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THE SHRINKING MIDDLE: EXPLORING THE NEXUS BETWEEN INFORMATION AND COMMUNICATION TECHNOLOGY, GROWTH, AND INEQUALITY

Yeongjun YEO[1], Won-Sik HWANG[2*], Jeong-Dong LEE[3]

[1]National Assembly Futures Institute, 1 Uisadang-daero, Yeongdeungpo-gu, Seoul 07233, Republic of Korea
[2]Department of Economics, Jeonbuk National University, 567 Baekje-daero, Deokjin-gu, Jeonju-si, Jeollabuk-do 54896, Republic of Korea
[3]Technology Management, Economics, and Policy Program, College of Engineering, Seoul National University, Technology Management, Economics and Policy Program, Seoul National University, Gwanak-gu, Seoul 151-742, Republic of Korea

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Abstract. To implement specific actions to respond to challenges accompanied by technological advances, it is essential to realize the foreseen future at different levels. This study aims to generate the forecasts of different prospects of different industries, labor market, and households, depending on the pervasiveness of the information and communication (ICT) software (SW) in production. For the analysis, we propose a computable general equilibrium (CGE) model that explicitly incorporates diverse impact channels induced by ICT SW investments. Our simulation results suggest that the development of ICT SW technology can bring about both opportunities and challenges in the economic system. The results also show that advancements in ICT SW can aggravate inequalities within the economic system, while driving higher economic growth effects by accelerating the polarization of the labor market and wages/income distributions. Accordingly, our results suggest that policymakers should formulate tailored policy options to mitigate structural problems and widen income disparities driven by ICT-specific technological advances to achieve economic inclusiveness.

Keywords: ICT advances, ICT SW, growth, distribution, computable general equilibrium.

JEL Classification: C68, L86, L88, O11, O38, O40.

Introduction

To implement specific actions to respond to challenges accompanied by ICT advances, it is essential to realize the foreseen future at different levels, and understand interdependencies between the socioeconomic elements and the technology developments. Using these antici-

*Corresponding author. E-mail: *yel0sik@jbnu.ac.kr*

patory results, possible actions leading to the desired future can be generated, and policy options be explored to guide the effective development of technology, essential institutions, and key applications (Chen et al., 2016). So far, different kinds of experimental and quantitative methods are used to explore the multiple alternatives futures, and to allow the opening up and shaping of present worlds (Järvensivu et al., 2021). However, there has been lack of forecasting methods which systematically take into account the ICT advances and their connections with other socioeconomic elements (Yeo et al., 2021; Hwang et al., 2021).

In this context, a computable general equilibrium (CGE) approach has the potentials to answer the question, whether and how it is possible to make scientific forecasts through incorporating stronger foundations in economic and scientific theories, and involving country- and regional- specific datasets to enhance reliability of the forecasts (Guo et al., 2021). CGE models are widely used to generate forecasts of the prospects of different industries, labor force groups, and households under different scenarios. Therefore, CGE models have been used to answer "*what if*" questions. As a more detailed and comprehensive model for scenario evaluation, CGE model gives information on "*most likely picture*" of future events which are explained in terms of changes in exogenous variable. These forecasts are utilized by policymakers in their mid- and long-term planning decisions.

With this background, this study aims to propose a forecasting model for the analysis of mid- and long-term country-specific futures driven by ICT advances, focusing on the Korean economy. A growing body of studies has estimates the degree and pace of the ICT-driven technological progress, based on the economic hypotheses including skill-biased technological change (SBTC) (Buera et al., 2022; Doraszelski & Jaumandreu, 2018; Taştan & Gönel, 2020; Hagsten & Sabadash, 2017; Mallick & Sousa, 2017), capital–skill complementarity (Grossman & Oberfield, 2022; Alvarez-Cuadrado et al., 2018; Autor & Salomons, 2018), and routine-biased technological change (RBTC) (Cirillo et al., 2021; Böhm, 2020; Lankisch et al., 2019). However, there are few attempts to analyze the economy-wide impacts of ICT progress in the mid- and long-run, considering both the direct impacts of biased technological progress and, indirect impact channels induced by ICT advances (Yeo et al., 2021; Berg et al., 2018).

In order to gain a better understanding of the future possibilities in economic landscapes triggered by ICT advances, we need to incorporate structural and institutional characteristics of socioeconomic system, and multi-sectors approaches. In this context, we are to present a general equilibrium model to analyze the implications of ICT advances for industrial sectors, labor markets, and institutions. It can be understood that CGE models can be useful for policymakers in analyzing the economy-wide effects of changes in exogenous variables with institutional and structural details and predicting the long-run socioeconomic responses induced by these changes (Babatunde et al., 2017).

Specifically, this study aims to generate the forecasts of different prospects of different industries, labor market, and households, depending on the pervasiveness of SW in production. The distinctive features of the ICT-specific CGE model developed in this study and other standard CGE models include describing the intrinsic attributes of ICT-specific technological progress, and taking into account interlinkages between ICT advances and different socioeconomic elements in comprehensive manners. To fulfill this objective, we attempt to collect a wide-range of evidences from existing literatures on economic history, and technology-driven social changes, to frame our methodological elements and provide scientific avenues to forecast potential impacts of ICT-specific technological progress with economy-wide perspectives.

In this regard, this study expects to shed light on novel approach that contributes to scientific forecasts and scenario-based simulation exercise in the economic studies. Based on the proposed CGE model, we are to forecast different levels of socioeconomic impacts that ICT progress could lead to, focusing on Korean economy. Accordingly, we intend to add further insights in a discussion on anticipating potential impacts of advanced ICT, and corresponding policy actions to mitigate disadvantages and dangers through providing forecasts information.

The rest of this paper is organized as follows. Section 1 introduces relevant previous literature. Section 2 provides an overall description of our CGE model. Section 3 explains the policy scenarios and Section 4 presents comparative assessments of policy scenarios using the CGE model. Finally, in the conclusion part we discuss policy implications.

1. Literature review

Although the transformational impacts of ICT advances are expected to be significant within the economic system, linking ICT development and socioeconomic performance quantitatively has been challenging. A growing body of empirical studies suggests that as a general-purpose technology, ICT affects firm productivity growth and performance by promoting product and process innovation.

To evaluate the impact of ICT usage on firm-level performance, various studies generally apply econometric production functions (Taştan & Gönel, 2020; Cardona et al., 2013). For example, Cardona et al. (2013) showed that the majority of previous studies found positive relationships between ICT adoption and firm productivity. In this respect, Donati and Sarno (2013) found that firms tend to exploit productivity growth from ICT investments by conducting econometric analysis based on data from Italian manufacturing firms from 2001–2006. Moreover, DeStefano et al. (2018) show that ICT causally affects firm sales growth and employment expansion. In this regard, the majority of previous studies have examined the impact of ICT on firm-level performance in terms of growth, productivity, and profitability.

In contrast, other studies have investigated the complementarities between ICT usage and human capital (Taştan & Gönel, 2020; Hagsten & Sabadash, 2017). For example, Giuri et al. (2008) examined the complementarity between ICT and skill from the microdata of Italian manufacturing firms during the period from 1995–2003. From the analysis, ICT capital-skill complementarity was evident, and firms that adopt ICTs tend to demand more skilled labor, which supports the SBTC hypothesis. Additionally, Taniguchi and Yamada (2019) examined the existence of capital-skill complementarity and the degree of factor-biased technological change using cross-country panel data. Based on the econometric analysis of the data from OECD countries, they have shown that changes in skill premiums are significantly explained by the adoption and usage of ICT in most of the countries. These findings suggest that workers with higher skills and ICT-specific skills can manage ICTs better, which leads to increases in the wage gaps between high-skilled workers and relatively low-skilled workers. Those studies provide empirical evidence supporting the hypotheses including SBTC and capital–skill complementarity, which implies the bias of the ICT-driven technological progress.

More specifically, recent studies have tested the routinization hypothesis and provided evidence of job and wage polarization from ICT advances. For example, Acemoglu and Autor (2011) found that ICT replaces middle-skill workers who perform routinized tasks, while ICT complements high-skilled and low-skill workers who tend to engage in non-routinized tasks. In this regard, a growing body of literature indicates that ICT advances increasingly substitute middle-skilled labor in routine tasks, resulting in "*routine-biased technological change* (*RBTC*)" (Cirillo et al., 2021; Caines et al., 2017; Heyman, 2016; Akerman et al., 2015; Feng & Graetz, 2015). In this respect, Goos et al. (2014) found a vivid pattern of job polarization with a significant increase in employment shares in the highest- and lowest-wage occupations, hence supporting the RBTC hypothesis.

As mentioned above, ICT advances affect firm performance by creating variants in innovation-related activities (i.e., product and process innovation), human capital compositions, and organizational changes (Taştan & Gönel, 2020). Furthermore, ICT advances with the expansion of ICT investments and may form various impact transmission channels through which firm performance affects socioeconomic performance. In this context, Yeo and Lee (2020) state that it is essential to examine not only the direct effects, but also the indirect effects of ICT advances on the economic system, considering diverse compensation mechanisms in understanding the socioeconomic impacts of ICT advances.

However, the majority of previous studies attempted to demonstrate the direct effects of the usage and adoption of ICT on firm performance based on firm-level analysis with microdata. This impedes the in-depth understanding of the economy-wide effects of ICT advances, while considering inter-industrial linkages, institutional characteristics, and various compensation mechanisms. This study considers the limitations of previous studies and aims to conduct a quantitative analysis of the linkages between ICT advances and socioeconomic effects. For the analysis, we use the CGE model, which has the methodological advantages of quantifying the economy-wide effects of exogenous policy shocks with institutional details, and forecasting the medium- to long-run socioeconomic responses of structural policies.

Although the CGE approach is appropriate for investigating the medium- to long-run effects of permanent policy changes as it does not account for the uncertainty faced by economic system, it has limitations to address the unexpected events and abnormal economic phenomenon. In this regard, this approach has drawbacks in fitting the model to real situations in the dynamic sense through incorporating the uncertainty (Yeo & Lee, 2020; Park & Park, 2020; Park et al., 2017; Rickman, 2010). However, CGE models have advantages of dealing with institutional details with multi-sectoral approaches.

In this regard, CGE models have the merits of analyzing and predicting the sectoral and economy-wide responses of policy shocks within the institutional and country-specific contexts in detail (Yeo & Lee, 2020; Babatunde et al., 2017). Accordingly, with understandings of CGE model's usefulness, this study aims to provide the methodological foundations within a CGE model to analyze the long-run socioeconomic effects of proposed policy changes.

Specifically, we focus on ICT SW investments and their effects on the economic system. The 4IR (Industrial Revolution)-related applications such as big data, machine learning, and

AI allow the development of a new type of SW development, that automatically discovers hidden patterns, processes large amounts of data/information, and proposes new algorithms used to predict and classify the aforementioned patterns (Hesenius et al., 2019). In this regard, the impressive progress in 4IR-related technologies in recent years has been significantly driven by an exponential increase in the availability of SW and computing power (Brynjolfsson et al., 2019). However, Korea ranks 62nd in computer software spending among 134 economies, while it performs particularly well in ICT HW investments (Network Readiness Index [NRI], 2020). This implies that Korea has often ignored the importance of software in the production process compared with ICT HW.

With this background, in recent years, the Korean government has announced the "*Digital New Deal plans for the post-COVID-19 era*" which highlights AI and software development as a future growing business. The development of new software technologies and applications can contribute to output and productivity growth positively, by promoting the agility of organizations, facilitating better integration of firm functions and decision-making processes, and reducing the costs of applications of underpinned ICT HW infrastructures (Taştan & Gönel, 2020). In contrast, it can generate job displacement effects within the production process by reducing the demand for middle-skill workers in routinized tasks, as direct effects. These diverse effects, which affect socioeconomic performance are transmitted to industries, labor markets, and households. Accordingly, this study aims to empirically examine the linkages between ICT SW investments and economy-wide effects in terms of growth and distribution effects, based on key concepts drawn from theoretical foundations and macroeconomic settings, while focusing on the Korean economy.

2. Methodological specifications

2.1. Construction of a Social Accounting Matrix

A social accounting matrix (SAM) describes the interlinkages and interdependences among industrial production activities, factor markets, incomes, and consumption expenditures by institutions. This SAM serves as an underlying dataset that captures the base year's economic condition, which is used by the CGE model to derive the income and expenditure equations. To construct a SAM, we used the 2014 Input-Output (I-O) table published by the Bank of Korea. Based on the sectoral classifications of the I-O table, we considered 24 industrial sectors (see Table A1 in Appendix) within the SAM.

One of the key characteristics of the SAM constructed in this study is associated with the specifications of ICT-related elements. We consider ICT capital (ICT HW and SW capital) as separate production factors, following the approaches of previous studies (Hwang & Shim, 2021). The I-O table only describes the physical capital account, which includes all types of assets in the value-added account. Accordingly, we calculated the relative shares of physical and ICT capital by industry using data from Korea within the WORLD KLEMS database[1].

[1] It provides time-series information on input factors, capital stocks, investment by asset type, as well as value-added and industrial outputs by industrial type. The datasets for Korea are compiled by the Korea Productivity Center (KPC).

In this regard, we have multiplied these values by the gross value added on physical capital identified in the 2014 I-O table to describe ICT capital as a separate factor input by industrial type[2].

Additionally, we specify the ICT capital formation account within the SAM framework. Following the guidelines of the System of National Accounts 2008's guidelines, the original I-O table implicitly includes investments in ICT capital within the physical capital formation account. Accordingly, the capital expenditures amounts from ICT HW/SW manufacturing sectors are deducted from the fixed capital formation account. The same amounts are then moved to ICT capital formation. Through this process, we can derive the SAM dataset that explicitly considers investments in ICT capital as a separate account.

Along with the descriptions of the ICT-related elements within the SAM framework, we classify the single labor account into three groups, based on educational attainment levels, following Yeo and Lee (2020)'s approach. We consider master's and doctor's degree holders as high-skilled labor. College and university graduates are considered skilled labor, whereas low-skilled labor is characterized by lower educational attainment levels. Furthermore, the household account is classified into 10 quantiles based on income levels. We use micro-level data from the Household Income and Expenditure Survey published by the Statistics of Korea. Using this dataset, we extract information on each household's earnings, consumption expenditures, and savings. Through this, we attempt to describe the heterogeneity of households in terms of income and consumption structures.

2.2. The structure of the ICT-specific CGE model

2.2.1. Production structure of final goods

Within the CGE framework, we considered 24 industries as key economic entities that produce a single commodity in a competitive market. In the CGE model, it is assumed that each industrial sector i produces the final outputs (Z_i) by inputting the value-added composite (VA_i) and intermediate goods composite (M_i). Here, a value-added composite is produced by combining the high-skilled ($L3_i$), skilled ($L2_i$), low-skilled labor ($L1_i$), physical capital (K_i), ICT HW capital (HW_i), and ICT SW capital (SW_i), under the multi-level constant elasticity of substitution (CES) production, as shown in Figure 1. In this regard, the industrial sector faces profit maximization under the production functions shown in Eq. (1). Here, A_i represents the total factor productivity, while α_i^M and ρ^Z indicate the share parameters for the intermediate inputs composite and elasticities of substitution between value-added and intermediate goods composites, respectively.

Specifically, to describe the skill-biased technological changes effected by increasing ICT capital explicitly, following the approaches of previous studies (Berg et al., 2018; Eden & Gaggl, 2018; Michaels et al., 2014), it is assumed that ICT capital composite ($ICTCAP_i$), which comprises ICT HW capital (HW_i), and ICT SW capital (SW_i), has a substitutive relationship with skilled labor ($L2_i$). After combining $ICTCAP_i$ composite and $L2_i$ to generate $ICTS_i$ composite, it is modeled that $ICTSK_i$ composite is produced by combining physical capital

[2] Among 11 types of assets specified in the WORLD KLEMS database, we specify the ICT HW capital which includes computing equipment and communications equipment assets, and ICT SW capital.

(K_i) and $ICTS_i$ composite, assuming that these factors are complementary. This approach is associated with the descriptions of the capital-augmenting technological progress induced by ICT capital penetration. Furthermore, it is assumed that N_i composite is combined with high-skill ($L3_i$) and low-skill labor ($L1_i$) under complementary relationships to form a value-added composite within the production function.

$$Z_{i,t} = A_{i,t}\left(\alpha_i^M M_{i,t}^{\frac{\sigma^Z-1}{\sigma^Z}} + (1-\alpha_i^M)\, VA_{i,t}^{\frac{\sigma^Z-1}{\sigma^Z}}\right)^{\frac{\sigma^Z}{\sigma^Z-1}}, \quad (1)$$

where i = 1, 2, ..., 24.

The underlying assumptions behind this form of multi-level CES production function are significantly associated with the descriptions of factor-biased technological change, effected by increasing ICT capital. Recently, several studies have shown that ICT capital is distinct from conventional capital, and highlighted that ICT capital serves as a substitute for labor that performs potentially automatable tasks (Acemoglu & Restrepo, 2020). A growing body of literature stresses that workers with intermediate skill levels (i.e., middle-skill) are likely to be automatable and replaced by ICT capital or automation technologies (Berg et al., 2018; Eden & Gaggl, 2018). In this regard, previous empirical findings suggest that ICT capital or AI capital competes for some tasks engaged by skilled labor (i.e., routinized tasks-intensive), while complementing low- and high-skilled laborers who perform highly non-routine tasks.

Furthermore, previous studies also assert that ICT capital accumulation has a positive effect on traditional capital accumulation, which facilitates capital-augmenting technological progress (Berg et al., 2018). In this regard, we adopt multi-level CES production functions to explicitly describe the substitution possibilities among factor inputs effected by ICT capital accumulation. Accordingly, the value of the elasticity of substitution between $ICTCAP_i$ and

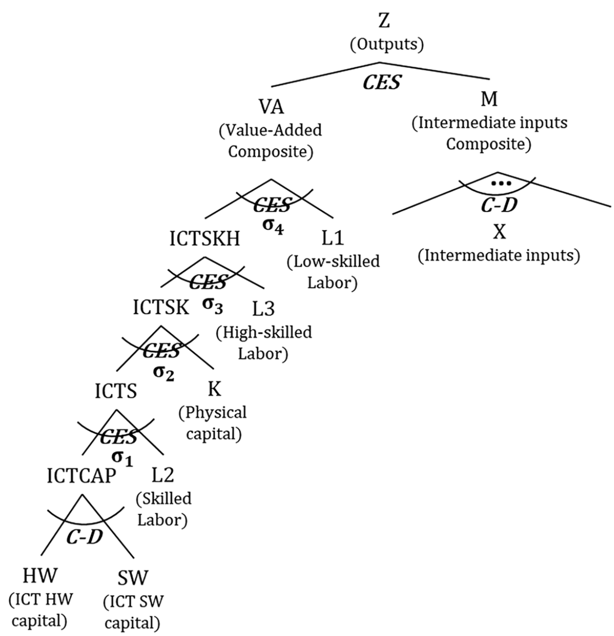

Figure 1. Production structure of final goods

$L2_i$ is set to be greater than 1 (σ_1 = 2.50), while the values for $ICTS_i$ and K_i are set to be less than 1 (σ_2 = 0.67). Additionally, the value of the elasticity of substitution between $ICTSK_i$ and $L3_i$ is set to be σ_3 = 0.39, whereas the values for $ICTSKH_i$ and $L2_i$ are set to be σ_4 = 0.75, which explains the different marginal productivity among heterogeneous types of labor. We adopted the values for the elasticities of substitution within the multi-level CES function from the findings of previous studies (Berg et al., 2018; Eden & Gaggl, 2018; Jung et al., 2017; Michaels et al., 2014).

2.2.2. Productivity improvements from ICT-specific technological change

Within the CGE framework, we also attempted to incorporate the direct and indirect impact channels effected by ICT-specific technological change via embodied technological changes in intermediate inputs and investment goods. First, exogenous technological progress is reflected in the production function for each industry. Specifically, we describe the disembodied technological change in the form of exogenous neutral technological progress (A_i) within the production function (see Eq. (1)). From the data of the Korean Productivity Center (2016), we calculated the average value of the growth rate of the total factor productivity (TFP_i) for the last 10 years by industrial type. Based on these calculated values of TFP_i, we incorporated the disembodied technological progress within the production function. In this regard, it is assumed that 24 industries benefit from the exogenous neutral technological progress rate of (1+ TFP_i) per year (see Eq. (2)).

$$Z_{i,t} = A_{i,t}\left(\alpha_i^M M_{i,t}^{\frac{\sigma^Z-1}{\sigma^Z}} + (1-\alpha_i^M)\, VA_{i,t}^{\frac{\sigma^Z-1}{\sigma^Z}}\right)^{\frac{\sigma^Z}{\sigma^Z-1}}, \tag{2}$$

where $A_{i,t} = A_{i,0}\cdot\left(1+TFP_i\right)^t$ for $i = 1,2,3,\ldots,24$.

Moreover, embodied technological changes in ICT investment goods and intermediate inputs were considered within the model. One key difference between ICT capital (including ICT HW and SW capital) and conventional capital (i.e., physical capital) can be interpreted in terms of quality improvements. For example, Hwang and Shin (2017) note that it is essential to adjust the quality of investment goods via technological efficiency units when comparing their contributions to output growth (or productivity growth).[3] In this respect, they estimated that the embodied technological change in traditional capital is relatively slower than that of ICT capital, using producer price indexes for ICT tangible and intangible assets, while focusing on the Korean economy.

Referring to Hwang and Shin (2017)'s approach, we describe the ICT and non-ICT capital accumulation process as shown in Eqs (3), (4) and (5), by incorporating the parameter $\varnothing$ (e.g., $\varnothing^{hv}$, $\varnothing^{sv}$, and $\varnothing^{k}$) which represents the embodied technological change in investment goods in terms of efficiency unit. Within Eqs (3), (4), and (5), *INVHW* and *INVSW* indicate the gross investments for ICT tangible and intangible capital, respectively, whereas

[3] For example, Schreyer (2000) mention that quality adjustment in the investment goods can be captured by comparing the prices with (P_t^{k*}) and without quality adjustment (P_t^k). In this regard, investment-specific technological change $\varnothing_t^k$ can be calculated using the relative ratio between P_t^k and P_t^{k*} as: $\varnothing_t^k = P_t^k / P_t^{k*}$. Based on this approach, Hwang and Shin (2017) used the producer price indexes for ICT capital assets to measure the P_t^{k*}, while the values of investment deflators in the WORLD KLEMS data are used for quantifying prices without quality adjustments P_t^k.

INVK represents gross physical capital investments. Additionally, parameter δ represents the depreciation rates for ICT and non-ICT capital stocks. Values for the parameters ∅ and δ are adopted by the estimated values from previous studies (Hwang & Shin, 2017; Pyo et al., 2009). Moreover, gross expenditures on fixed capital formation (including *INVHW*, *INVSW* and *INVK*) are distributed across industrial sectors using fixed shares of π_i to form industry-specific assets, following the approaches of previous studies (Hwang & Shin, 2017; Hong & Lee, 2016). Based on these approaches, we attempt to explicitly describe ICT-specific technological improvements embodied in investment goods.

$$HW_{i,t} = \left(1-\delta_{hw}\right)\cdot HW_{i,t-1} + \pi_{i,hw}\cdot \varnothing^{hw}\cdot INVHW_t; \tag{3}$$

$$SW_{i,t} = \left(1-\delta_{sw}\right)\cdot SW_{i,t-1} + \pi_{i,sw}\cdot \varnothing^{sw}\cdot INVSW_t; \tag{4}$$

$$K_{i,t} = \left(1-\delta_{k}\right)\cdot K_{i,t-1} + \pi_{i,k}\cdot \varnothing^{k}\cdot INVK_t. \tag{5}$$

Along with investment-specific technological advances, ICT-specific technological change makes intermediate components (goods) or services associated with ICT more efficient. ICT-using sectors can facilitate productivity improvements by adopting advanced ICT equipment and software and applying these technologies to the production process. For example, industries adopting ICT technologies and platforms can establish the groundwork from which process innovations can be developed. The diffusion of advanced ICT technologies and automation methods on production lines has led to the emergence of new or significantly improved production or delivery processes (Hwang & Shim, 2021). In this regard, within the CGE framework, we incorporated the technological change embodied in intermediate inputs and its effects on ICT-using sectors in terms of productivity improvements.

Similar to the descriptions of investment-specific ICT technological advances, the quality adjustments in terms of technological efficiency units are considered to account for embodied technological changes in the intermediate inputs. Assuming that increases in the quality-adjusted quantities corresponds with a reduction in the quality-adjusted prices of intermediate inputs, the quality improvements of intermediate inputs produced by ICT sectors can be captured by the parameter $\varphi^{ICT}\left(ICT \in \left\{ICT \text{ producing sectors}\right\}\right)$. For example, Hwang and Shin (2017) estimated the annual average quality improvement of ICT intermediate products and services by constructing an estimation equation as follows: $\varphi_t^{ICT} = \frac{M_{i,t}^{ICT*}}{M_{i,t}^{ICT}} = \frac{P_t^{ICT}}{P_t^{ICT*}}$. Here, $M_{i,t}^{ICT*}$ and $M_{i,t}^{ICT}$ denote the quantities of ICT intermediate goods/services produced by the ICT-producers with and without quality adjustment, respectively. Additionally, P_t^{ICT*} and P_t^{ICT} indicate the presence and absence of the quality adjustment prices of ICT intermediate goods, respectively. Based on this equational form and using the time-series data for price data for ICT products and services, Hwang and Shin (2017) derived the annual average quality improvement of ICT intermediate products and services.

Referring to their estimated values, we incorporated the embodied technological changes in ICT intermediate products/services, as shown in Eq. (6). Here, μ_i^M and $beta_j$ indicate a scale parameter for intermediate input composite used by industry *i*, and share parameter within the Cobb-Douglas production function. Additionally, $\varphi^{ICT,i}$ denotes the quality improvement of ICT intermediate products/services used by industry *i*, whereas $X_{j,i}$ indicates the intermediate transaction values from other industries $\left(j \neq i\right)$. Here, we adopted the values of $\varphi^{ICT,i}$ from Hwang and Shin's (2017) work. Moreover, it is assumed that intermediate goods produced by other industries except for ICT-producing manufacturing and service sectors, are not affected by embodied technological change ($\varphi^{j,i} = 1$, where $j \in \left\{ICT \text{ producing sectors}\right\}^c$). In this regard, we attempt to describe the disembodied and embodied technological changes within the model, while focusing on the impact channels induced by ICT-specific technological advances. Figure 2 shows this in detail.

$$M_{i,t} = \mu_i^M \cdot [\sum_j (\varphi^{ICT,i} \cdot X_{j,i})^{beta_j}]. \quad (6)$$

2.2.3. Institutions: Households and government

We considered different types of households in terms of income levels, to investigate the distribution effects driven by policy changes. Specifically, we specify 10 income level quantiles to incorporate the heterogeneous characteristics of each income quantile in terms of earnings and consumption structures. Accordingly, each household's total earnings by income quantile comprises wages, physical capital earnings, and ICT capital earnings. The total wage income by skill type (i.e., *u*: low-skilled (1); *s*: skilled (2); *h*: high-skilled (3)) can be described by Eq. (7), while total earnings from physical capital and ICT capital are expressed by Eqs (8) and (9), respectively. In Eqs (7) and (8), PL_{type} represents the wage by skill type, while *PK* indicates the rental price of physical capital. Similarly, in Eq. (9), *PHW* and *PSW* represent the rental prices of ICT HW and SW capital, respectively.

The gross household income from each factor input (as described by Eqs (7), (8), and (9), is distributed to the 10 income quantiles, in proportion to the relative share of each quantile, to describe the different income structures. The income earned by households is used as

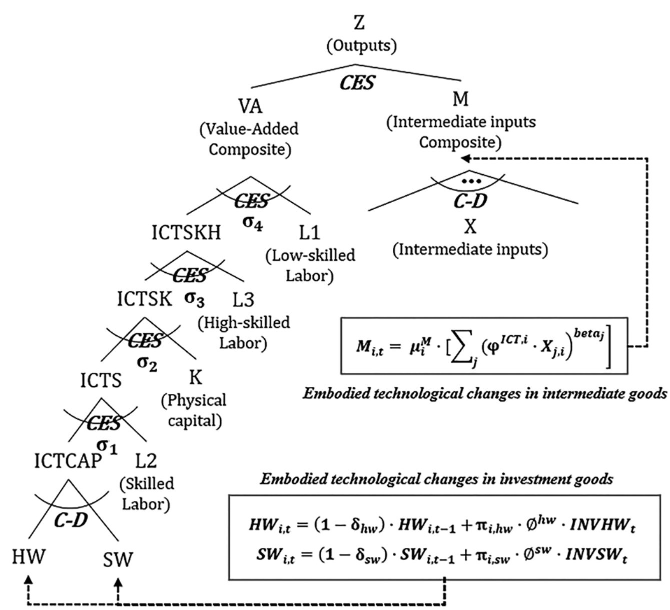

Figure 2. Descriptions of ICT technological progress

household savings and tax payments to the government. By deducting these expenditures from the income, households undertake consumption.

$$HLINC_{type} = \sum_i \left(L_{i,type} \cdot PL_{type} \right), \text{ where } type \in \{u,s,h\}; \tag{7}$$

$$HKINC = \sum_i (K_i \cdot PK); \tag{8}$$

$$HICTINC = \sum_i (HW_i \cdot PHW) + (HW_i \cdot PSW). \tag{9}$$

Moreover, the government earns by levying different types of taxes (i.e., indirect taxes *Tz*, corporate taxes *Tcor*, income taxes *Tinc* and import tariffs *Ttar*). Indirect tax (*Tz*) indicates the production tax imposed on the final outputs of industries. Corporate tax (*Tcor*) is imposed on the capital income earned by industries, while income tax (*Tinc*) represents taxation on household earnings. Moreover, import tariffs *Ttar* are imposed on imported goods. The net income of the government (*Ginc*), which comprises tax income, government debt *Bg*, and household transfers *TG* (see Eq. (10)), are used for savings (*SG*) and government consumption (*Xg*). Additionally, investment levels within the model are considered policy variables.

$$Ginc = Total_{TZ} + Total_{Tinc} + Total_{Tcor} + Total_{Ttar} + Bg + TG. \tag{10}$$

3. Policy scenario settings

3.1. Business-As-Usual scenario

We conducted policy simulations based on the constructed policy scenarios and the methodological specifications within the CGE framework. First, the benchmark scenario assumes that the ratios of investments in ICT SW capital to GDP do not change from the base year to 2030. In the base year, 2014, the ICT SW investment intensity (i.e., the ratio of investments in ICT SW capital to GDP) was found to be 0.75%. Therefore, the benchmark scenario (i.e., business-as-usual (BAU)) assumes that ICT SW investment intensity is maintained from 2014 to 2030. To describe the benchmark scenario, we also utilized the projection data for population growth (i.e., total working-age population) from 2014 to 2030, adopted from Statistics Korea. In this regard, it can be concluded that BAU is a reference to which the results of counterfactual policy scenarios can be compared[4].

3.2. Policy scenario settings

As mentioned above, this study aims to examine the economy-wide effects of ICT SW investments on employment structure and economic growth. Regarding the analysis, we constructed three policy scenarios. In the first scenario (SCN1), ICT SW intensity gradually decreased from 0.75% in the base year, 2014 to 0.65% in 2020. In the second scenario (SCN2), ICT SW intensity gradually increased from 0.75% in the base year to 0.85% in 2020. Furthermore, in

[4] We conducted sensitivity test for the elasticities of substitution in production structure to attest the validity of our CGE model. In this regard, we have presented the key sensitivity analysis results within the Appendix B (see Tables B1–B4).

the third scenario (SCN3), we assume that ICT SW intensity gradually increased from 0.75% in 2014 to 0.90% in 2020. For the analysis, we set the target year as 2030 and assume that the ICT SW intensity for each scenario in 2020 is maintained until 2030. Within the CGE model, we assume that ICT SW investment intensities are exogenously determined as a policy variable, while savings are adjusted according to the ICT SW intensity. In this regard, we consider ICT SW intensity a proxy variable that represents the advances in ICT SW technology. Table 1 summarizes the policy scenarios constructed for this analysis.

Table 1. Policy scenario descriptions

	ICT SW intensity in base year	ICT SW intensity in 2020–2030
BAU Scenario (BAU)	0.75%	0.75%
Scenario 1 (SCN1)	0.75%	0.65%
Scenario 2 (SCN2)	0.75%	0.85%
Scenario 3 (SCN3)	0.75%	0.90%

4. Main results

4.1. Effects on economic growth

In this subsection, we present the main results that represent the economic impacts of different levels of ICT SW investments. Figure 3 depicts the changes in the GDP levels in the policy scenarios, compared with the BAU level. The GDP levels in the BAU fits relatively well at the difference below 10 percent with the actual GDP data in the near future to the year 2019. As shown in Figure 3, SCN3 stimulates the highest economic growth, while the SCN1 shows a lower GDP level compared to BAU.

The results suggest that a higher level of ICT SW investments promotes long-term economic growth, while reduced ICT SW intensity hinders economic growth, hence shrinking the economy. This result is also supported by other studies in that ICT investment plays an important role in boosting economic growth, by affecting the GDP growth bi-directionally in the long-run (Sawng et al., 2021). In addition, it is understood that a higher level of ICT SW investments leads to productivity improvements through ICT-specific technological

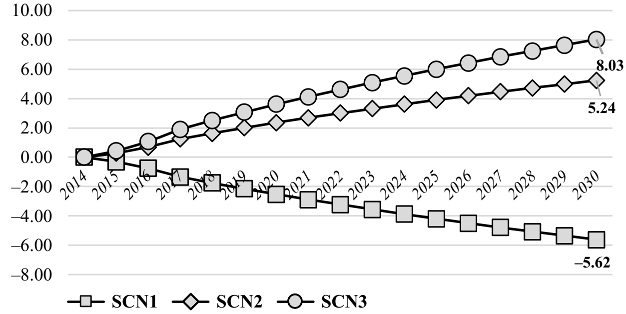

Figure 3. GDP difference from the benchmark scenario, 2014–2030 (%)

change (via embodied technological change in intermediate goods, and embodied technological change in ICT investment goods), which fosters the expansion of production activities. Therefore, it can be concluded that these ICT-specific technological advances and associated productivity gains spur long-term economic growth.

To understand the key drivers and relevant mechanisms behind the different economic growth patterns generated by policy scenarios, we illustrate the results representing the changes in industrial outputs, as shown in Table 2. For the analysis, we reclassify 24 industries into six types of industries[5]. As presented in Table 2, it is shown that a higher level of ICT SW investments has positive impacts on the growth of the industrial outputs of ICT-producing services (i.e., ICT SW sector) and manufacturing sectors (i.e., ICT HW sector). It is noted that industrial outputs produced by the ICT-producing manufacturing and service sectors grow remarkably under the SCN2 and SCN3 to meet the increasing demand for ICT SW investment goods.

Evidently, an increase in ICT SW investments, especially for the SCN3 with the highest increases in ICT SW investments, leads to the expansion of ICT-producing sectors, as well as

Table 2. Industrial outputs differences from the BAU scenario by sector (%)

		2015	2020	2025	2030
Total Industries	SCN1	–0.22	–2.73	–4.43	–5.89
	SCN2	0.20	2.56	4.15	5.51
	SCN3	0.31	3.93	6.37	8.46
ICT Producing Service	SCN1	–0.79	–6.16	–7.62	–8.69
	SCN2	0.73	5.84	7.26	8.30
	SCN3	1.12	8.99	11.20	12.80
ICT Producing Manufacturing	SCN1	–0.45	–4.87	–6.99	–8.49
	SCN2	0.42	4.60	6.64	8.07
	SCN3	0.63	7.08	10.23	12.44
ICT Using Service	SCN1	–0.60	–5.18	–6.88	–8.19
	SCN2	0.55	4.89	6.54	7.81
	SCN3	0.84	7.53	10.07	12.04
ICT Using Manufacturing	SCN1	–0.73	–5.74	–7.20	–8.34
	SCN2	0.67	5.41	6.83	7.95
	SCN3	1.02	8.31	10.52	12.25
Non-ICT Service	SCN1	0.55	1.62	–0.14	–1.51
	SCN2	–0.51	–1.60	–.008	1.11
	SCN3	–0.78	–2.49	–0.20	1.58
Non-ICT Manufacturing	SCN1	–0.25	–2.72	–4.11	–5.25
	SCN2	0.23	2.56	3.86	4.94
	SCN3	0.35	3.93	5.94	7.60

[5] We reclassify the sectors into six types of sectors, according to the share of the ICT capital inputs in the value-added composite by industry), following the approaches proposed by previous works (Yeo & Lee, 2020).

the ICT using service and manufacturing sectors (ICT producing service: 12.80%; ICT producing manufacturing: 12.44%; ICT using service: 12.04%; ICT using manufacturing: 12.25% relative to BAU levels). This can be explained by productivity improvements and spillover effects through ICT-specific technological changes. We can infer that as ICT-producing sectors grow significantly, they bring about greater positive impacts on the growth of ICT-using sectors, by supplying more productive intermediate goods via embodied knowledge spillover effects. In this regard, we can understand the ICT virtuous circulation mechanisms are promoted to spur greater scale effects, as noted by other previous studies (Vu et al., 2020; Jorgenson & Vu, 2016; Hwang & Shin, 2017).

To be specific, it is noted that technological progress induced by the investments in ICT SW capital develops ICT-producing sectors and ICT-using sectors, mainly benefited by product- and process- innovations, through utilizing high-performance intermediate inputs (e.g., semiconductors and electronic equipment with higher speed, higher density and lower power), as well as the advanced production equipment and relevant intangible assets (e.g., automated production facilities and advanced SW algorithms). These effects derive higher productivity improvements of whole economic system, which leads to higher economic growth. In this sense, it can drive the growth of investments in ICT capital, which spur the ICT virtuous circulation mechanisms in the long-run.

Additionally, we explore how changes in the composition of gross value added appear in each policy scenario to understand the underlying factors behind economic and industrial growth, as presented in Figure 3 and Table 2. Figure 4 shows the changes in value-added compositions for SCN1, SCN2, and SCN3 compared with the BAU levels. This shows that SCN3 shows the most significant increase in factor income compared with the BAU level. Specifically, it is found that SCN3 has shown the largest increase in factor income from ICT SW capital, ICT HW capital, and high-skill labor. This suggests that economic growth with increasing ICT SW investments can stimulate the accumulation of ICT capital stocks and facilitate a greater demand for high-skilled workers. It also implies that scale effects and growth-enhancing effects tend to increase, through facilitating ICT capital-skill complementarity, thereby creating indirect demand increases towards those factor inputs, as noted by previous studies' findings (Acemoglu & Restrepo, 2022; Autor & Salomaons, 2018; Berg et al., 2018). Accordingly, we can infer that these disproportionate increases in demand for factor inputs can accelerate the degree of bias in ICT-specific technological advances.

4.2. Effects on employment structure

In this subsection, we examine the changes in employment structures according to scenario type. Figure 5 illustrates the total labor demand differences from the BAU. Figure 5 shows that the aggregate labor demand grows the most under SCN3, in which ICT SW investments are made at the highest level. In contrast, SCN1 with decreasing ICT SW intensity shows a lower employment level relative to the BAU. These results imply that a higher level of ICT SW investments creates many more jobs with the significant expansion of industrial production activities by offsetting the effects of capital- and skill-biased technological change, which can lower the employment level in the economy.

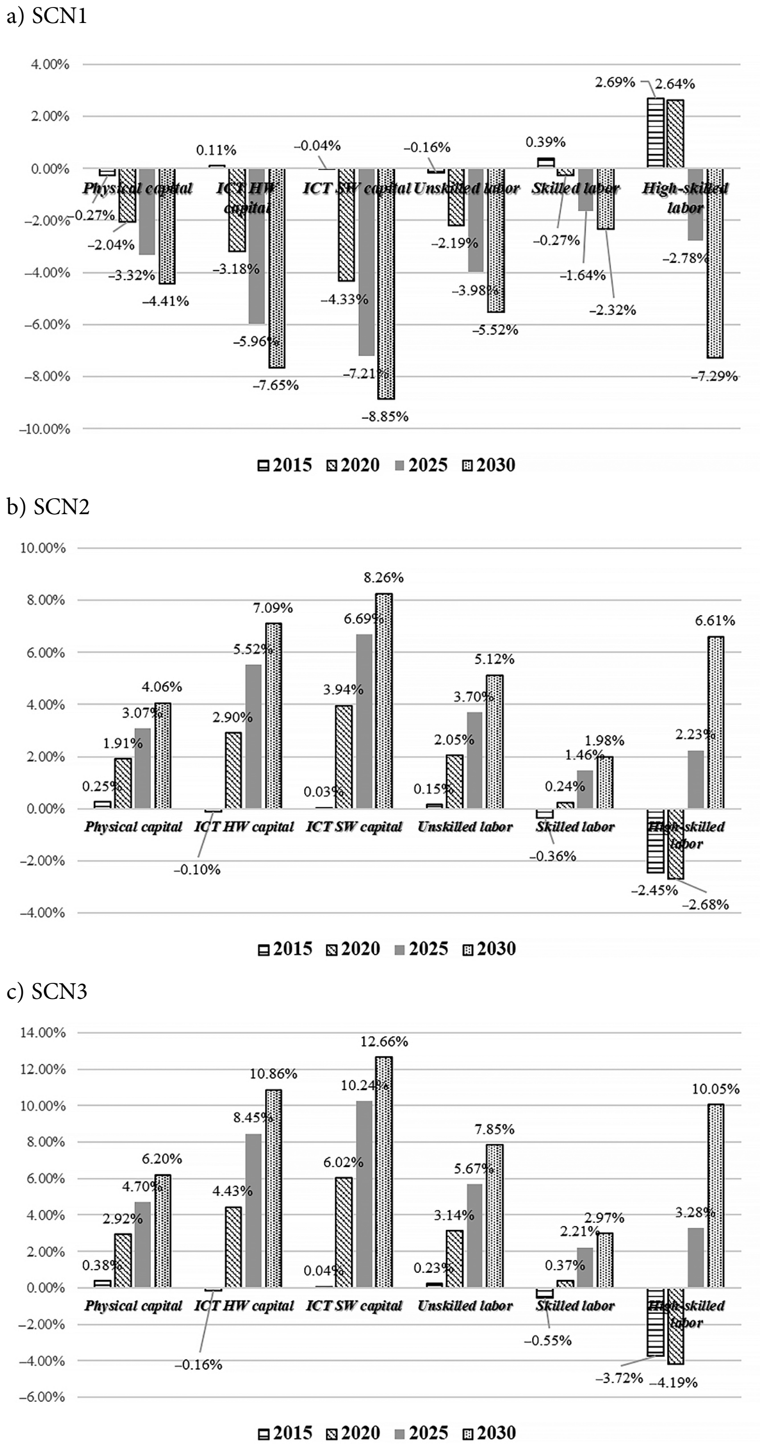

Figure 4. Changes of the value-added in policy scenarios (% relative to the BAU)

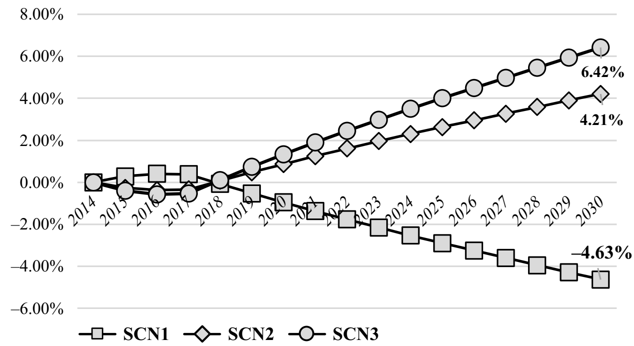

Figure 5. Differences of aggregated labor demand from the BAU (%)

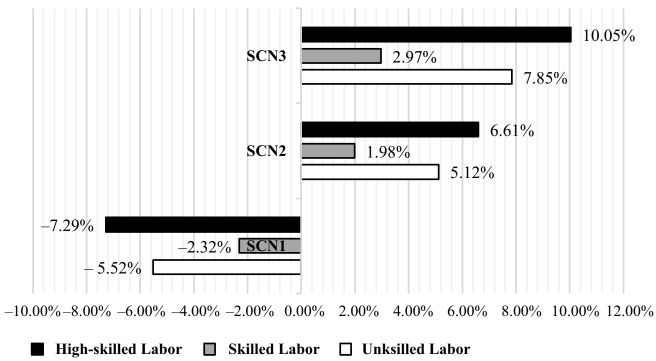

Figure 6. Differences in labor demand from the BAU in 2030 (%)

Additionally, Figure 6 depicts the changes in labor demand by skill type for policy scenarios compared with the BAU in 2030. Figure 6 suggests that a higher level of ICT SW investment could accelerate the polarization of the workforce. ICT-specific technological advances resulting from a higher level of ICT SW investments can expand aggregate labor demand, as shown in Figure 5. However, ICT SW can polarize the skill structure. The results suggest that ICT-driven technological advances have comparatively stronger impacts on the increase in demand for high-skill and low-skill labor, while it leads to the greatest increase in demand at the top (high-skilled). However, notably, a higher level of ICT SW intensity drives a relatively low level of demand in the middle-skilled. This ICT-based polarization becomes more apparent as the intensity of ICT SW investments increases.

It can be understood that these results support the RBTC hypothesis, which propose implications of ICT advances for labor markets. According to the RBTC framework, occupations and workforces are considered as the bundles of tasks, and middle-skill workforces are susceptible to automation and ICT advances, as they tend to engage in routinized tasks intensively (Cirillo et al., 2021; Böhm, 2020; Acemoglu & Restrepo, 2019; Acemoglu & Autor, 2011). In this regard, it is noted that routine task intensity of workforces is the critical predictor of changes in wage and employment structures (Caines et al., 2017; Frey & Osborne, 2017). Accordingly, we can understand that in Korean economy, middle-skill labor has relatively lower comparative advantage over other types of workforces, as their occupations are intensive in routine tasks, implying that they are under greater pressures of automation and technological unemployment driven by ICT-specific technological progress.

Accordingly, it can be understood that ICT-specific technological advances favor high-skill and unskilled workers much more than middle-skill workers in Korean economy. It can be inferred that ICT-driven technological changes result in *"polarization"* in the labor market in the sense that workers in the middle of the wage and skills distribution appear to be left behind than those at the bottom and the top. Furthermore, Figure 7 illustrates the differences in labor demand from the BAU levels in 2030 by industrial sector, focusing on the SCN1 and SCN3 scenarios. As shown in Figure 7, it suggests that ICT-intensive industries (with higher levels of ICT capital investments and ICT capital stocks) enhance ICT-driven polarization effects substantially by shifting labor demand and providing greater employment opportunities to those with in-demand skills.

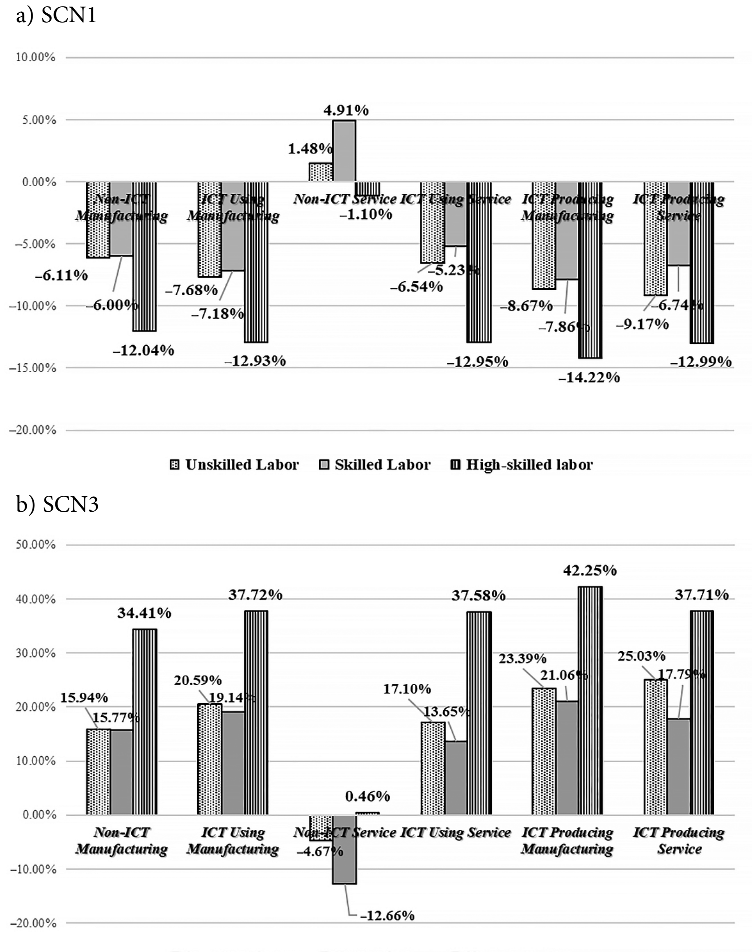

Figure 7. Differences in labor demand from the BAU in 2030 by industrial type (%)

These results imply that interlinkages between the production activities of the industrial sectors and their derived demands for workforces determines the pace and direction of the ICT advances. To be specific, it can be understood that higher scale effects fulfilled by the ICT-intensive industries trigger relatively higher employment expansion effects towards high-skilled and unskilled labor, thereby facilitating the ICT capital-skill complementarity. Accordingly, it can deepen the extent of biased technological progress, and spur the polarization in the labor market in terms of employment structure, as shown in the results presented by Figure 6 and Figure 7.

4.3. Effects on wage and income distribution

The increase in labor demand is linked to the expansion of employment and a rise in workers' wages. In this regard, differences in labor demand for particular skills cause wage differentials between workers with different skills. From the results on changes in labor demand by skill type, it is found that ICT-specific technological advances increase the demand for high-skill and unskilled labor over skilled labor (i.e., intermediate level of skills), disproportionately. In this regard, Figure 8 illustrates the changes in wage differentials for policy scenarios, which is defined as the ratio of the wages of either high-skill to skilled workers or skilled to unskilled workers in 2030, compared with those of BAU.

As shown in Figure 8, with a higher level of ICT SW intensity (SCN2 and SCN3), the skill premium for high-skill workers increases steadily and over time as the relationship between high-skill wage growth and ICT intensity growth is found to be strong. In contrast, the skill premium for skilled workers decreases, as the demand for skilled workers is relatively lower than for other types of workers, and the demand for unskilled workers is relatively higher than that for skilled workers. Based on these results, it can be inferred that ICT-driven technological changes tend to accelerate job polarization trends, where employment and wage growth effects are concentrated among high- and low-skill workers, while workers in the middle of skill distribution are diminished. This suggests that the relative demand for intermediate-skill labor is likely to decline with the increase in ICT adoption, as they often work in routinized tasks, compared with other types of labor.

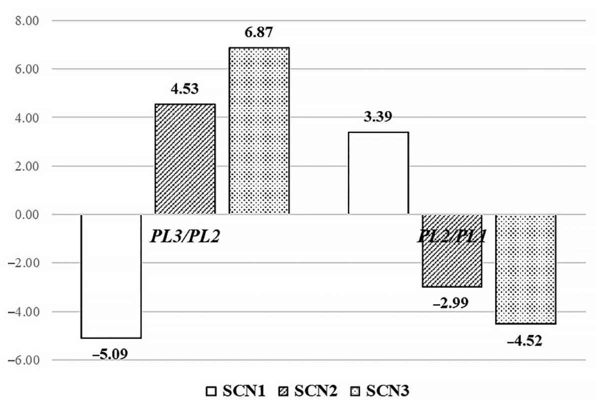

Figure 8. Changes of wage differentials among workers in 2030 (% relative to the BAU)

Accordingly, it can be understood that ICT-driven technological progress facilitates wage polarization with shrunk intermediate-skill labor. In this regard, it is noted that when the ICT-specific advances are facilitated through expansions of ICT SW investments, the polarization of wage and employment structures is expected to deepen in the Korean economy, as noted by other studies (Acemoglu & Restrepo, 2019, 2022; Richmond & Triplett, 2018; Caines et al., 2017). In this regard, our results suggest that there should be supplementary policy alternatives, as to resolve and alleviate the labor market polarization effects caused by the ICT advances, not only solely focusing on the ICT advances with greater investments.

As noted above, we have analyzed the impacts of ICT SW investments on employment structure and economic growth. From these analyses, it is found that ICT-driven economic growth favors highly skilled and unskilled workers much more than middle-skill workers, resulting in the ICT-based polarization of skill structure. Furthermore, we find that economic growth triggered by ICT-specific technological advances, is sourced from the transition of the value-added composition toward high-skill labor, ICT HW, and SW capital. This factor-biased technological progress driven by ICT SW investments is significantly associated with wage inequality and income polarization. Therefore, it is meaningful to analyze the key indicators of the income distribution of the economy.

To examine the income distribution among income quantile groups (HOU1–HOU10), we examined the changes in the share of each income quantile group in 2030 compared with the BAU. As shown in Figure 9, it is expected that the income share of the middle-income class would be decreased when a higher level of ICT SW investment is made. This suggests that a higher level of ICT SW spending can accelerate income polarization among households. Furthermore, Table 3, which presents the changes in the wage inequality indicator (i.e., SDPI: Standard Deviation of Personal Incomes) in each policy scenario compared with the BAU, supports the fact that the household income inequality indicator increases markedly with respect to that in BAU when there is a higher level of ICT SW investments. As ICT-specific technological progress is accelerated, it suggests that income inequality among economic entities may intensify, implying the advent of the "Superstar" economies (Tambe et al., 2020).

Based on these results, we can conclude that the relative proportion of the middle-income class could be decreased when investment in ICT SW increases. This implies that middle-income classes tend to engage in intermediate-skill intensive work. Through this, it can be understood that as the ICT SW investment intensity increases, the relative proportion of the household income quantile of the middle class can decreases further, which can lead to a noticeable income polarization phenomenon. Furthermore, with diminishing shares of middle-income households, income inequalities are increased through the provision of higher returns to high-skill workers and capitalists.

Widening inequalities between rich and poor are considered as one of the critical challenges faced by global economies, as well as the Korean economy. Especially, income inequality is deeply linked with economic instability and less social wellbeing (Yeo et al., 2021). In this regard, it is noted that policymakers should prepare and implement a wide range of policy instruments, such as reforms in educational/learning systems, and taxation schemes, in order to deal with inequality issues.

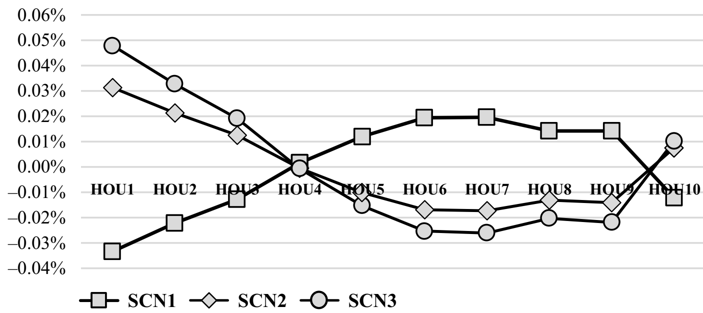

Figure 9. Changes in the share of each income quantile group in 2030 (%p relative to the BAU)[6]

Table 3. Changes in the SDPI in policy scenarios (% change relative to the BAU)

		2015	2020	2025	2030
SDPI	SCN1	0.50%	–0.40%	–2.46%	–4.43%
	SCN2	–0.45%	0.33%	2.18%	3.98%
	SCN3	–0.69%	0.48%	3.29%	6.05%

Conclusions

To implement specific actions to respond to challenges accompanied by ICT advances, it is essential to realize the foreseen future at different levels (i.e., economy-, sector-, labor market-, household- levels), and understand interdependencies between the socioeconomic entities and the technology developments. With this background, this study aims to propose a forecasting model for the analysis of mid- and long-term country-specific futures driven by ICT advances. Specifically, this study aims to generate the forecasts of different prospects of different industries, labor market, and households, depending on the pervasiveness of SW in production.

From the analysis, it is found that when investments in ICT SW capital increase to facilitate ICT-driven technological progress, it promotes higher growth with higher scale and productivity improvement effects. However, in terms of the employment structure, the pervasiveness of software in the production process can accelerate the polarization of the labor market by concentrating employment opportunities for high- and low-skill workers, while workers in the middle of skill distribution are diminished.

Additionally, our results suggest that skill premiums appropriated by workers with intermediate skills tend to decrease with the promotion of ICT-driven technological progress, which leads to the further weakening of the middle-income households exposed to higher possibility of being left behind relative to high-and low-paying households. Accordingly, we find that advancements in ICT SW have the potential to increase inequalities within the economic system while driving higher economic growth effects by accelerating the polarization of the labor market and wages/income distributions.

[6] Here, HOU1 indicates the bottom 10% of the households with the lowest income, while HOU10 represents the top 10% of the households with the highest earnings.

Our study is significant in that it quantifies the economy-wide impacts of ICT-driven technological changes by considering both direct and indirect impact channels driven by ICT SW investments. Moreover, our results imply that the development of ICT SW technology can create both opportunities and challenges in the economic system. Accordingly, our results suggest that policymakers should formulate tailored policy options to mitigate the structural problems (i.e., polarization of the labor market) and widening income disparities driven by the expansion of SW applications and associated ICT-specific technological advances to achieve inclusiveness of the economy.

Our simulation results suggest that promoting ICT-specific technological advances with the expansion of SW investments within the economic system is essential to achieve a higher economic growth state and aggregate employment expansion. This suggests that ICT SW technologies can serve as a key enabler for economic growth and expansion of scale effects. Therefore, we can infer that to achieve the growth objectives, investment promotion policies should be implemented to enhance the positive externalities induced by ICT SW capital accumulation via inter-industrial linkages. Specifically, policymakers should design and formulate policy instruments to trigger higher ICT-specific investment activities by granting subsidies, revising market regulations, and supporting networking activities among industries or firms, to further spur higher positive externalities and growth-enhancing effects within the economy.

Furthermore, considering the increasing economic inequality among countries due to technological progress, our results and implications can be extended to the global perspective, not only within a country. In this sense, policy measures to promote ICT SW investment are more crucial for developing and low-developed countries to take opportunities and benefits from emerging technologies.

On the other hand, policymakers should consider investigating how to resolve the structural problems driven by advancements in ICT SW, such as the polarization of the labor market and income inequality issues. From the analysis, it is shown that the growth-enhancing effects driven by ICT-specific technological changes are promoted at the expense of middle-skilled labor. Accordingly, it is noted that the extent of growth and distribution patterns of the economic system with skill/routine-biased technological changes in the long-run depend on the degree of wage and employment polarization.

The problem of polarization in the labor market is likely to deprive individuals of opportunities to improve social mobility in the mid- to long-term and expand side effects such as various confusion, discrimination, and inequality in society. Therefore, our main findings suggest that policymakers should adopt systemic approaches, as to mitigate the effects of polarization on the labor market with widespread ICT applications in the 4IR era. Accordingly, we are to draw upon following policy implications to deal with the problem of polarization in the labor market attributed to skill/routine-biased technological changes.

Firstly, policy priorities should be redefined to help middle-skill workers navigate sufficient opportunities for skill accumulation and lifelong learning, to further cope with rapid technological changes. Therefore, existing workplace-based vocational training and lifelong learning programs should be reorganized to create opportunities for workers to learn new skill sets and transform their tasks, to further remain compatible with ICT-driven technological changes. Secondly, along with expanding employment opportunities for middle-skilled workers via government-led programs, it is necessary to increase productivity and quality of jobs engaged by those workers, as well as increase the flexibility in the labor market to enhance their social mobility.

Thirdly, unemployment income support systems and relevant social protection systems should be tailored, as to manage the obsolescence of many middle-skilled workers. High benefit replacement rates might be a complementary policy option to incentivize unemployed middle-skilled workers to participate in up-skilling and re-training programs that facilitate re-entry into the labor market and smooth transition process of those affected workers. Furthermore, tax and redistribution policies should be considered as part of broader structural reforms for inclusive growth. In this regard, policymakers should consider the potential trade-offs between growth and equity objectives in designing tax and redistribution schemes, to spur the inclusiveness of the economy by promoting ICT-specific technological advances.

The limitation of this research lies in the underlying assumptions of the methodological settings. Firstly, we have set the base year of 2014 to conduct the policy simulations due to the data availability and interconnectivity between various data resources in constructing the SAM for the calibration process. In this respect, future research should include describing the economic and social situation more realistically within the CGE model, by using recent data resources and updating model parameter values. Secondly, within the conventional CGE framework, we have incorporated the fixed-coefficients assumptions in describing the production and allocation functions. This approach has limitations to account for the adaptation process induced by economic crisis or unexpected shocks (e.g., COVID-19 and the Russia-Ukrane war), and fit the model to reality in dynamic sense. In this regard, we are to explore alternative approaches to overcome the fixed-coefficients assumptions proposed by other previous studies, and incorporate those frameworks within the model, as to increase the reliability of the model forecasts results. Thirdly, in order to describe the household sector and the labor market more realistically and specifically, various complementary data are to be explored. For example, by searching for complementary data to reflect different consumption and income propensity characteristics for each household quintile, we intend to achieve an in-depth analysis of the impact of each household quintile.

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Author contributions

Prof. Jeong-Dong Lee proposed the creative idea and designed this research. Based on the idea, Dr. Yeongjun Yeo and Prof. Won-Sik Hwang have cooperatively implemented the computable general equilibrium model. In addition, Dr. Yeongjun Yeo was responsible for the interpretation of the results and wrote the first draft of the article.

Disclosure statement

The authors declare no conflict of interest.

References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2022). Demographics and automation. *The Review of Economic Studies*, *89*(1), 1–44. https://doi.org/10.1093/restud/rdab031

Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, *130*(4), 1781–1824. https://doi.org/10.1093/qje/qjv028

Alvarez-Cuadrado, F., Van Long, N., & Poschke, M. (2018). Capital-labor substitution, structural change and the labor income share. *Journal of Economic Dynamics and Control*, *87*, 206–231. https://doi.org/10.1016/j.jedc.2017.12.010

Autor, D., & Salomons, A. (2018). *Is automation labor-displacing? Productivity growth, employment, and the labor share* (NBER No. 24871). National Bureau of Economic Research. https://doi.org/10.3386/w24871

Babatunde, K. A., Begum, R. A., & Said, F. F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, *78*, 61–71. https://doi.org/10.1016/j.rser.2017.04.064

Berg, A., Buffie, E. F., & Zanna, L. F. (2018). Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics*, *97*, 117–148. https://doi.org/10.1016/j.jmoneco.2018.05.014

Böhm, M. J. (2020). The price of polarization: Estimating task prices under routine-biased technical change. *Quantitative Economics*, *11*(2), 761–799. https://doi.org/10.3982/QE1031

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0001

Buera, F. J., Kaboski, J. P., Rogerson, R., & Vizcaino, J. I. (2022). Skill-biased structural change. *The Review of Economic Studies*, *89*(2), 592–625. https://doi.org/10.1093/restud/rdab035

Caines, C., Hoffmann, F., & Kambourov, G. (2017). Complex-task biased technological change and the labor market. *Review of Economic Dynamics*, *25*, 298–319. https://doi.org/10.1016/j.red.2017.01.008

Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, *25*(3), 109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002

Chen, H., Yu, J., & Wakeland, W. (2016). Generating technology development paths to the desired future through system dynamics modeling and simulation. *Futures*, *81*, 81–97. https://doi.org/10.1016/j.futures.2016.01.002

Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digitalization, routineness and employment: An exploration on Italian task-based data. *Research Policy*, *50*(7), 104079. https://doi.org/10.1016/j.respol.2020.104079

DeStefano, T., Kneller, R., & Timmis, J. (2018). Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. *Journal of Economic Behavior & Organization*, *155*, 110–139. https://doi.org/10.1016/j.jebo.2018.08.020

Donati, C., & Sarno, D. (2013). The impact of ICT on productivity of Italian firms: Evaluation of the micro-complementarity hypothesis. *Applied Economics Letters*, *20*(4), 349–352. https://doi.org/10.1080/13504851.2012.703309

Doraszelski, U., & Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, *126*(3), 1027–1084. https://doi.org/10.1086/697204

Eden, M., & Gaggl, P. (2018). On the welfare implications of automation. *Review of Economic Dynamics*, *29*, 15–43. https://doi.org/10.1016/j.red.2017.12.003

Feng, A., & Graetz, G. (2015). *Rise of the machines: The effects of labor-saving innovations on jobs and wages* (IZA Discussion Paper No. 8836). https://doi.org/10.2139/ssrn.2564969

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Giuri, P., Torrisi, S., & Zinovyeva, N. (2008). ICT, skills, and organizational change: Evidence from Italian manufacturing firms. *Industrial and Corporate Change*, *17*(1), 29–64. https://doi.org/10.1093/icc/dtm038

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Grossman, G. M., & Oberfield, E. (2022). The elusive explanation for the declining labor share. *Annual Review of Economics*, *14*, 93–124. https://doi.org/10.1146/annurev-economics-080921-103046

Guo, Z., Zhang, X., Ding, Y., & Zhao, X. (2021). A forecasting analysis on China's energy use and carbon emissions based on a dynamic computable general equilibrium model. *Emerging Markets Finance and Trade*, *57*(3), 727–739. https://doi.org/10.1080/1540496X.2019.1597704

Hagsten, E., & Sabadash, A. (2017). A neglected input to production: The role of ICT-schooled employees in firm performance. *International Journal of Manpower*, *38*(3), 373–391. https://doi.org/10.1108/IJM-05-2015-0073

Hesenius, M., Schwenzfeier, N., Meyer, O., Koop, W., & Gruhn, V. (2019, May). Towards a software engineering process for developing data-driven applications. In *2019 IEEE/ACM 7th International Workshop on Realizing Artificial Intelligence Synergies in Software Engineering* (*RAISE*) (pp. 35–41), Montreal, QC, Canada. IEEE. https://doi.org/10.1109/RAISE.2019.00014

Heyman, F. (2016). Job polarization, job tasks and the role of firms. *Economics Letters*, *145*, 246–251. https://doi.org/10.1016/j.econlet.2016.06.032

Hong, C., & Lee, J. D. (2016). Macroeconomic effects of R&D tax credits on small and medium enterprises. *Economic Systems Research*, *28*(4), 467–481. https://doi.org/10.1080/09535314.2016.1240067

Hwang, W. S., & Shim, D. (2021). Measuring the impact of ICT-driven product and process innovation on the Korean economy. *Global Economic Review*, *50*(3), 235–253. https://doi.org/10.1080/1226508X.2021.1884114

Hwang, W. S., & Shin, J. (2017). ICT-specific technological change and economic growth in Korea. *Telecommunications Policy*, *41*(4), 282–294. https://doi.org/10.1016/j.telpol.2016.12.006

Hwang, W. S., Yeo, Y., Oh, I., Hong, C., Jung, S., Yang, H., & Lee, J. D. (2021). CGE analysis of R&D investment policy considering trade-offs between economic growth and stability. *Science and Public Policy*, *48*(3), 295–308. https://doi.org/10.1093/scipol/scaa068

Järvensivu, P., Räisänen, H., & Hukkinen, J. I. (2021). A simulation exercise for incorporating long-term path dependencies in urgent decision-making. *Futures*, *132*, 102812. https://doi.org/10.1016/j.futures.2021.102812

Jorgenson, D. W., & Vu, K. M. (2016). The ICT revolution, world economic growth, and policy issues. *Telecommunications Policy*, *40*(5), 383–397. https://doi.org/10.1016/j.telpol.2016.01.002

Jung, S., Lee, J. D., Hwang, W. S., & Yeo, Y. (2017). Growth versus equity: A CGE analysis for effects of factor-biased technical progress on economic growth and employment. *Economic Modelling*, *60*, 424–438. https://doi.org/10.1016/j.econmod.2016.10.014

Korean Productivity Center. (2016). *Productivity statistics*. Korea Productivity Center.

Lankisch, C., Prettner, K., & Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*, *81*, 161–169. https://doi.org/10.1016/j.econmod.2018.12.015

Mallick, S. K., & Sousa, R. M. (2017). The skill premium effect of technological change: New evidence from United States manufacturing. *International Labour Review*, *156*(1), 113–131. https://doi.org/10.1111/j.1564-913X.2015.00047.x

Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, *96*(1), 60–77. https://doi.org/10.1162/REST_a_00366

Network Readiness Index. (2020). *Network Readiness Index 2020: South Korea*. Portulans Institute.

Park, C., & Park, J. (2020). COVID-19 and the Korean Economy: When, how, and what changes? *Asian Journal of Innovation and Policy*, *9*(2), 187–206. https://doi.org/10.7545/ajip.2020.9.2.187

Park, J., Moore, J. E., Gordon, P., & Richardson, H. W. (2017). A new approach to quantifying the impact of hurricane-disrupted oil refinery operations utilizing secondary data. *Group Decision and Negotiation*, *26*(6), 1125–1144. https://doi.org/10.1007/s10726-017-9537-7

Pyo, H. K., Hee, K., & Ha, B. (2009). Estimation of labor and total factor productivity by 72 industries in Korea (1970–2003). In *Productivity measurement and analysis* (pp. 527–550). OECD Publishing, Paris. https://doi.org/10.1787/9789264044616-25-en

Richmond, K., & Triplett, R. E. (2018). ICT and income inequality: A cross-national perspective. *International Review of Applied Economics*, *32*(2), 195–214. https://doi.org/10.1080/02692171.2017.1338677

Rickman, D. S. (2010). Modern macroeconomics and regional economic modeling. *Journal of Regional Science*, *50*(1), 23–41. https://doi.org/10.1111/j.1467-9787.2009.00647.x

Sawng, Y. W., Kim, P. R., & Park, J. (2021). ICT investment and GDP growth: Causality analysis for the case of Korea. *Telecommunications Policy*, *45*(7), 102157. https://doi.org/10.1016/j.telpol.2021.102157

Schreyer, P. (2000). *The contribution of information and communication technology to output growth: A study of the G7 countries*. OECD Publishing.

Tambe, P., Hitt, L., Rock, D., & Brynjolfsson, E. (2020). *Digital capital and superstar firms* (NBER Working Paper 28285). National Bureau of Economic Research. https://doi.org/10.3386/w28285

Taniguchi, H., & Yamada, K. (2019). *ICT capital-skill complementarity and wage inequality: Evidence from OECD countries.* OECD publishing.

Taştan, H., & Gönel, F. (2020). ICT labor, software usage, and productivity: Firm-level evidence from Turkey. *Journal of Productivity Analysis*, *53*(2), 265–285. https://doi.org/10.1007/s11123-020-00573-x

Vu, K., Hanafizadeh, P., & Bohlin, E. (2020). ICT as a driver of economic growth: A survey of the literature and directions for future research. *Telecommunications Policy*, *44*(2), 101922. https://doi.org/10.1016/j.telpol.2020.101922

Yeo, Y., & Lee, J. D. (2020). Revitalizing the race between technology and education: Investigating the growth strategy for the knowledge-based economy based on a CGE analysis. *Technology in Society*, *62*, 101295. https://doi.org/10.1016/j.techsoc.2020.101295

Yeo, Y., Lee, J. D., & Jung, S. (2021). 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. *Journal of the Asia Pacific Economy*, 1–37. https://doi.org/10.1080/13547860.2021.1982193

APPENDIX

Appendix A. Sectoral classifications for the analysis

Table A1. Sectoral classifications

No.	Sectoral classifications
S01	Agriculture, forestry and fishing
S02	Mining and quarrying
S03	Food, beverages and tobacco products
S04	Textile and apparel
S05	Wood, paper products and printing
S06	Petroleum and coal products
S07	Chemicals, drugs and medicines products
S08	Non-metallic mineral products
S09	Basic metal products
S10	General machinery and equipment
S11	ICT HW products
S12	Transportation equipment
S13	Furniture and other manufactured products
S14	Electricity, gas, steam and water supply
S15	Construction
S16	Wholesale, retail trade, accommodation and food services
S17	Transportation
S18	ICT SW products and services
S19	Finance and insurance services
S20	Real estate and business services
S21	Public administration and defense
S22	Education
S23	Health and social work services
S24	Other services

Appendix B. Sensitivity analysis results

We conducted sensitivity test for the elasticities of substitution in production structure. The four parameters include *i*) the elasticity of substitution between ICT capital and skilled labor (σ_1), *ii*) the elasticity of substitution between ICT capital composite and physical capital (σ_2), *iii*) the elasticity of substitution between capital composite and high-skilled labor (σ_3), *iv*) the elasticity of substitution between capital-skill composite and low-skilled labor (σ_4) as in Figure 1. Varying each parameter from –20, –10, 10 to 20 per cent, we compared the results with ones in the BAU scenario. Overall, resultant values of major variables are robust against variation of parameters as shown in the following tables. It is notable that the elasticities of substitution for each labor type have critical effects on the employment of the corresponding labor type, but these do not change the results and insights in this study.

Table B1. Major variables under alternative elasticity of substitution between ICT capital and skilled labor (σ_1)

	–20%			–10%			10%			20%		
	2020	2025	2030	2020	2025	2030	2020	2025	2030	2020	2025	2030
GDP	–0.013	–0.157	–0.579	–0.006	–0.071	–0.262	0.005	0.060	0.221	0.009	0.111	0.410
Industrial Output												
Total Industries	–0.002	–0.122	–0.513	–0.001	–0.055	–0.232	0.001	0.046	0.196	0.002	0.086	0.364
ICT Producing Svc.	0.031	–0.135	–0.694	0.014	–0.060	–0.310	–0.012	0.048	0.255	–0.021	0.089	0.468
ICT Producing Mnf.	0.345	0.776	0.834	0.154	0.350	0.381	–0.127	–0.293	–0.323	–0.234	–0.540	–0.599
ICT Using Svc.	–0.012	–0.140	–0.527	–0.005	–0.063	–0.240	0.004	0.053	0.204	0.008	0.099	0.378
ICT Using Mnf.	–0.100	–0.437	–1.136	–0.045	–0.197	–0.517	0.037	0.166	0.438	0.069	0.307	0.813
Non-ICT Svc.	–0.070	–0.349	–0.941	–0.031	–0.157	–0.426	0.026	0.132	0.358	0.048	0.243	0.662
Non-ICT Mnf.	–0.061	–0.253	–0.663	–0.028	–0.114	–0.301	0.023	0.096	0.254	0.042	0.177	0.472
Employment												
Unskilled Labor	–0.020	–0.174	–0.587	–0.009	–0.078	–0.265	0.008	0.066	0.222	0.014	0.122	0.411
Skilled Labor	0.638	2.269	5.150	0.286	1.023	2.332	–0.238	–0.857	–1.960	–0.437	–1.585	–3.630
High-skilled Labor	–0.220	–1.170	–3.180	–0.099	–0.529	–1.447	0.082	0.445	1.227	0.152	0.824	2.281
Income distribution												
SDPI	0.164	0.343	0.153	0.074	0.155	0.068	–0.061	–0.130	–0.055	–0.113	–0.241	–0.100

Note: All values are percentage difference from BAU scenario.

Table B2. Major variables under alternative elasticity of substitution between ICT capital composite and physical capital (σ_2)

	–20%			–10%			10%			20%		
	2020	2025	2030	2020	2025	2030	2020	2025	2030	2020	2025	2030
GDP	0.004	–0.026	–0.073	0.001	–0.012	–0.034	–0.001	0.011	0.030	–0.002	0.020	0.056
Industrial Output												
Total Industries	0.007	–0.024	–0.076	0.003	–0.011	–0.035	–0.002	0.010	0.031	–0.005	0.018	0.058
ICT Producing Svc.	–0.379	–0.216	0.211	–0.174	–0.100	0.096	0.150	0.086	–0.082	0.280	0.162	–0.152
ICT Producing Mnf.	0.017	–0.001	–0.142	0.009	0.000	–0.064	–0.008	–0.001	0.053	–0.016	–0.004	0.098
ICT Using Svc.	0.129	0.034	–0.170	0.059	0.015	–0.078	–0.050	–0.013	0.068	–0.094	–0.025	0.128
ICT Using Mnf.	–0.048	–0.064	–0.026	–0.022	–0.030	–0.013	0.019	0.026	0.012	0.036	0.049	0.024
Non-ICT Svc.	–0.140	–0.098	0.022	–0.064	–0.046	0.010	0.055	0.040	–0.007	0.104	0.075	–0.012
Non-ICT Mnf.	0.075	0.009	–0.093	0.034	0.004	–0.043	–0.029	–0.004	0.037	–0.054	–0.007	0.070
Employment												
Low-skilled Labor	0.023	–0.014	–0.103	0.011	–0.006	–0.048	–0.008	0.006	0.041	–0.016	0.011	0.077
Skilled Labor	1.130	0.669	–0.858	0.520	0.311	–0.388	–0.446	–0.272	0.322	–0.834	–0.512	0.594
High-skilled Labor	–0.686	–0.436	0.163	–0.315	–0.202	0.072	0.272	0.176	–0.057	0.509	0.332	–0.102
Income distribution												
SDPI	0.179	0.056	–0.150	0.082	0.026	–0.068	–0.070	–0.023	0.058	–0.130	–0.045	0.108

Note: All values are percentage difference from BAU scenario.

Table B3. Major variables under alternative elasticity of substitution between capital composite and high-skilled labor (σ_3)

	–20%			–10%			10%			20%		
	2020	2025	2030	2020	2025	2030	2020	2025	2030	2020	2025	2030
GDP	0.019	0.032	0.000	0.009	0.014	–0.001	–0.007	–0.012	0.002	–0.013	–0.021	0.004
Industrial Output												
Total Industries	0.027	0.057	0.053	0.012	0.025	0.023	–0.010	–0.021	–0.018	–0.019	–0.038	–0.032
ICT Producing Svc.	–0.286	–0.949	–2.376	–0.129	–0.427	–1.072	0.108	0.354	0.890	0.201	0.653	1.636
ICT Producing Mnf.	–0.003	–0.065	–0.283	–0.001	–0.028	–0.122	0.001	0.022	0.094	0.002	0.040	0.168
ICT Using Svc.	0.087	0.248	0.509	0.039	0.111	0.227	–0.033	–0.091	–0.184	–0.061	–0.168	–0.336
ICT Using Mnf.	0.090	0.257	0.536	0.041	0.115	0.239	–0.034	–0.095	–0.195	–0.062	–0.174	–0.356
Non-ICT Svc.	–0.072	–0.244	–0.626	–0.033	–0.110	–0.283	0.027	0.092	0.236	0.051	0.170	0.436
Non-ICT Mnf.	0.087	0.254	0.537	0.039	0.114	0.240	–0.033	–0.094	–0.196	–0.061	–0.172	–0.357
Employment												
Low-skilled Labor	–0.007	–0.039	–0.141	–0.003	–0.018	–0.065	0.003	0.016	0.057	0.006	0.030	0.107
Skilled Labor	–0.431	–1.307	–2.955	–0.195	–0.589	–1.334	0.163	0.489	1.109	0.301	0.901	2.039
High-skilled Labor	4.778	11.094	17.870	2.159	4.982	8.014	–1.808	–4.125	–6.596	–3.343	–7.586	–12.087
Income distribution												
SDPI	0.448	1.340	2.944	0.203	0.600	1.315	–0.169	–0.496	–1.074	–0.312	–0.910	–1.964

Note: All values are percentage difference from BAU scenario.

Table B4. Major variables under alternative elasticity of substitution between capital-skill composite and low-skilled labor (σ_4)

	–20%			–10%			10%			20%		
	2020	2025	2030	2020	2025	2030	2020	2025	2030	2020	2025	2030
GDP	–0.071	–0.256	–0.619	–0.032	–0.116	–0.280	0.027	0.097	0.236	0.027	0.097	0.236
Industrial Output												
Total Industries	–0.051	–0.202	–0.512	–0.023	–0.092	–0.233	0.019	0.077	0.196	0.035	0.142	0.364
ICT Producing Svc.	0.343	0.701	1.080	0.152	0.310	0.474	–0.123	–0.249	–0.378	–0.223	–0.453	–0.683
ICT Producing Mnf.	0.941	1.803	2.540	0.423	0.810	1.143	–0.352	–0.673	–0.950	–0.650	–1.240	–1.751
ICT Using Svc.	–0.092	–0.308	–0.704	–0.041	–0.139	–0.319	0.033	0.115	0.268	0.060	0.212	0.495
ICT Using Mnf.	–0.219	–0.611	–1.278	–0.098	–0.274	–0.576	0.081	0.228	0.479	0.150	0.419	0.884
Non-ICT Svc.	–0.135	–0.391	–0.852	–0.061	–0.177	–0.385	0.052	0.149	0.324	0.097	0.277	0.600
Non-ICT Mnf.	–0.368	–0.910	–1.693	–0.165	–0.410	–0.767	0.137	0.342	0.644	0.252	0.631	1.191
Employment												
Low-skilled Labor	1.674	3.478	5.566	0.754	1.564	2.501	–0.628	–1.300	–2.076	–1.159	–2.398	–3.825
Skilled Labor	–0.636	–1.531	–2.806	–0.284	–0.687	–1.263	0.233	0.568	1.049	0.426	1.043	1.935
High-skilled Labor	–0.234	–0.847	–1.936	–0.092	–0.358	–0.841	0.054	0.261	0.650	0.079	0.447	1.151
Income distribution												
SDPI	–1.381	–3.064	–5.227	–0.619	–1.376	–2.347	0.514	1.138	1.944	0.944	2.095	3.577

Note: All values are percentage difference from BAU scenario.