on observable data in aggregate sense. Especially, it is difficult to interpret the relationship between the education and technology in practical sense with national aggregate data. Those studies are also lack of quantitative explanations on how policy shocks affect the underlying mechanisms associated with the changes in employment structure and income inequality. So, it can be understood that there has been lack of empirical studies based on national datasets which focus on the interaction between changes in labor demand from technological change and labor supply from educational investments to draw the policy implications for the inclusive growth in the knowledge-based economy.

As we have seen above, most of the policy suggestions proposed by previous studies largely depend on the partial static equilibrium framework. In other words, those policy suggestions are involved with ad-hoc nature of policy design and implementation. 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. 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. 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.

In addition, policy options for the inclusiveness of the economy suggested by previous studies are also rather fragmented, and not deeply associated with empirical analyses (or, relevant findings). To be specific, it is hard to find empirical findings that reflect economy-wide perspective using macroeconomic models based on identifiable macroeconomic data. These methodological limitations constrain in-depth discussions on designing policy packages to resolve conflicts between inclusiveness and growth within the knowledge-based economy. The limitations of underlying assumptions and perspectives of previous studies are presented in Figure 1, by highlighting our conceptual framework for this study. One of key intuitions of our proposed conceptual framework is that socio-economic institutions need to be adjusted to the pace and direction of technological progress, to ensure both the quality of economic growth and the quantitative expansion. 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.



	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 1. Conceptual framework for this study

2.2. Development of a 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 inclusiveness in the knowledge-based economy, aiming to mitigate the side effects driven by the factor-biased technological change. Among several types of policy options, this study focuses on the educational investments from the government to promote skill upgrading (i.e., human capital accumulation) 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 R&D investments as a representative policy instrument within 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, 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 on-the-job training and workplace-based vocational programs. In other words, the educational or learning 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 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 and McGuire, 2015; Cobo, 2013; Goldin and Katz, 2008; Grossman et al., 2017; He and Liu, 2008; Pan, 2014). In this regard, the public sector's investments in education is highlighted, along with the investments in innovation activities (Rotherham and Willingham, 2010).

In addition, the income tax is considered as a representative policy option to address the problems of widening income disparities (Eissa and 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 additional income tax as presented in Ojha et al. (2013)'s work. Furthermore, we are to consider the R&D investments as a representative policy instrument in innovation policy. Based on these settings, this study aims to analyze the impacts of different types of policy packages comprising of an enhancement in R&D investments, and tax-financed increases in public expenditures on human capital formation from the point of view of growth as well as equity. Our logical framework can be described as Figure 2.

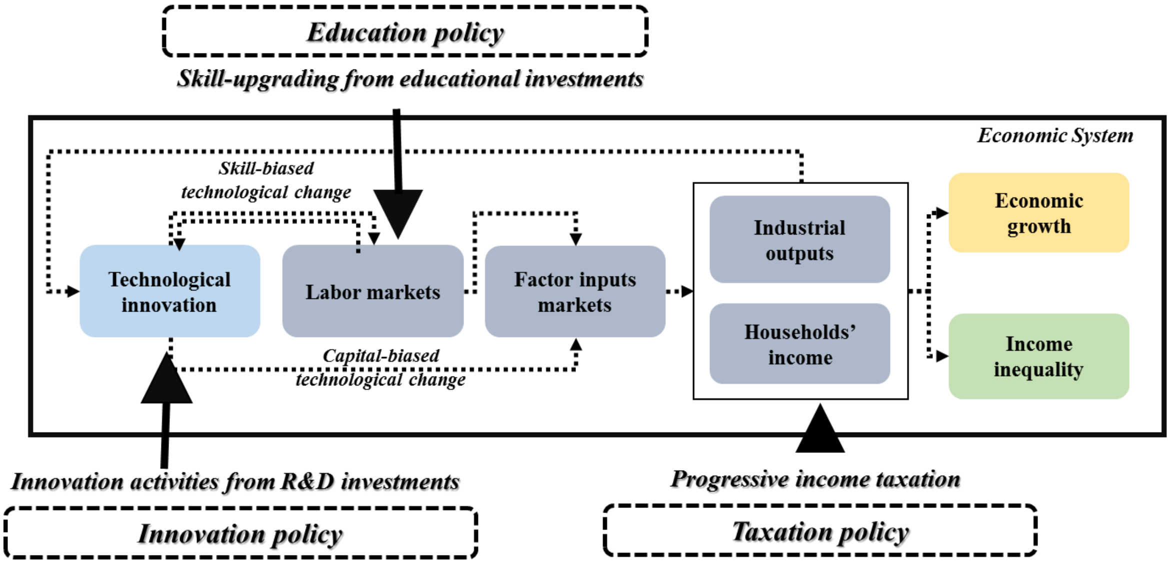


Figure 2. Logical framework for considerations of policy options in this study

As shown in Figure 2, the improvement of workers' skills through learning (i.e., 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 increases in 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 fiscal 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.

3. Methodological Approach: CGE Modeling

In this paper, we utilize a CGE model to quantitatively analyze the macroeconomic impacts of different types of policy mixes on growth and distribution patterns of national economy. Firstly, it is important to incorporate innovation-related activities (R&D) and characteristics of knowledge (e.g., knowledge capital accumulation and spillover effects) into the CGE model, in order to capture the direct and indirect scale effects generated by knowledge capital accumulation. In this context, we construct the knowledge-based CGE model by adding R&D descriptions and characteristics of knowledge, with a series of equations based on a knowledge-based Social Accounting Matrix (SAM). Secondly, it is also essential to classify the labor account by skill level, to examine the variants in employment structures arising from technological innovation via factor-biased technological change. From this perspective, the labor input for production of final goods and knowledge production is classified into three types of labor, based on the educational attainment level: high-skilled, skilled, and low-skilled labor. Furthermore, households are classified into 20 quantiles, based on income levels, using micro data of household level survey datasets to investigate the income distribution impacts arising from changes in employment structure. The following subsections show approaches for constructing datasets, including SAM, and modeling equations that reflect those considerations.

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

SAM summarizes the interdependences among 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. Since SAM not only includes information of inter-industrial transactions listed in input-output (I-O) tables, but also focuses on the relationships 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. This SAM serves as an underlying database which describes the baseline economy in the CGE model by capturing the structure of the economy in which the income and expenditure equations and associated aggregate accounting relationships are derived. Basically, in constructing a SAM dataset, we have utilized 2010 I–O table from the Bank of Korea (the central bank of South Korea), and tax-related data in the 2010 Statistical Yearbook of National Tax, published by the National Tax Service in Korea. In addition, the data on household and government savings were extracted from national accounts.

Key differences of the SAM developed in this study, compared to other standard SAMs, are descriptions on R&D activities and specifications of labor and household types. In this study we have represented knowledge as a factor of production and introduce knowledge capital formation in the investment account[1] by applying methods proposed by Yang et al. (2012), Hong et al. (2014, 2016), and Jung et al. (2017). Within the SAM used for this study, current expenditure on R&D, which was initially included in intermediate goods transactions, has been moved to the production factor account. In addition, capital expenditure on R&D, which was initially included in physical capital formation, has been moved to the knowledge capital formation account. Furthermore, the knowledge capital formation account has been classified into private and public accounts, according to who spent it.

Along with descriptions of the knowledge-related elements within the SAM framework, we have also specified the labor and households accounts to consider the heterogeneity of economic entities. To consider different types of labor, we have classified the single labor account into three types, based on the educational attainment levels to incorporate

[1] The SAM used in this study accepts the recommendation of the 2008 SNA, in order to incorporate additional accounts for knowledge capital. According to the 1993 System of National Accounts (SNA), R&D spending is treated as intermediate consumption, which is used up in the production process. However, the 2008 SNA extends the range of fixed assets and clarifies how to incorporate R&D spending into fixed capital formation.

heterogeneous human capital accumulation for workers. When disaggregating the single labor input 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. Based on these classifications, we extract information on labor inputs and wages by labor type for production activities from satellite datasets.[2] Furthermore, the households account is also classified into 20 quantiles based on income levels. We use micro-level data of Household Income and Expenditure (HIE) Survey issued by Statistics Korea. Based on this dataset, we extract each household’s earnings, consumption expenditure, physical capital investment, and R&D investment levels into the SAM. Table 1 shows a final form of the SAM, constructed for the analysis. The numbers in the cells of Table 1 indicate the size of matrix of each account.

[2] We extract labor inputs and wage levels by labor types for production activities from the 2010 Household Income and Expenditure Survey (HIE Survey) micro data, from the Korea National Statistical Office, and the 2010 Wage Structure Statistics from the Ministry of Employment and Labor.

Table 1. Construction of knowledge-based SAM

		Activity	Factor inputs			Institution		Investments			Tax	ROW		**Tot.**
		Intermediate	Labor	Capital	Knowledge	Household	Government	Physical Capital	Knowledge capital [e)] Private	Knowledge capital [e)] Public		Export	Import	
Activity	Intermediate	28*28[a)]				28*20	28*1	28*1	28*1	28*1		28*1		
Factor inputs	Labor[c)]	3*28							3*1	3*1				
	Capital	1*28							3*1	3*1				
	Knowledge[e)]	1*28												
Instituti-ons	Household[d)]		20*3	20*1	20*1									
	Government					1*20					1*1			
Investm-ents	Physical Capital					1*20	1*1							
	Know. Capital Private					1*20	1*1							
	Know. Capital Public					1*20	1*1							
Tax[b)]		1*28												
ROW	Export												1*1	
	Import	1*28						1*1						
Total														

a) Within the SAM, sectors are classified into 28 sectors

b) Tax account includes indirect, corporate, income, and tariffs in the SAM

c) Labor inputs for production of final goods and knowledge production are split into three types; high-skilled, skilled, and low-skilled labor

d) Household is classified into 20 quantiles based on the income level

e) In this knowledge-based SAM, knowledge is explicitly presented as one of the factor inputs, and knowledge capital formation account has been added into an investment account

3.2. The structure of the knowledge-based CGE model

This section provides an overview of the knowledge-based CGE model designed in this study. The overall structure of the knowledge-based CGE model developed in this study, including the relationships between key elements (i.e., economic transaction relationships) can be expressed as Figure 3. The main characteristics of the CGE model used in 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 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 propose a CGE model for analyzing growth and distribution effects under different forms of policy scenarios.

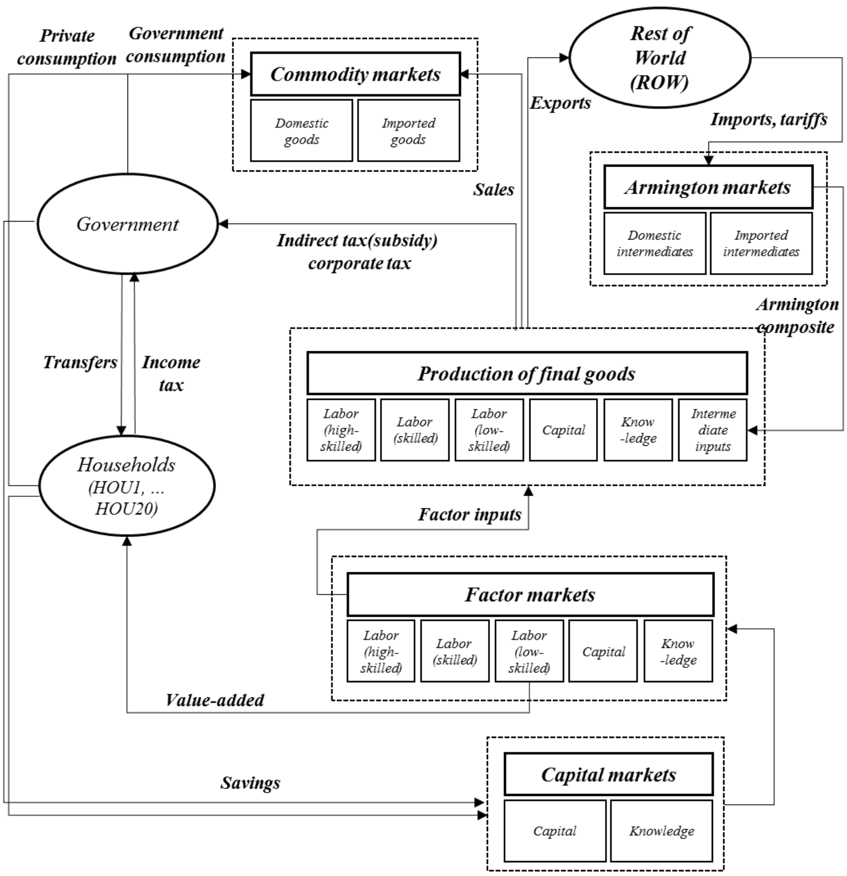


Figure 3. Overall structure of the knowledge-based CGE model

3.2.1. 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, low-skilled labor), physical capital, and knowledge capital under the multi-level constant elasticity of substitution (CES) productions. 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 represents that there is no substitutability between the value-added composite VA_i and intermediate inputs $X_{j,i}$, as represented by Equation (1),. In the equation, $ax0_{j,i}$[3] and $ava0_i$, respectively, represent intermediate inputs and the value-added composite required to produce a unit of output in industry *i*.

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

where i = 1,2, … 28

On the other hand, the value-added composite (VA_i) is assumed to be produced under the multi-level nested CES (constant elasticity of substitution) production function, as shown in Figure 4. Within the two-level nested CES production function, as the first stage the HLK_i composite is produced by combining high-skilled labor ($L3_i$), physical capital (K_i), and knowledge (H_i) assuming that those factor inputs are complements within the production function. 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 ($L1_i$), assuming that HLK_i has substitutive relationships with $L2_i$ and $L1_i$.

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 among HLK_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).

[3] Symbols with 0 indicate the parameters obtained by variable values of knowledge-based SAM of base year.

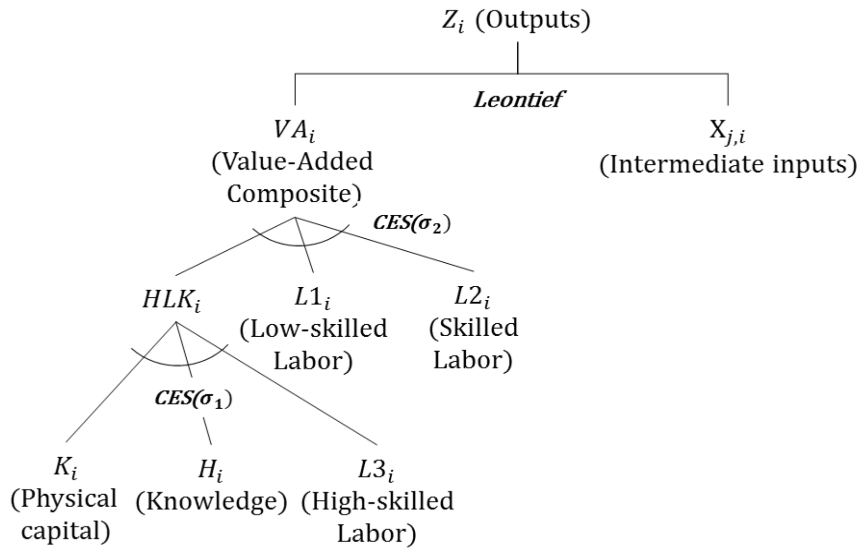


Figure 4. Production structure of final goods in CGE model

3.2.2. Production structure of R&D investment goods

Another characteristic of the CGE model developed for this study is detailed descriptions 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. It is also assumed 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.

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 5. Within the two-level nested CES production function, as the first stage the RHK_{rdt} composite is produced by combining the high-skilled labor ($RLS3_{rdt}$) and physical capital inputs for R&D activities (RK_{rdt}). In addition, within the second stage of this multi-level nested CES production function for the R&D sector, it is modelled that the value-added composite for the R&D sector (RVA_{rdt}) is generated by combining RHK_{rdt} composite, skilled ($RLS2_{rdt}$) and low-skilled labor ($RLS1_{rdt}$) for R&D activities.

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.

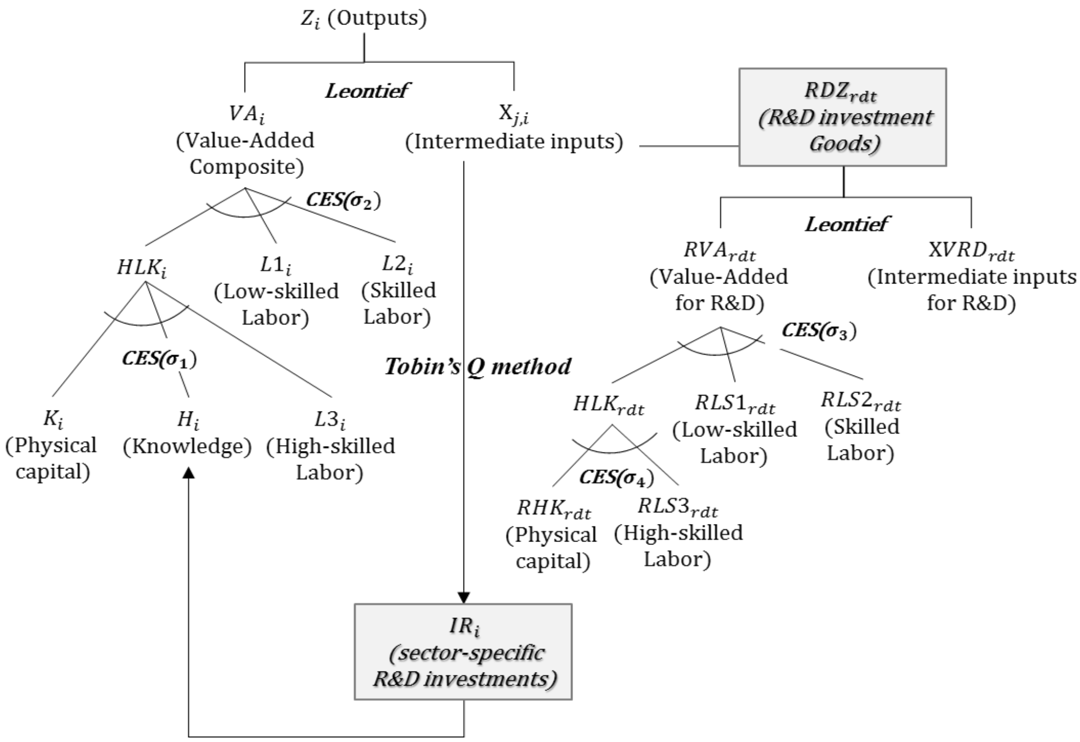


Figure 5. Production structures of R&D investment goods and final goods

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. 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 Equation (2)), 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 Equation (3). Moreover, 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). Furthermore, the perpetual inventory method (PIM) has been also applied to describe the dynamic accumulation process of the physical capital stocks (KS_t) with values of physical capital investments ($INVK_t$) and depreciation rates (δ_{CAP}), as expressed by the Equation (4).

$$H_{public,t} = (1 - \delta_{know}) \cdot H_{public,t-1} + RDZ_{public,t-1} \quad \text{... Eq. (2)}$$
$$H_{i,t} = (1 - \delta_{know}) \cdot H_{i,t-1} + IR_{i,t-1} \quad \text{... Eq. (3)}$$
$$KS_t = (1 - \delta_{CAP}) \cdot KS_{t-1} + INVK_t \quad \text{... Eq. (4)}$$

3.2.3. Productivity improvements from knowledge spillover effects

The economic importance of knowledge capital accumulation is associated with the 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 Equation (5), 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 weighted 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.

$$INTINDST_i = \sum_{j,j \neq i} other0_{j,i} \cdot H_j \quad \text{... Eq. (5)}$$

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 Equation (6). 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. Values for elasticities of private and public knowledge stocks are drawn from previous studies (Hong et al., 2014; Hwang et al., 2008).

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 (AVA_i), as expressed by Equation (7). This can be easily understood from Figure 6 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;*
rdelas: Elasticity of private knowledge stocks;
grdelas$_i$*: Elasticity of public knowledge stocks* ... Eq. (6)

$$AVA_i = ava0_i / SPCOEFF_i$$ ... Eq. (7)[4]

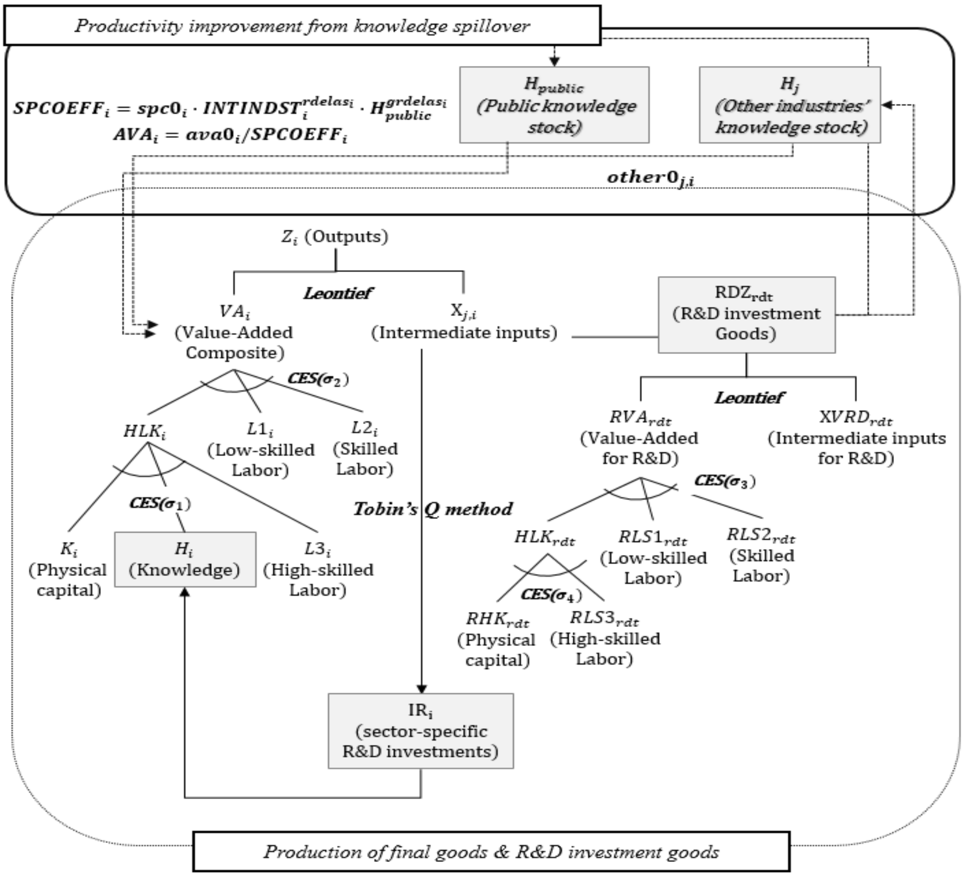


Figure 6. Productivity improvements from the knowledge spillover effects

3.2.4. Endogenous skill accumulation of workers 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 investments 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).

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[4] In the Equation (7), $ava0_i$ 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.

As expressed by Equation (8), it is designed that the labor supply of workers ($LS_{u,t}$) who have completed skill accumulation 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 educational investments in the economic system (EDU_t)[5] 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 undertake learning-related decision making based on the expected returns (i.e., earnings), and the institutional conditions for learning shaped by the level of educational investments within the model, as addressed by previous studies including Kaufman et al. (2001), Jung and Thorbecke (2003) and Ojha et al. (2013).

With the consideration of the Equation (8), the exogenous values for the economic growth rate g_t and discount rate (i.e., interest rate) ir_t are also considered to describe the supply of newly educated workers who completed skill accumulation. In the Equation (8), ρE represents the elasticity parameter determining the returns on educational investments, while $\emptyset_1$ and $\emptyset_2$ respectively represents the relative weight of each component. Those parameters' values are assumed to be same values in Jung and Thorbecke (2003) and Ojha et al. (2013).

$$LS_{u,t} = \emptyset_1 \cdot EDU_t^{\rho E} + \emptyset_2 \cdot \left(w_{t-1}^{u} / w_{t-1}^{l} \right) \cdot [\frac{1+g_t}{1+ir}] \qquad \text{... Eq. (8)}^{6}$$

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 Equation (9)). 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 (10). 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-

[5] 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).

[6] The detailed derivation process of this equational form can be found in Jung and Thorbecke (2003)'s work

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 Equation (10). 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 Equation (10)), and reflected the value for the human capital depreciation rate (*labdep = 0.015, 1.5%*) estimated by Ban (2017).

$$LS_{t+1} = (1 + gl_t) \cdot LS_t \quad \text{where } LS_t = L1_t + L2_t + L3_t \qquad \text{... Eq. (9)}$$

$$\begin{aligned} L1_{t+1} &= (1 - labdep) \cdot L1_t - LS_{s,t} \\ L2_{t+1} &= (1 - labdep) \cdot L2_t + LS_{s,t} - LS_{h,t} \\ L3_{t+1} &= (1 - labdep) \cdot L3_t + LS_{h,t} \end{aligned} \qquad \text{... Eq. (10)}$$

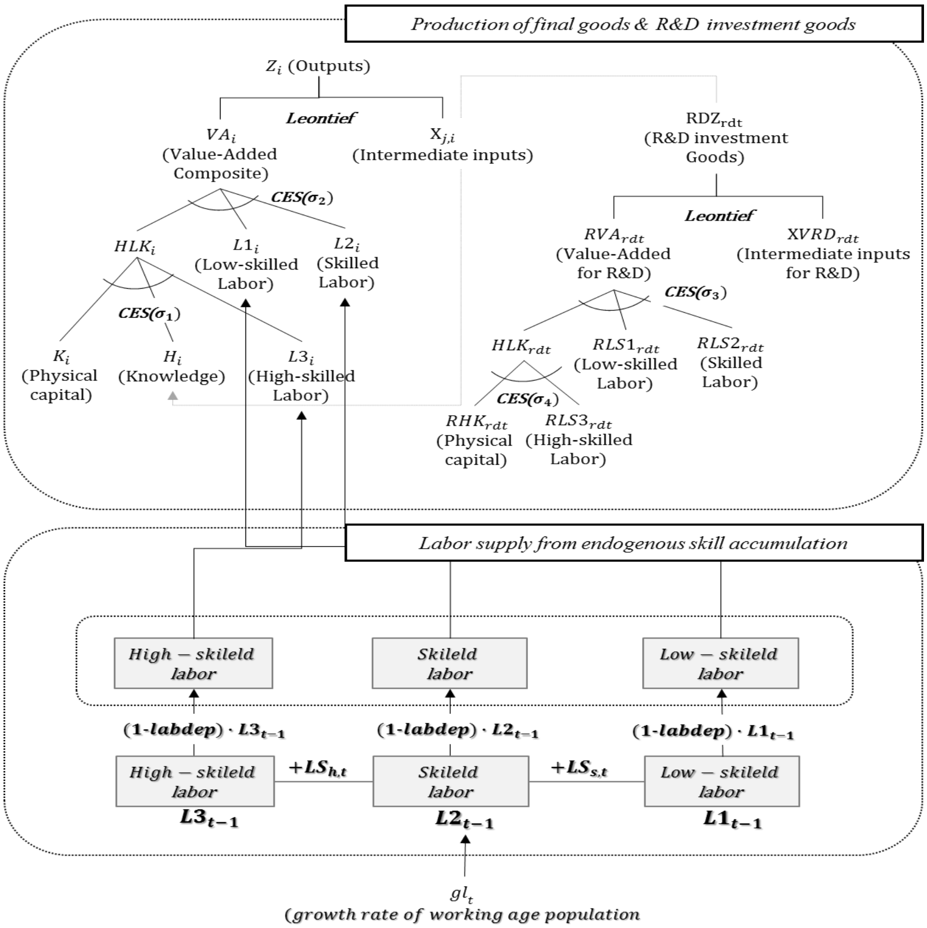


Figure 7. Relationships between changes in labor supply from human capital accumulation and production function

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 7. In this regard, this study has endogenized the skill accumulation process of workers within the CGE model, thereby enabling to capture the dynamic evolution of the human capital compositions.

3.2.5. 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 Equation (11), Equation (12), and Equation (13). Furthermore, the aggregate household earning from each primary factor described in Equations (11), (12), and (13) is allocated to 20 groups of households, in proportion to the share of each income quantile, to characterize the distribution of households' incomes. The incomes of households are either saved or paid to the government as transfer payments. The remaining incomes are then spent for consumption.

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

where $L_{i,type}$: *Labor inputs for sector i by skill type;* ... Eq. (11)
$RLS_{rdt,type}$: *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. (12)
RK_{rdt}: *Physical capital inputs for R&D investments;*
PK: *Returns of capital*

$$HHINC = \sum_{i}(H_i \cdot PH_i)$$

where H: *Knowledge capital inputs for sector i;* ... Eq. (13)
PH_i: *Factor price of knowledge capital*

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. Net incomes of the government ($Ginc$) consisting of tax revenues, government debt Bg, and household transfers TG_{hh}(see Equation (14)) are used for savings (SG) and consumption expenditure for the government (Xg).

$$Ginc = Total_{TZ} + Total_{Tinc} + Total_{Tcor} + Total_{Ttar} + Bg + \sum_{hh} TG_{hh} \quad \text{... Eq. (14)}$$

4. Policy Scenario Settings

4.1. Business-As-Usual (BAU) scenario

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, educational investments intensity by the Korean government (public sector) is also assumed to be maintained at 4% of GDP by 2030. Here, for the BAU scenario we do not consider that educational investments in the public sector affect the endogenous skill accumulation of workers within the model. For this, we set the BAU scenario by reflecting the value of EDU_t subtracted the public sector’s expenditures on the educational investments. 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 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 (OECD, 2017b; Kang et al., 2011; Lim, 2006).

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 private educational investments works efficiently within the 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 those assumptions 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. 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.

4.2. Policy scenario settings

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 2. 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 taxation policy.

Table 2. 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 as in the case of the BAU scenario the R&D intensity is maintained at 4% of GDP. However, 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 heavily 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 taxation 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, other assumptions on the education and tax policy dimensions are the same except for the R&D intensity level. Based on this SCN3 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) *taxation policy*: reforming the tax system by introducing progressive income taxation. The potential impact channels induced by each policy instrument can be illustrated as Figure 8, 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.

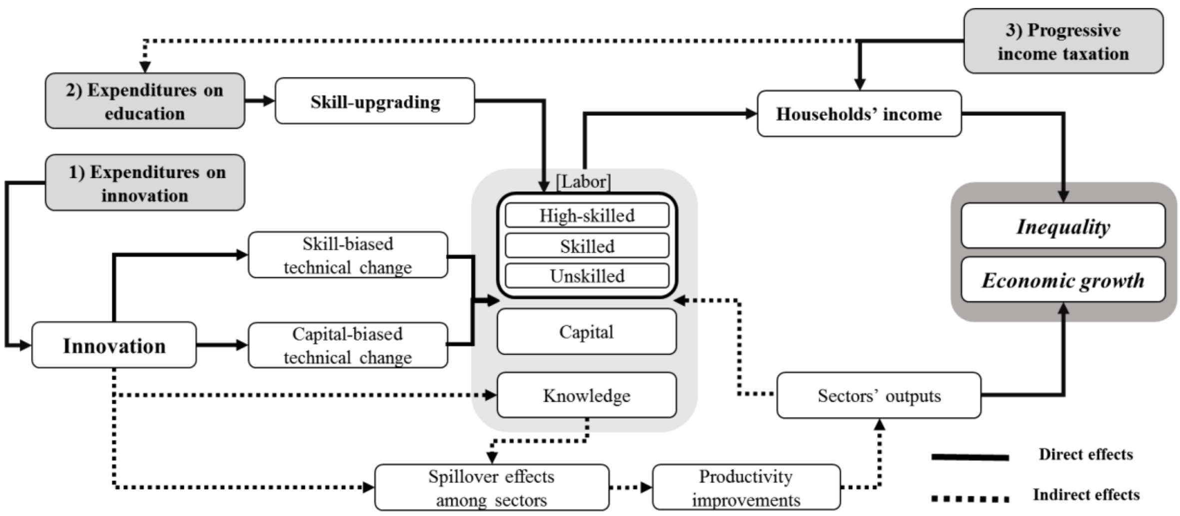


Figure 8. Potential impact channels of policy instruments in terms of the CGE model

5. Results Analysis

5.1. 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 Figure 9, the highest economic growth is found to be achieved under the SCN3 scenario (19.41% higher compared to the BAU level in 2030), followed by the SCN1 (15.61% higher compared to the BAU in 2030), and SCN2 (2.75% higher compared to the BAU in 2030) scenarios.

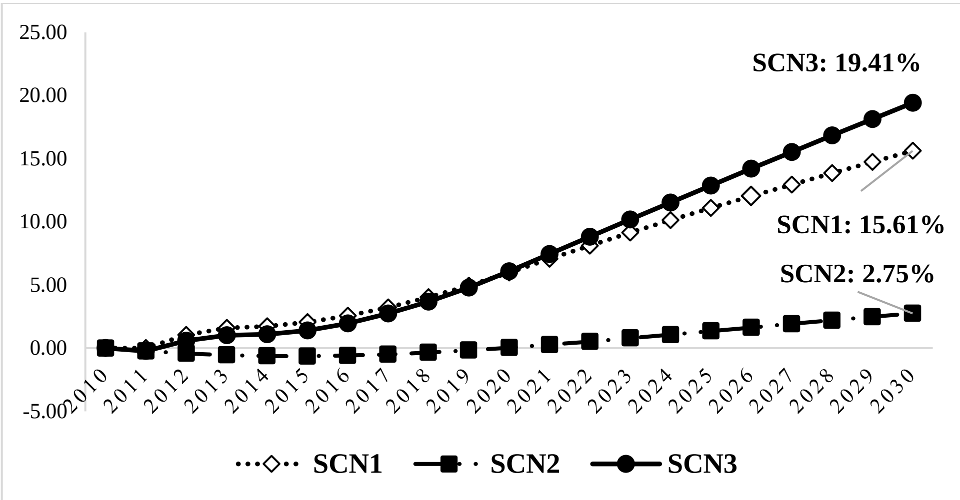


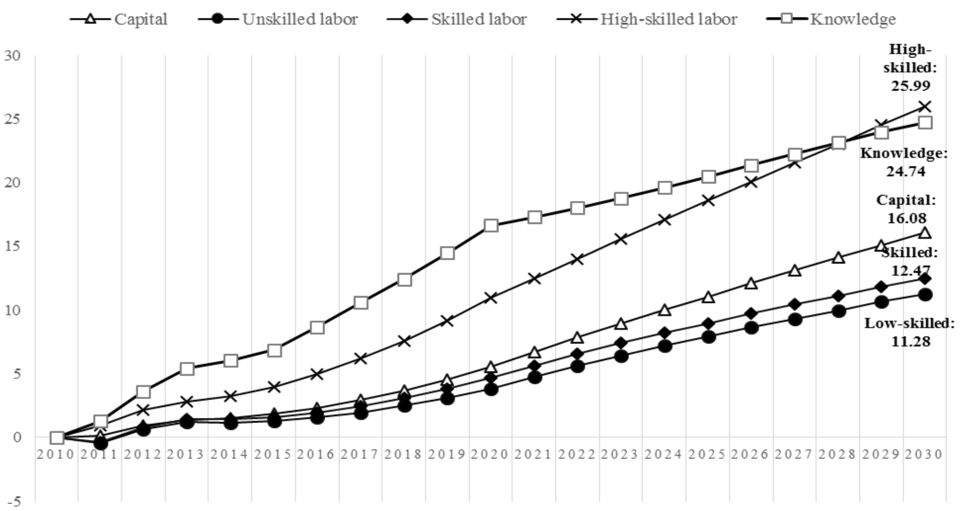
Figure 9. Changes of GDP level (Unit: % change relative to the BAU scenario in 2030)

The GDP growth effects generated by the SCN2 scenario (compared to the BAU level) suggest the complementary relationship between the education policies aiming to spur efficient skill accumulation of workers through learning activities (i.e., vocational training, informal lifelong learning, etc.), and the taxation policies which affect the income redistribution within the households. In addition, it can be understood that under the SCN2 scenario, the expansion of workers with skill accumulation induces scale effects within the economy through indirectly facilitating the endogenous knowledge capital accumulation, on the basis of complementarity between knowledge and high-skilled labor. However, the lower GDP growth effects generated by the SCN2 compared to the SCN1, and SCN3 scenarios imply that the growth effects may be constrained when innovation is not accompanied with the human capital accumulation of workers, which limits the efficient interaction between innovation and human capital.

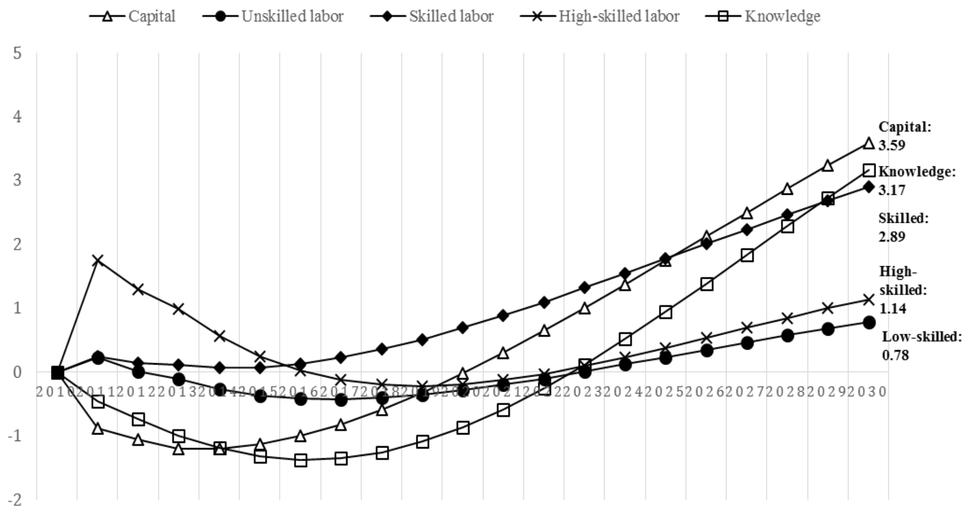
On the other hand, the growth-enhancing effects driven by the SCN1 scenario reaffirm that technological innovation is an important driver for the economic growth in the knowledge-based economy. A higher level of R&D investments leads to productivity improvements, which, in turn, lowers the production 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 can spur the scale effects within the economy, and drive economic growth.

In addition, the highest economic growth effects generated by the SCN3 scenario suggest the complementarity between the policy instruments from three different dimensions (i.e., innovation policy, education policy, and taxation policy). Especially, the growth-enhancing effects of 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 other words, it implies the importance of co-evolution of labor demand triggered by changes in R&D intensity via factor-biased technological change, and labor supply driven by human capital accumulation of workers to spur long-run economic growth.

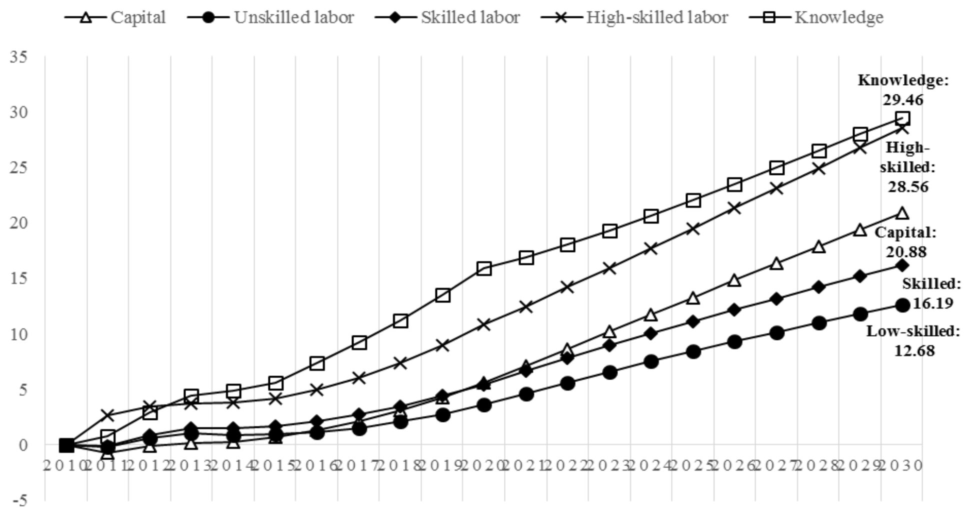
To understand the key determinants and associated impact channels behind the economic growth, we have examined the changes in the compositions of value-added appeared in different scenarios. Figure 10 illustrates the changes of the value-added compositions for each scenario (SCN1, SCN2, and SCN3) from the base year to the target year. In the case of SCN2, it can be seen that the increases in the elements of value-added composition over BAU show 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 factor incomes are found in earnings of high-skilled labor, knowledge capital, and physical capital under the SCN1 scenario (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 in 2030). It can be explained by the complementary relationship among those factor inputs within the production function.



(a) SCN1 scenario



(b) SCN2 scenario



(c) SCN3 scenario

Figure 10. Changes of the value-added composition compared to BAU level (Unit: %)

In addition, in the case of the SCN3 scenario, it reveals 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 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.

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.

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. When the progressive income taxation is levied to the households in order to finance the educational investments (as SCN2 and SCN3), 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, Table 3 depicts the changes of the disposable incomes earned by households under the different scenarios compared to the BAU scenario. As can be seen in Table 3, 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 other scenarios.

Table 3. Changes of disposable incomes of households and private consumption (Unit: %)

Scenario	Average disposable incomes of households relative to BAU (2030)	Growth rates of private consumption (2010-2030)
BAU	-	40.36%
SCN1	15.35%	43.24%
SCN2	1.50%	35.51%
SCN3	14.18%	37.86%

Such a decrease in household disposable income can be attributed to a decline in consumption activities in the private sector. As depicted by Table 3 which also represents the growth rates of private consumption under different scenarios over the period of analysis. Table 3 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 and private consumption growth rates are relatively low compared to the BAU levels. Nevertheless, the SCN2 scenario has shown relatively higher economic growth than BAU (see Figure 9). 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.

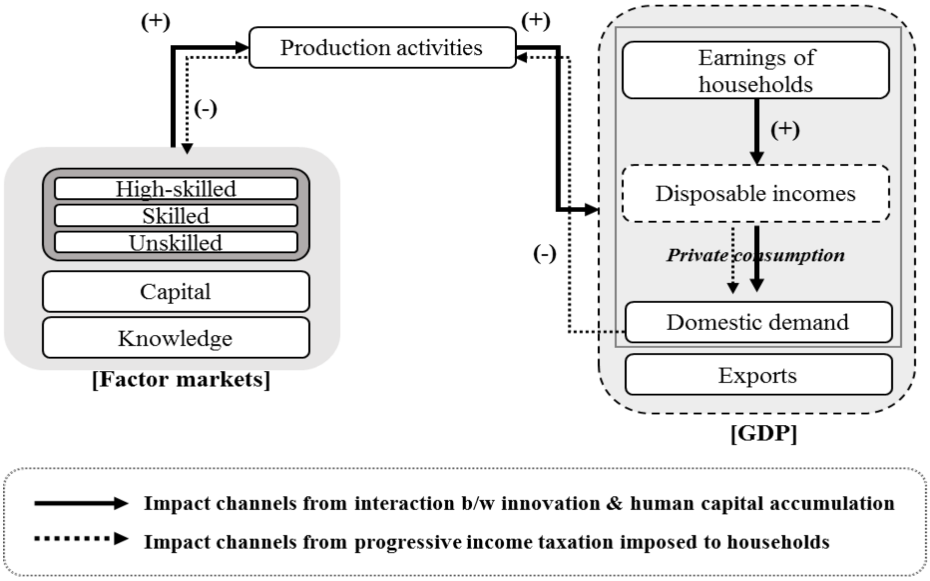


Figure 11. Key impact channels of interaction between innovation and human capital accumulation, and progressive income taxation imposed to households

This interpretation is also possible for the SCN3 scenario. Under the SCN3 scenario, it is found that disposable incomes and consumption levels of households are relatively low compared to those of SCN1. However, in terms of the GDP level, it is found that SCN3 scenario has 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 11 which contains key impact channels from interaction between innovation and human capital accumulation to the expansion of scale effects, and those from progressive income taxation imposed to households to the depression of private consumption. It addresses that when implementing a progressive income taxation, there should be carefulness to consider both the scale effects generated by endogenous interaction between innovation and human capital, and private demand depression effects due to the increases of tax burdens.

Moreover, we will investigate changes in industrial outputs for each scenario. Figure 12 presented below depicts gross industrial outputs under different scenarios. As can be seen in Figure 12, 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: 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.

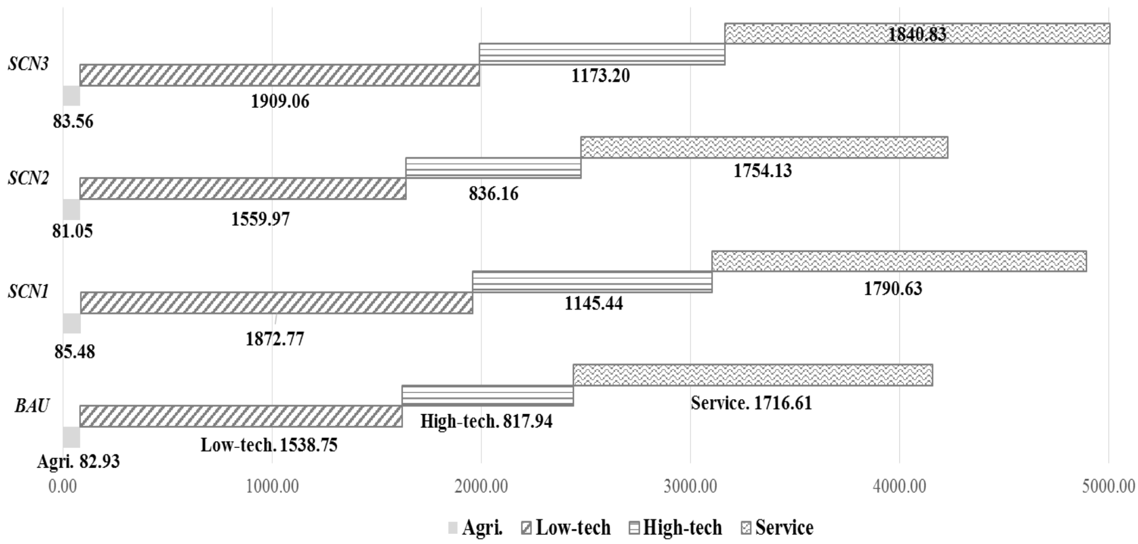


Figure 12. Gross industrial outputs under different scenarios in 2030 (Unit: trillion KRW)

5.2. Effects on employment structure

This subsection provides key results on how changes in the employment structures appear in different scenarios. Table 4 represents 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 4, it is understood that all constructed policy scenarios show higher levels of total employment compared to the BAU. Table 4 also reveals that the aggregate 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.

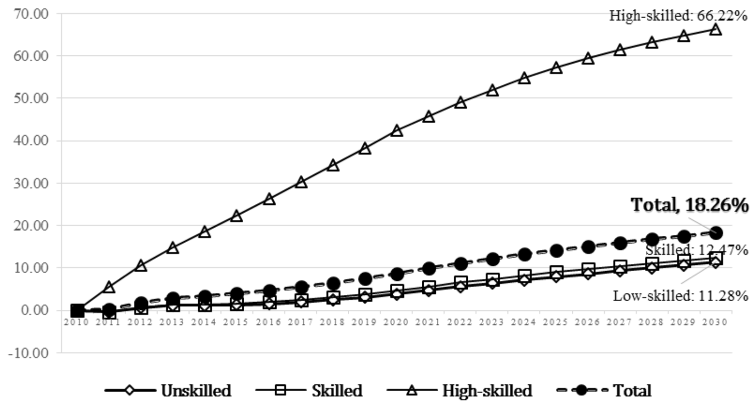
Table 4. Changes of the aggregate labor demand under different scenarios (Unit: %)

	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%

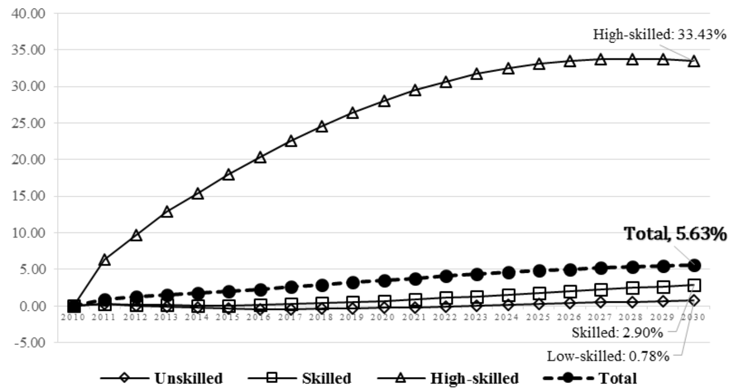
The difference in results between SCN2 and SCN3 scenarios suggests the importance of matching the supply of skilled labor (through education and learning process of workers) and the corresponding increase in demand for skilled labor with the increase of innovation activities (through additional R&D investments). 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 this regard, it is highlighted that to maximize the employment growth effects in the knowledge-based economy, the right types of skills and knowledge should be provided and built up through learning activities, 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 systems should keep pace with technological change and evolving labor markets. It implies that synergies between the evolution of labor demand triggered by innovation and the adaptability of labor supply from education and learning should come together.

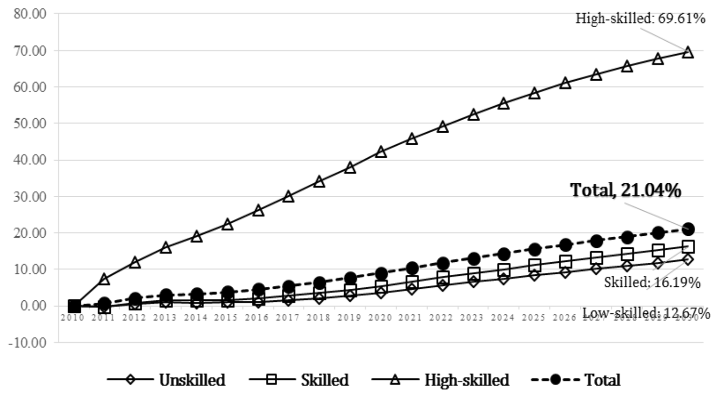
To be specific, when examining the changes of employment by skill type for policy scenarios as shown in Figure 13, we can see that the employment growth effects of high-skilled labor are relatively greater than those of skilled and low-skilled labor. Figure 13 depicts time series' trends in changes of employment level by skill type for SCN1, SCN2, and SCN3 compared to the BAU scenario. As can be seen in Figure 13, 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 other scenarios (high-skilled: 33.43%, skilled: 2.90%, low-skilled labor: 0.73% higher than BAU levels in 2030).



(a) SCN1 scenario



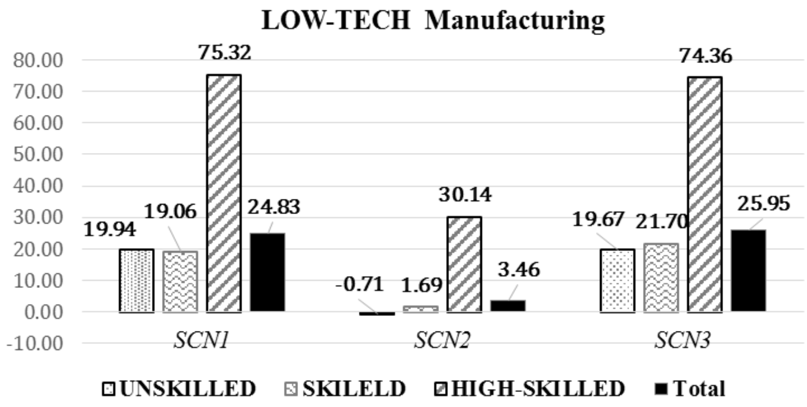
(b) SCN2 scenario



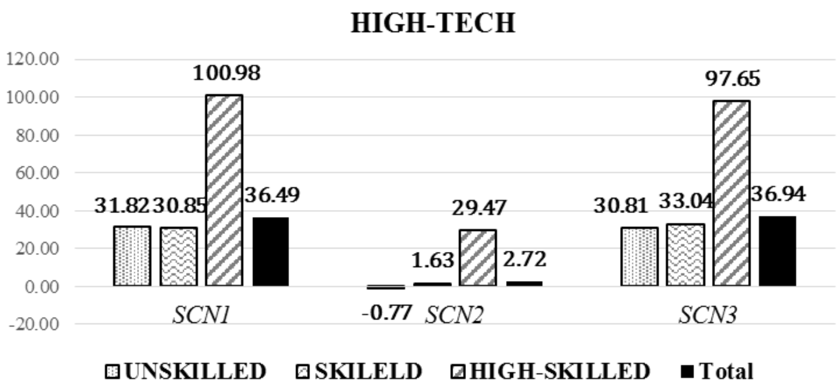
(c) SCN3 scenario

Figure 13. Changes of the employment level by skill type compared to BAU (Unit: %)

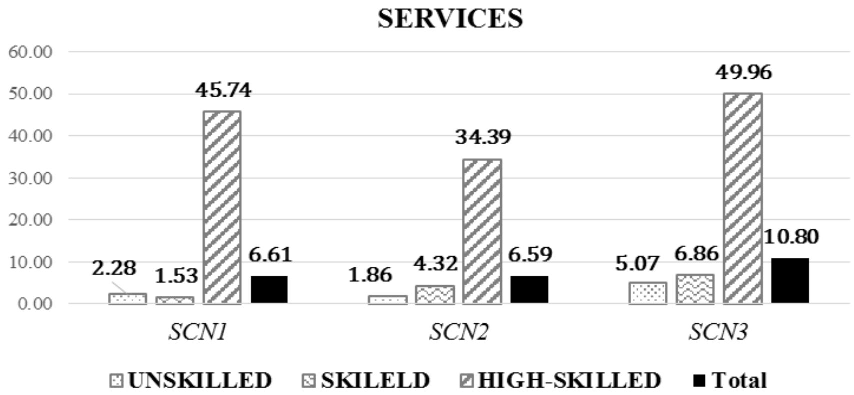
In addition, Figure 14 shows the changes of employment levels by industry. As shown in Figure 14, it is found that under the SCN3 scenario, there are significant increases in total employment levels across industries (low tech manufacturing sector: 25.59%, high-tech manufacturing sector: 36.94%, service 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 employment growth effects 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.



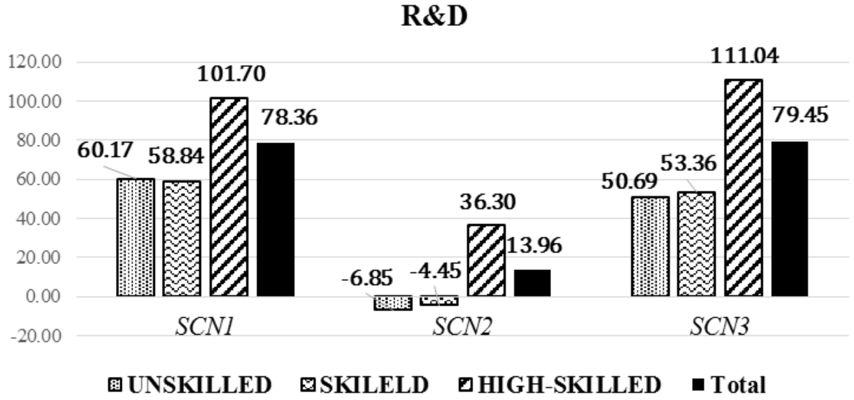
(a) Low-tech manufacturing industry



(b) High-tech manufacturing industry



(c) Service industry



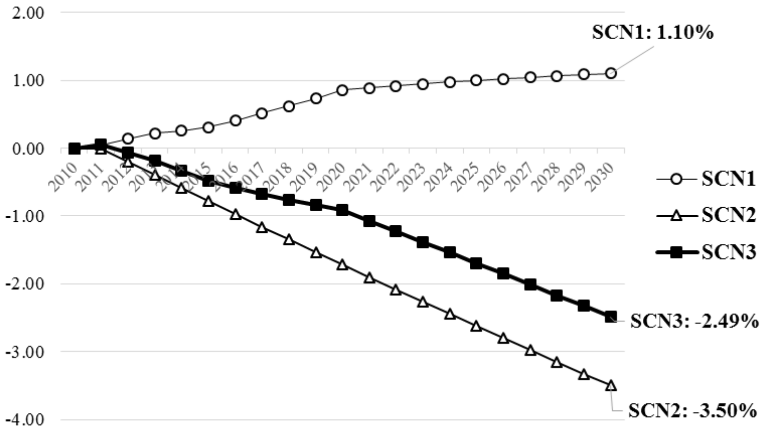
(d) R&D industry

Figure 14. Changes of the employment level by industry compared to BAU in 2030 (Unit: %)

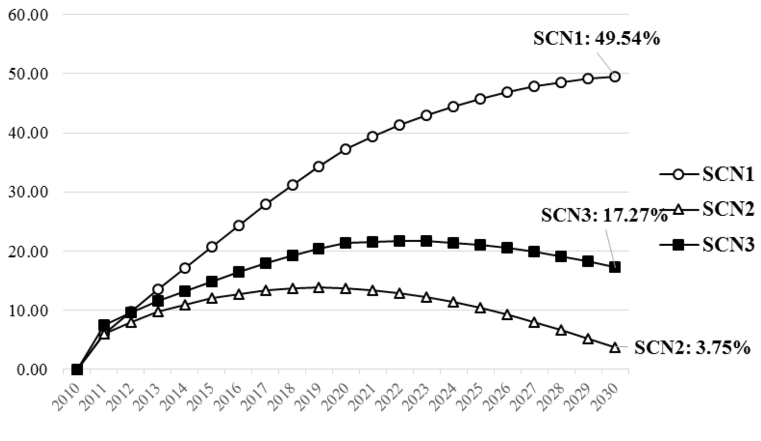
5.3. Effects on income distribution

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 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 15. Figure 15 depicts changes of skill premium, which is calculated as the ratio of the wages of either skilled (PL2) to low-skilled labor (PL1) (Figure 15(a)), or high-skilled (PL3) to low-skilled labor (PL1) (Figure 15(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. It is also 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.



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

However, it is found 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., taxation policy) can play a role in mitigating the structural problems caused by the factor-biased technological change.

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 5. As depicted by Table 5, 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 15 and Table 5, 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 5. Comparison of standard deviation of personal incomes (SDPI) in 2030

	BAU	SCN1	SCN2	SCN3
SDPI	49.63	57.64	49.04	55.48

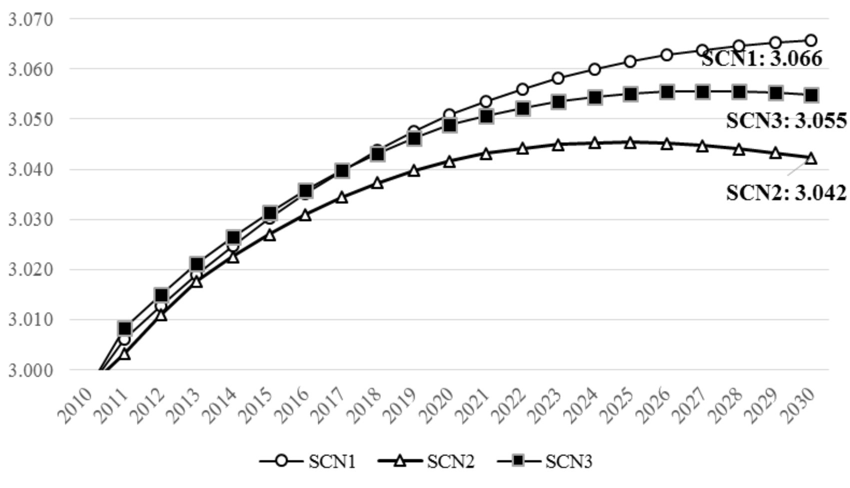


Figure 16. The decile distribution ratio under different scenarios

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 17 illustrates the values of the decile distribution ratio for different policy scenarios. As depicted by Figure 17, 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. Conclusions and Discussions

Recently, many countries 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. 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. The question is then how to formulate and coordinate policy options from various dimensions to achieve inclusive growth in the knowledge-based economy. 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.

With this background, 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, 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) *taxation policy*: reforming the tax system by introducing progressive income taxation. The main findings and implications of this study can be summarized as follows.

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 factor-biased technological change 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.

Conflicts of Interest

The authors declare no conflict of interest.

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