Ph.D. Dissertation in Engineering

A Computable General Equilibrium Modeling for Socioeconomic Impact Analysis in the Emergence of Robot Capital

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Jiyeon Jung

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지도교수 구윤모

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Abstract

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Jiyeon Jung
Technology Management, Economics, and Policy Program
The Graduate School
Seoul National University

The emergence and diffusion of robot capital impact the economy and its aspects, such as industry, labor, and economic growth, signaling many positive and negative socioeconomic changes. Robotization is altering production environments, and its impact on labor varies by labor type and industries, as robots replace labor to a different degree. Therefore, this study aims to examine how the labor replacement phenomenon differs by industries, labor types, and households, as well as to observe inter-relationships among economic variables, including price, demand, supply, utility level, and economic growth. Thus, based on these findings, a computable general equilibrium (CGE) model that considers different labor replacement rates between industries and labors can be constructed.

The CGE model is able to systematically analyze the ripple effects of various policies, and it is used in various research fields such as economic growth and innovation policies. Using this model, the study aimed to elucidate the labor replacement problem and social and economic impacts of robot capital, which has recently become a major social concern. In particular, labor replacement issues are feared to have a large social impact, thereby requiring research on its mechanisms and ripple effects on economic growth.

This study subdivided labor and household accounts within the social accounting matrix (SAM) data to reflect the different effects of labor replacement depending on the heterogeneous characteristics of labor types and industries. In addition, the model in this study defines a new type of capital concept termed robot capital. Accordingly, investment and capital are divided into general and robot capitals. Furthermore, a model and data system that can analyze different effects on economic subjects according to economic or policy shocks were established. Based on the designed and proposed CGE model, this study attempted to empirically identify different paths and effects of labor replacement on the economy.

Furthermore, the effect of labor replacement due to the technological development in society during 2015–2050 was analyzed using the recursive dynamic CGE model. SAM classifies households, labor, investment, and capital, and different elasticities of substitution are estimated according to industries and labor occupations. This study analyzed the impact of robot capital’s labor replacement on each industry, household, and labor and examined the social impact of technology’s labor replacement in various aspects through the scenario analysis.

The results show that the price of robot capital decreases due to the productivity improvement and increase in the amount of robot capital. The higher the labor replacement rate, the more labors are replaced with robots. The decrease in labor prices was the largest in the occupational group with a high replacement rate, and for this reason, the increase in the labor income of the households belonging to the labor types with the high replacement rate was the smallest. To compare results from the production perspective, 35 industries were classified into four industrial types according to the probability of replacement and capital intensity. In case of capital-intensive industries with high replacement probability, the growth rate of producer prices and consumer prices was high for the period 2015–2050 due to the relative decline in labor prices. The results indicate that this industrial type with high replacement probability and being capital intensive has a high consumption ratio of low-income class, and the decrease in utility is large as the price increases. Conversely, in the case of labor-intensive industries with low replacement probability, producer prices and consumer prices fell. This industrial type corresponds to an industry in which the high-income group exhibits a relatively higher consumption. This can be used to explain the effect of lowering the product price of the products of corresponding industrial types, that is, the purchasing power of the product has improved. This further can be interpreted as a change in household utility, which is why the utility growth rate of the high-income class is higher.

Furthermore, scenario analysis of socially concerned situations related to the

characteristics of robot capital was conducted. In the scenario with unbalanced distribution of robot capital, there is income polarization between low- and high-income households. For the robot tax scenario, the degree of polarization would be alleviated as the income from robot capital of the high-income households is reduced, but this scenario leads to a decrease in the production and lowered economic growth rate.

This study made the following contributions in terms of methodology and practicality. First, from the methodological perspective, robot capital with different characteristics in terms of the speed of replacement and accumulation from general capital was defined, and the CGE model was designed to reflect different replacement rates considering various industries. In addition, in the current situation where the labor replacement of robot capital is emerging as an important social problem, it makes a practical contribution to the understanding of the interaction mechanism between each subject, in terms of influence, that can discriminate against households and industries. In particular, the results of this study are valuable as they provide policymakers with practical directions, considering various perspectives to design innovative policies reflecting the social issue of labor replacement.

Keywords: human capital, robots, growth, innovation, inequality

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Chapter 1. Introduction

1.1 Research background

The computable general equilibrium (CGE) models often used as economy simulation tools for empirical economic analysis, which are extensively used by policy analysts and economists. With its advantage of being able to describe the motivations and behaviors of all producers and consumers and the linkages among them, CGE model is widely used as an economy-wide model to analyze economic phenomenon, policy changes, and driving economic growth. As it allows to systematically analyze the ripple effects of changes in the economy, recent studies addressed innovation, R&D, and economic growth using the CGE model (Diao, Roe, & Yeldan, 1999; Yeo, 2019; Ghosh, 2007). Further, it has extensive applications from tax and trade policies (Bhattarai et al., 2016) to climate change policy (Gebreegziabher et al, 2016) and economic development analysis (Taylor, 2016; Yeo, 2017).

Although literatures conduct on innovation, R&D and economic growth-related analysis using the CGE model, few research analyzes the labor replacement by robot capitals with CGE model. The reason for lacking CGE modeling on labor replacement by robot capitals may due to the following two reasons. Firstly, there is not much information nor enough historical data accumulated for robots as the emergence and development of robot have occurred recently. Secondly, there is no consensus on the concept of robot yet. The definition of robot is differently conceptualized depending on scholars, research institutes, and stakeholders. However, robots get high attentions as they are expected to affect the economy hard. With rising robots, production environments are changing in many industries and replacing labors to different degrees in different occupations.

Due to the development of core technologies in the era of Industry 4.0, automation is rapidly and widely taking place. Robots are replacing human capital in various fields including industry, home, medical, military, and education. International Federation of Robotics (IFR) reported that the number of units of industrial robots installed worldwide in 2019 was 373,240 units, worth about $13.8 billion. As of 2019, Korea is second highest to have robot density in manufacturing industry, followed by Singapore, indicating the installation of 855 industrial robot units per 10,000 workers (IFR, 2020). The industrial ecosystem that has existed by far will be restructured and expected to impact the workplaces significantly in the industry. The World Economic Forum alerted that the Fourth Industrial Revolution would fundamentally change the concept of workplaces. Concerns are raised about the possible decline of employment as technology development enables to produce more goods and products with less labor. Rising concerns that technology will replace jobs in the era of Industry 4.0, the industrial ecosystem that has existed by far will be restructured and expected to impact the economy and workplaces.

As simple repetitive and structured tasks can be performed through artificial intelligence or automated machine with lower labor cost, work that can be performed through automation is replaced with robots and machines. For example, artificial intelligence is replacing the call center business that has to give the same answers to the standard questions that customers have. Production and manufacturing personnel who carry and inspect defective products are being reduced by the influence of automated robots and image recognition systems at smart factories. In this manner, technological innovation has extended the variety of tasks that can be machinated. On the other hand, a comprehensive and immediate connection became possible in the era of Industry 4.0, new and varied jobs are created and some are replaced by existing jobs.

Although technological advances have played a major part in improving growth in labor productivity and economic, people have concerns about the social effects of labor being replaced by robots. Robots that used to perform only simple repetitive tasks have developed into intelligent robots that recognize the external environment, judge situations on their own, and operate autonomously, and are being distributed at a faster pace. These concerns rise as the scope of labor replacement is continuously expanding. With the rapid advance of new technologies such as AI, automation, and mobile robotics, jobs that requires higher-level of thinking and higher proficiency, which were thought to be unique areas for humans are gradually being replaced.

The rapid development and diffusion of industrial robots has increased productivity in the manufacturing industry, and enabled rapid growth of economic development. However, concerns are increasing for the "jobless growth," which refers to an economy that is growing without concomitant growth in the number of jobs and employees.

Because industrial robots have incomparable work speed, precision, and power compared to humans, they are rapidly replacing labor and amplifying anxiety about future generations' employment prospects. In general, economic growth rate and employment have been known to have a positive relationship, but since 1990, there has been no correlation between long-term growth rate and employment rate.

The public's concern and concern about the advent of robots is that automation and mechanization will polarize jobs, resulting in severe wage and income polarization (Shell, 2018). As jobs that used to perform middle-skilled jobs are replaced by machines, many unemployed people must engage in low-wage labor, which could further enlarge the income differences between high- and low-wage labors. Like this, risk and effect of labor replacement resulting from technological development varies by households and labors.

As mentioned above, workplace environments are changing due to robots' automation and mechanization as a result of technology development. And, the impacts are different by labor types, classified by skills, education levels, and/or industries. While lacking understanding of how the robotization is impacting the economy even though it is an important issue, there is a need to examine the labor replacement with the computable general equilibrium modeling approach.

1.2 Research motivation

This study aims to develop a computable general equilibrium (CGE) model that can analyze the effects of labor replacement and its economic impact in various scenario settings, in consideration of how the impact of labor replacement differ in social economy, households, labor groups, and industries. As smart factorization, automation, mechanization, and digitalization have recently progressed, robot-based production methods have been introduced in various industries. The development and introduction of such automated technology improve labor productivity while replacing the work of existing workers and causing unemployment.

The effects on the industries are different. It is crucial to understand which industries and labors are being replaced. The effects of taxation that can alleviate the gap in the household economy should be considered thoroughly. Although imposing robot taxes is often discussed to resolve inequality issue that may be caused by labor replacement from technological development, the imposition of robot taxes may hinder the growth of innovative industries. Using the CGE model to analyze the level of inhibition of technological development and innovation of the industry and the level of resolving inequality as the robot tax rate increases and compare the interactions between each economic account. Using the CGE model, this study aims to analyze the economic phenomena caused by labor replacement. It aims to analyze robot tax imposition measures and compare the interactions between each economic agent.

Using the CGE model that can analyze economic ripple effects, this study aims to propose alternatives to solve social problems caused by the emergence and diffusion of robot capital, by understanding the social phenomenon caused by labor replacement and analyzing the scenarios related with concerns raised by the emergence of robot capitals.

1.3 Research outline

This study contains six chapters to develop a CGE model that analyzes the impact of labor replacement by robot capitals on the social economy. Chapter 1 describes the necessity and purpose of this study based on the background of labor replacement and presents the scope and content of the overall study. Chapter 2 reviews theoretical backgrounds and previous literatures. The theoretical framework for research is established by examining the results of previous studies, such as literature related to the impact of labor substitution due to technological development on each industry, labor, and household. Chapters 3, 4, and 5 are chapters containing the main contents of this study and are organized as shown in Figure 1.1. Chapter 3 identifies the current status of data on major assumptions required for the model and builds social accounting matrix, the primary data for the analysis. Chapter 4 aims to establish a macro model that considers different labor replacement rates by industries and labor types. Chapter 5 utilizes the CGE model developed in Chapter 4. It analyzes social changes caused by labor replacement and the impact on the labor market and social economy according to the scenario for the biased distribution of robot capitals and robot tax imposition. Finally, Chapter 6 concludes the study, summarizes and presents the research results of Chapter 5, which were conducted earlier, and derives policy implications based on this. Finally, the study concludes by describing the policy and academic significance and limitations of this study.

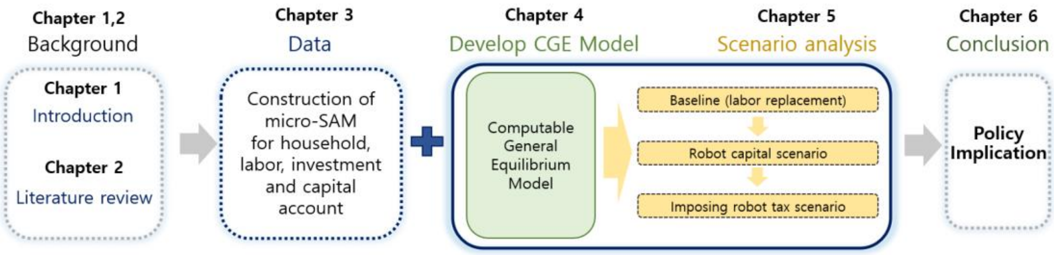

Figure 1.1 Research outline

Chapter 2. Literature Review on Theoretical and Methodological Approaches

2.1 Computable General Equilibrium model

The Computable General Equilibrium (CGE) model is often used to simulate and analyze the socioeconomic impact of exogenous changes in the market (Yeo, 2019; Jung et al., 2017; Lee 2020).

Jung et al. (2017) quantitatively evaluated the macroeconomic impact of innovation and technological development on the structure of employment and economic growth using the CGE model. They considered R&D investment as endogenous a variable. Further, they included knowledge stock and factor-biased technology changes to the model. As a result of the study, an increase in the level of investments on research and development stimulates economic growth with increased total demand of labor. But, innovation-driven economic growth has created a skills premium, in which highly skilled workers are preferred. This implies deepen wage imbalance among workers, and the results of income distribution was shown that high-income earners are relatively highly skilled and benefit from skill premiums.

Ojha et al. (2013) conducts empirical study on the efficiency of various policy scenarios using CGE model from the perspective of growth and equity for human capital, physical capital, and technological development (eg. technology factor productivity), which are the three sources of economic growth. Scenarios are constructed by altering the following: physical and human capital investment, sources of capital, and technological development. In results of the study, more GDP growth is observed in scenarios where more physical capital is invested in the mid- to long-term, but from a long-term perspective, a tremendous level of reversal of GDP growth in cases where more investment is made in public education expenditure. From the perspective of equity, investing in human capital rather than investing in physical capital will bias the production structure to the technology-intensive sector, resulting in a small number of high and medium skilled labors at cost of the majority unskilled workers. It suggests that more equitable growth may occur if increased investment for both human and physical capital promotes technological development, and it also promotes technological development in the unskilled labor-intensive sector, which stimulates demand for unskilled labor.

Yeo (2019) constructed a knowledge-based CGE model, in which knowledge is explicitly representing a factor of production and used in knowledge capital formation in the investment account. By endogenizing innovation-related components within the CGE model, author examines the knowledge spillover effects from the knowledge stock accumulation that affect the productivity within the production function of industrial sectors. For the analysis, author disaggregated the labor skills with education level, and households with income level to capture the distribution effects induced by changes in wage structure and income distribution.

Figure 2.1 shows a simultaneous relationship, indicating the causal and effect links.

For example, prices change causes the change in the amount of demand and supply. Price are decided at the equilibrium level of supply and demand, and so it becomes the equilibrium prices.

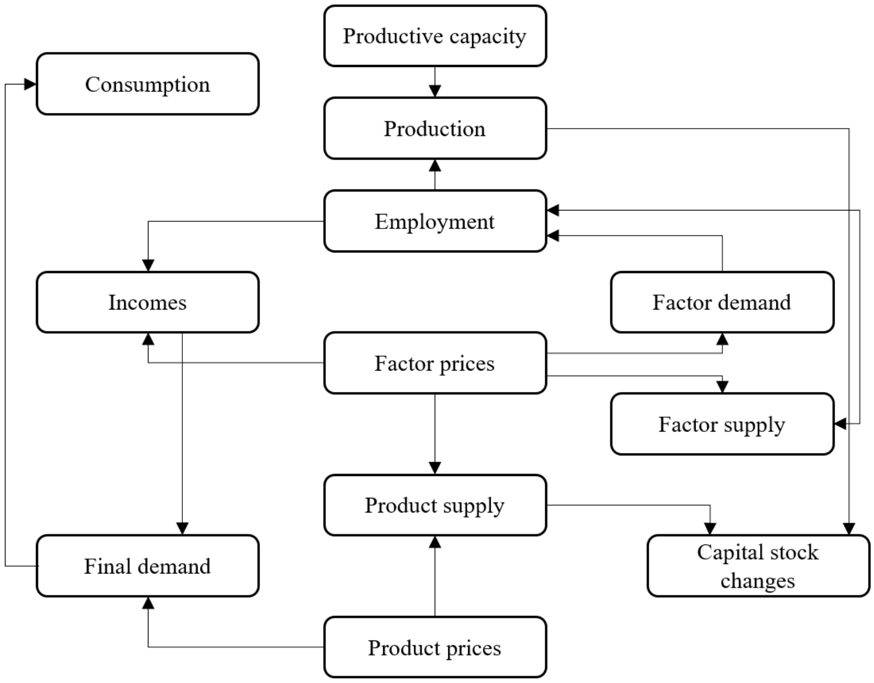

Figure 2.1 Causal chains of the CGE model (Perali & Scandizzo, 2018; redrawn by author)

Some studies point out that the division of the wage structure and income inequality cannot be solely explained by the technological progress (Freeman, 1979; Hamermesh, 1993). Various studies are recently expanding the discussion and including consideration of heterogeneous properties, human capital, and marginal products.

2.2 Labor replacement

2.2.1 Technology and economic growth from the historical perspectives

At the center of change in human history has always been the emergence and innovation of new technologies. Technological changes have caused major changes in the social and economic features, and studies on correlation between technological development and labor has been accompanied with the age of early Industrial Revolution. With recent advent of Fourth Industrial Revolution, it is anticipating a period of upheaval in the labor market once again.

Before considering the industrial revolution, it basically requires understanding the origin and meaning of terms. The Industrial Revolution was defined by the English historian Arnold Toynbee in the 「Lectures on the Industrial Revolution of the Eighteenth Century in England」 (Toynbee & Jowett, 1884). In general, the industrial revolution is defined by dividing it into the first, second, third, and fourth industrial revolution as shown in table 2.1. The first industrial revolution was called the coal, metal, and textile revolution in England in 1780, and the second industrial revolution was called the petroleum, chemical, electrical, and steel revolution, which began in Germany and the United States around 1870. The third industrial revolution was an economic revolution based on information and communications technology (ICT), biology technology (BT), nano technology (NT), and renewable energy technologies in the 1970s and was defined in Jeremy Rifikin's book「Third Industrial Revolution」(Rifikin, 2011). Lastly, the Fourth Industrial Revolution, in which occurred social transformation of humans and objects, such as superintelligence, in which technology replaces human intelligence, and others, was defined by Klaus Schwab. Schwab (2017), who argued that the Fourth Industrial Revolution is distinct from the Third Industrial Revolution, said that the change is at an exponential speed, and emphasized that it is a scope and depth that combines various science and technologies is leading to a digital revolution to lead to unprecedented paradigm shift. Third, it involves changes in the entire system of countries, companies, industries, and society. In other words, it means that all-round social structure reform and consciousness reform are important factors that must change simultaneously with technology in the Fourth Industrial Revolution (Kim, 2017).

Table 2.1 Classification of industrial revolution (Kim, 2017)

Ordinary classification	New Classification	Period	Description
First Industrial revolution	Commercial revolution	1780 (England)	Coal, metal, textiles
Second Industrial revolution	Industrial revolution	1870 (Germany, United States)	Petroleum, chemical, electricity, steel
Third Industrial revolution (Rifikin, 2011)	Knowledge industrial	1970	ICT and renewable energy technologies

Fourth Industrial Revolution (Schwab, 2017)	revolution	Present	Convergence technologies such as ICT, BT, NT

After having the Industrial Revolution in England, the second, third, and fourth rounds have continued, and the economy has grown rapidly. Industrial society continued its accelerated growth trend when the accelerated growth by the first industrial revolution reached its limit, and when the growth trend reached its limit, new products by new technologies created new demand and continued its accelerated growth trend. Due to the industrial revolution, it developed based on the manufacturing industry of the expanded reproduction system (Kim, 2017).

According to Kim (2017), economic and social transformations called the Third and Fourth Industrial Revolution can be reclassified as the knowledge based revolution, which promoted by technological innovation and knowledge accumulation in the fields of IT, BT, and NT. By converging the traditional technologies with newly created innovations, new demands on product and services rose at a fast rate, and established positive effects on supply and demand cycle in the value creation system. As such, technological development and innovation continued to create new products, leading to accelerated economic growth.

However, as the Industrial Revolution is called the inflection point of human social development, social conflicts and resistance were accompanied by social changes. An example is the Industrial Revolution and the Luddites movement, which showed strong rejection of technology for fear of high unemployment and made social upheaval. The British Luddites movement in 1786 is an example. In the early 19th century, the textile industry lost its jobs due to the supply of new machines, and in protest, the machines were destroyed by workers. The representative of unmanned mechanization, which was introduced into production during the Luddites movement and caused fear to workers, was a machine that replaced the spinning process in which horses and skilled workers worked in wool production. The introduction of machines into woolen production led to the difficulty of spinning workers having to go through turnover procedures and unemployment periods to find other jobs, but the increase in income inequality resulted from the enhanced division through turnover procedures and unemployment periods to find other jobs, but the increase in income inequality resulted from the enhanced division of labor. Lindert and Williamson (1983) showed that the industrial revolution has improved inequality in this regards. However, in the long run, there has been arguments that mechanization of this period led to increased production and labor income and improved quality of life. Voth (2003) summarized the stylized facts of the Industrial Revolution as follows. Working hours per worker increased very significantly, a rapid population increase, and a larger expansion of the production market, as such the labor input and capital input increased significantly. The wild discussions on technical unemployment caused by technological development were actively conducted historically.

The rejection of the Fourth Industrial Revolution also stems from the anxiety that human jobs and even survival can be lost, a phenomenon that existed even when the

Industrial Revolution occurred. However, as explained earlier, the first, second, and third industrial revolutions and the Fourth Industrial Revolutions have a steeper growth curve, which is feared to cause social upheaval in a different pattern from the past industrial revolutions.

2.2.2 Mechanization, computerization, and robotization

In the previous sub-chapter, we reviewed how technology has been developed and how it has been changing the economy and lives of people from historical perspectives. Further, this sub-chapter aims to review on how mechanization, computerization, and robotization have affected the economy, specifically how much it is substituting or complementing human labors and which industries or type of labors are more or less affected by mechanization, computerization and robotization.

A report on jobs at the University of Oxford projected that 47% of the employment in the U.S. are at the high risk of being replaced by computers (Frey & Osborne, 2013). In order to examine the situations in Korea, Kim (2015) conducted the research similarly using the methodologies applied by Frey and Osborne (2013). As a result, Kim (2015) presented that 57% of all jobs in Korea as of 2014 belongs to a high-risk group that is likely to be replaced by employment due to technological progress in the future. In addition, as a result of a study of 21 OECD countries in Arntz et al (2016), it was found that approximately 9% of jobs had a high risk from automation. Accordingly, Nedelkoska and Quintini (2018) analyzed 32 OECD countries and shoed the result that approximately 14% of workplaces are facing high risk of replacement. As such, labors in specific industries or fields seem inevitable to be affected by automation caused by the technological developments. Acemoglu and Restrepo (2017) analyzed the impact of the increase in industrial robots on the labor market in the United States between 1990 and 2007, and revealed that 670,000 manufacturing jobs were lost due to industrial robots during the period, and few other jobs were created to replace them. Meanwhile, Korea has the largest number of robots in the world, and it is expected that the units of robots will increase or decrease in order to maintain or improve labor productivity at the current level. Robot density means the units of robots supplied per 10,000 workers, and Korea ranks first in the world with 478 robots per 10,000 workers. Japan and Germany are then ranked second and third with 314 and 292, respectively. China, which advocates a new robot powerhouse, has only 36 units, and the average global robot density is only 66.

Various studies have reviewed in which industry labors will be replaced more quickly than others (Frey and Osborne, 2013; OECD, 2019; Kim, 2015), the impact of technological development on economic development (Yeo, 2017) and unemployment (Autor 2015; Dorn, 2015). The impact of technological advances on employment (Action and Howitt, 1994; Frey and Osborne, 2017) discusses that computer-generated automation is expanding beyond the routine-cognitive field to the non-routine manual field with the recent development of machine learning and mobility robotics. Frey and Osborne (2013) analyzed the automation potential of 702 occupations and diagnosed that

47% of jobs face high automation potential. Telemarketers, accountants, retail salespeople, technical writing professions, real estate sales, word processor inputs, etc. are highly likely to be automated. Leisure activity therapists, dentists, fitness workers, priests, chemical engineers, editors, firefighters, etc. are less likely to be automated. Kim (2015) showed that in a similar study, the proportion of occupations with high potential for automation in Korea was 55-57%, which is higher than in the United States.

Frey and Osborne (2013) quantitatively analyzed the possibility of job loss in the US labor market due to employment replacement by computers over the next 10-20 years. Kim (2015) performed a job matching job descriptions in Korea's 2012 vocational dictionary compiled by the Korea Employment Information Service by referring to the job introduction data of the U.S. Bureau of Labor Statistics for jobs with estimated employment replacement probabilities, such as Frey and Osborne (2013). Kim (2015) allocated the Korean standard occupation/industrial classification code for 699 occupations, excluding 3 occupations that cannot be matched among 702 occupations of Frey and Osborne (2013), referring to occupations. The possibility of replacing computer employment granted by Frey and Osborne (2013) for each job was applied to the Korean labor market by converting the job/industrial classification code. In that way, Kim (2015) calculated the probability of computer replacement by major category occupation as shown in table 2.2 and the probability of computer replacement by major category industry as shown in table 2.3, and sorted the jobs and industrial sectors sensitive to technological progress in ascending order.

Table 2.2 Replacement and computerization probability by industries by labor type

Labor Type	Probability of Automation
1. Managers	0.309
2. Professionals	0.366
3. Technicians and associate professionals	0.731
4. Clerical support workers	0.518
5. Service and sales workers	0.978
6. Skilled agricultural, forestry and fishery workers	0.631
7. Craft and related trades workers	0.749
8. Plant and machine operators, and assemblers	0.806
9. Elementary occupations	0.716

Table 2.3 Replacement and computerization probability by industries in large-sized classification

Classification		Probability of Replacement
A	Agricultural, forest, and fishery goods	0.98
B	Mined and quarried goods	0.968
C	Manufacturing	0.561
D	Electricity, gas, and steam supply	0.955
E	Water supply, sewage and waste treatment and disposal services	0.276
F	Construction	0.772
G	Wholesale and retail trade and commodity brokerage services	0.794
H	Transportation	0.837
I	Food services and accommodation	0.806

J	Communications and broadcasting	0.444
K	Finance and insurance	0.878
L	Real estate services	0.975
M	Professional, scientific, and technical services	0.311
N	Business support services	0.547
O	Public administration, defense, and social security services	0.191
P	Education services	0.012
Q	Health and social care services	0.134
R	Art, sports, and leisure services	0.379
S	Other services	0.515
T	Others	0.867
U	international and foreign institutions	0.96

According to the OECD (2019), changes in technology and population structure are expected to have a significant influence on the labor market in Korea. About 43 percent of all workers face a significant risk of having their jobs fully automated by new technologies or going through substantial changes, and furthermore, expect this change to be happening with rapid aging.

Examining the previous literatures, we looked at how technological development has actually affected the labor market. First, it was confirmed that the change in the labor market due to technological innovation and the employment rate had a negative correlation. Acemoglu and Restrepo (2020) in the U.S. analyzed that the more robots are introduced compared to jobs, the more negatively it affects employment and wages. From 1990 to 2007, when one robot per 1,000 workers in the United States increased, the employment rate was estimated to be 0.2%p, and the average annual wage decreased by 0.42%. Dengler and Mattes (2018) analyzed that the employment growth rate also slows as the labor replacement area of technology expands. When the possibility of automation increased by 10% from 2013 to 2016, the employment growth rate decreased by 1.07%. As such, low and middle-skilled workers in existing industries will lose their jobs due to digital innovation, and considerable time and money will be used to relocate them to the industry. The average vocational education period in the fields related to the Fourth Industrial Revolution takes more than twice as long on average as in other fields. According to Andrieu et al. (2019), occupational transitions have been discussed as such the cost of 1 to 5% of GDP must be consumed every year to move automated high-risk workers to low-risk groups. The Ministry of Employment and Labor (2018) analyzed that as the Fourth Industrial Revolution progresses rapidly, the number of employment growth industries increases by 460,000 while the number of jobs decreases by 340,000 in industries that are replaced due to increased productivity due to technological innovations such as automation. OECD (2018) predicted that in Korea, job automation exposure is below the OECD average (45%), but the proportion of jobs (70%) that are replaced by robots will exceed OECD average.

However, unlike mentioned above, research results showed that changes in the labor market due to technological innovation have a positive effect. Gal et. al. (2019) analyzed that companies with higher productivity levels tend to show greater improvement in productivity due to the introduction of digital technology. It shows that even companies with low production levels improve their work efficiency relatively significantly. The OECD (2019) reveals that productivity improves significantly as online platforms develop in major service industries such as hotels and restaurants. As such, the development of online platforms is predicted to play a role in promoting the relocation of labor to highly productive companies. Accordingly, Autor and Salomons (2018) analyzed 19 major countries from 1970 to 2007, and found that employment in industries where productivity improvement occurred decreased, but total employment increased as more employment was created through industrial development and final demand. Japan's Adachi et al. (2021) represents that cost reduction through the introduction of robots leads to improved export competitiveness and increased overseas demand, thereby increasing employment. It is analyzed that when one robot per 1,000 workers increases between 1978 and 2017, employment increases by 2.2% and the increase in labor demand due to corporate growth overwhelms the effect of employment replacement. In addition, Germany's Dauth et al (2017) estimates that industrial robots reduced manufacturing jobs between 1994 and 2014, but the change in total employment was not significant as employment in the service industry increased through spin overs such as expanding corporate investment. As such, the impact of digital innovation on the labor market seems to vary somewhat from study to study.

Vermeulen et. al. (2018) examined the effect of automation on employment by sector, and the replacement according to occupation and the replacement. Like this, automation (computerization, introduction of robots and AI) mostly impact routinized tasks that are often in the predictable environments and the middle-skilled jobs (Wolfgang, 2016; Autor et al., 2003; Levy et al., 2007; Ford, 2015).

Now that the Fourth Industrial Revolution is approaching, it is predicted that robots will replace jobs in various occupational groups within the next 20 years. Acemoglu and Restrepo (2017) examined the impact of the increase in industrial robots on the labor market in the United States between 1990 and 2007, and revealed that 670,000 manufacturing jobs were lost due to industrial robots during the period, and few other jobs were created to replace them. In addition, the essence of the Fourth Industrial Revolution is digitalization and convergence of technology (Schwab, 2017), where jobs are polarized according to skill or level of such technology, and many predict that income polarization between countries or within certain societies will intensify due to the fundamental nature of economic growth. Therefore, social discussions are being triggered to derive policies to control jobs and polarization problems that are expected to intensify in the future.

Regarding labor replacement, skill-biased technological change (SBTC) predicts that technology will change in the direction of higher levels of compensation and improve the relative wage levels of highly educated people, resulting in lower unemployment (Bell, 1973; Berman, Bound, & Machin, 1998). According to Bell (1973), researchers based on human capital theory predicted that the development of technology would improve overall skill levels by promoting education in new fields. Bina and Finzel (2005) showed that the development of technology can act as a catalyst for the emergence of a new type of skill or can cause changes in social division of labor and lead to wage inequality by reducing the usefulness of existing skills. According to Entorf et al. (1999), wage differences between occupations were analyzed according to the use of computer and IT technology, confirming the complementarity between technical progress and skilled labor. Moreover, Blanchard and Katz (1997) argued that while the labor supply curve of unskilled labor is relatively elastic, the labor supply curve of skilled labor is inelastic, so if skill-biased technological progress occurs, employment may decrease.

It is argued that technological change will lead to job polarization because the routine-based technological change (RBTC) is replaced by repetitive work, and the repetitive work is mainly performed by middle-class jobs (Braverman, 1974). According to Braverman (1974), researchers in labor process theory predicted that technological progress would lead to an overall tendency to deskill. According to Choi & Cho (2008), it is clear that recent changes in the technology environment are affecting the skill composition of the labor market, but the change is not cognitive proficiency bias as predicted by STBC. In other words, in terms of supply in the labor market, the pattern of the labor market could change in a different direction than STBC's prediction, with the return on proficiency lowered due to the oversupply of highly educated people. According to Kristal (2020), class-bias technological change means that workers in structural positions with easy and fast access to information take the fruits of wage increases due to technological changes.

In other studies, there are many studies claiming complementary effects that have a positive correlation with technological development, employment, and wages. Atasoy (2013) analyzed the US panel data from 1999 to 2007 to show that the employment rate increased through broadband access. Dauth et al. (2018) investigated using German labor market data from 1994 to 2014, and their results showed industrial robots did not affect the total employment of the professional local labor market. In robot-intensive industries, the decline in manufacturing jobs due to robot adoption was offset by profits in the business service sector, and it was found that labor income ratio decreased but rather increased labor productivity in areas more exposed to robot automation. In addition, it was estimated that the introduction of industrial robots reduced manufacturing jobs, but the fluctuation of total employment was not significant as employment in the service industry increased through spinovers such as expanding corporate investment.

Prettner and Strulik (2020) analyzed using an R&D driven growth model to analyze the impact for the automation that affect. According to their results, automation increased number of college graduates, inequality of income and wealth, and decreased the number of employment. They implied the need for policies that can occur unintended effects such as widening the inequality of income or wealth, lowering the economic growth, and decrease the welfare of individuals. This paper reviews the dark side of R&D- driven technological change and considered situation that new technologies complement only high-skilled workers but substitute for low-skilled workers. According to the World

Economic Forum (WEF) (2018), probabilistic analysis of the economic impact of AI and automation expects AI technology to create 133 million new jobs worldwide by 2022 and drive innovation and economic growth that contributes 20% of China's GDP by 2030. A study by Zator (2019) showed that AI, digitization, and automation using German business data and employment data are generally introduced to replace labor when labor is scarce, and the introduction of new technologies replaces workers on average. However, while the average reduction effect of labor is driven by industries such as manufacturing, retail, and lodging, technology complements workers in industries such as education, health and finance, resulting in increased employment. Koch and Smolka (2021) also showed that the adoption of robot uses by Spanish companies using annual panel data from 1990 to 2016 leads to 10% net job creation within 4 years. Babina et al. (2020) also showed an increase in employment in companies investing in artificial intelligence technology. Companies investing in AI technology based on indicators for introducing AI technology for human capital increased corporate income and employment, which seemed to be directly linked to industrial-level growth. The impact of the development and use of technologies related to the Fourth Industrial Revolution due to digital transformation on corporate employment was different by industry and company. In manufacturing companies with relatively low average wages, technology development and utilization replaced labor, reducing employment, and in companies with high average wages, technology development, utilization, and employment were complementary, resulting in an increase in the employment ratio of office workers. In the case of service companies, technology development and utilization in industries with low industrial competition (high HHI) decreased employment, while technology development and utilization increased employment in companies with high capital intensity. Gal et. al. (2019) analyzes that companies with higher productivity levels tend to show greater improvement in productivity due to the introduction of digital technology. It was shown that even companies with low production levels improved their work efficiency relatively significantly. The OECD (2019) said that productivity improves significantly as online platforms develop in major service industries such as hotels and restaurants, and the development of online platforms is expected to play a role in promoting the relocation of labor to highly productive companies. Autor and Salomons (2018) analyzed 19 major countries from 1970 to 2007, and found that employment in industries where productivity improvement occurred decreased, but total employment increased as more employment was created through industrial development and final demand. Japan's Adachi et al. (2021) presented that cost decrease through the introduction of robots leads to improved export competitiveness and increased overseas demand, thereby increasing employment. From 1978 to 2017, the employment increased by 2.2% when one robot per 1,000 workers increased. The increase in labor demand due to corporate growth overwhelmed the employment substitution effect. Chui et al. (2015) found that 45% of 2,000 jobs in 800 jobs are automable with current technology. They Automated tasks are currently valued at $2 trillion.

2.2.3 Robot capitals and robot tax

The definition of robot is discussed in many areas depending on the size, range, and its capability. Robotics Institute of America defined a robot as those that an be programmed to be able to multifunction to move and conduct through specialized tools or devices (IEEE, 2022). According to such definition, robots are that are likely to replace labors. As further the robots are keep developing to enable conducting a higher level of tasks. Robots are able to sense the environment, carry out computations and make decisions, perform actions in reality. The size, design, capabilities are different, meaning that it is never easy to make a simple definition of robot. Neither too general nor too specific, no definition is perfect as there is no consensus on the definition among scholars, researcher, and stakeholders.

There is a discussion for the need for a robot tax. Economic reform is always accompanied by frictional and structural unemployment, especially the generalization of artificial intelligence and robots that are predicted to come in the near future will trigger massive unemployment in these various fields. The costs of digital transformation, namely economic and social transformation resulting from industrial transformation and economic reform, will be negligible, and material welfare will be needed in some way to maintain the existing system and enable sustainable growth. As one of the active labor market policies for this, the discussion of basic income has been proposed in such a way as to maintain full employment, guarantee the minimum income for everyone, or buy unemployment insurance.

Robot tax is a tax that is collected from people or businesses who own robots and is used to tax companies that cause job losses for workers using automated facilities. The robot tax collected is planned to slow down the pace of unemployment due to the introduction of robots and use it as a resource to support retraining of unemployed people. The debate over the robot tax began in February 2017 when the European Parliament passed a resolution designating AI robots as "electronic person" and became widely known in an interview with U.S. information technology magazine Quartz, claiming that "the labor of robots doing human-like things should be taxed." And so far, public debate continues.

Introduction of the robot tax may occur negative effects of job losses and lack of tax revenue due to robots. It is argued that it is necessary to delay the introduction of robots by lowering the marginal profit of robots by imposing taxes on companies with robots. It also cited the fact that it is possible to support workers who lost their jobs and the elderly through increased tax revenues, and to implement projects to increase jobs for the vulnerable. The effect of income redistribution - In the current situation where jobs have become important, if anyone loses their jobs due to robots, it is necessary to provide support and sufficient financial resources must be secured to make it effective. If there is a person who gains additional benefits from robots, the tax system will also play a role in income redistribution if it imposes more taxes on him and the tax will lead to financial support for those who lose their jobs through robots.

From the standpoint of opposing the introduction of the robot tax, it is difficult to define robots and can hinder the development of the robot industry, and companies that have increased productivity through the introduction of robots are already paying corporate tax, which can be double taxation. The International Federation of Robots (IFR) opposed the robot tax, arguing that "the robot tax will negatively impact competition and employment and hinder innovation." In addition, other opponents of the robot tax pointed out that there is no logical basis to point out only robots as the main culprits of stealing human jobs, and that computer programs such as kiosks, word processors, and mobile banking have reduced human labor activities, but have not been taxed. It also pointed out that it is difficult to meet the target of robot tax among various robots, and that robots that pay robot tax will move away from the target of accommodation, and that companies move factory facilities to countries that do not pay robot tax.

As such, many discussions should be supported because discussions on the pros and cons regarding the robot tax are disputable due to the spread of robots, and furthermore, taxing robots can cause several complex problems from a domestic and international perspective. A clear and agreed definition of robots, economic, technical, and justifiable from a constitutional point of view, is needed, and various taxation methods for robots should be reviewed (OECD, 2021).

2.2.4 Economic impact of technology changes and social issues

The relationship between technological innovation and job change/income polarization is examined. In major countries, job polarization due to technological innovation is leading to income polarization. In 1979, middle-class jobs (sales; office and administrative workers, operations) were 60% of total employment, but decreased to 49% in 2007 and 46% in 2012 (Author, 2015). Moreover, the employment rate of the high and low-wage classes continues to increase. It is argued that policy efforts, including education, will be needed to compensate for the phenomenon in which the polarization of employment expands to income polarization (Dorn, 2015). The relationship between employment polarization and income polarization increases abstract work and manual labor-oriented job employment, which AI cannot replace, but abstract work and manual labor-oriented work have differences in average wages, which lead to differences in workers' education or living standards. In particular, the polarization of jobs may intensify as repetitive work-oriented office jobs and production jobs are replaced by artificial intelligence

This leads to job polarization leading to income polarization and can cause social problems in terms of distribution. Therefore, it is argued that policy efforts, including education, are needed to compensate for this phenomenon (Author, 2015; Dorn. 2015).

Technological innovation has led to job changes. It is argued that through automation and computerization according to technological innovation, many jobs, especially office and production jobs of repetitive work, are being replaced, resulting in employment polarization. It is important to find solutions through policies, including education, as the importance of human abilities that artificial intelligence cannot replace, such as high abstract abilities and interpersonal relationships, is growing, and the polarization with manual labor tends to worsen.

Stahler (2021) said that aging population and improving robot productivity promote an increase rate of using robot. This is because the aging of the population reduces production per capita, and the progress of automation technology leads to production improvement from a long term perspective. In short, the effect of reducing production unit price obtained by replacing human labor with an automated robot increases. And by replacing human labor with automated robots, the proportion of labor income to individual income decreases.

When comparing the routine and the non-routine label, it is more likely that the route label will be replaced by an automation capital. Therefore, the decrease in labor income experienced by workers working in the routine labor is greater. Thus, polarization deepens with inequality for consumption wealth, and labor income rises.

Jaumotte and Papergiou (2013) analyzed 23 years (1981-2003) of panel data for 51 countries, and as a result, technological advances had a greater impact on polarization than globalization. It becomes clear when both developed and developing countries use newer and more reliable data as deepening polarization over the past 20 years is driven by technological changes. Although the income of most segments in almost all countries has increased, the income growth of those who have already received a high level of education or have advanced skills has been greater. Advances in technology in both developing and developed countries have increased the importance of skill, replacing low-skill. Technological progress, in both developing and developing countries, creates the premium on skills and tendencies to substate low-skill inputs, which eventually leads to higher demand for advanced technologies, resulting in income imbalances. Aghion and

Acemoglu and Autor (2011) summarized the causes of deepening wage inequality and pointed out technological changes as the main cause. Goldin and Katz (2010) argued that education failed to keep up with technological changes, and that the labor supply failed to respond to the changed labor demand. It is argued that changes in the system are the cause of deepening income inequality. Card and DiNardo (2002) argued that rapid technological changes in the late 1980s have limitations in explaining the deepening of income inequality that has occurred since the 1990s, and that falling minimum wages and falling union membership rates are likely to cause income inequality. Although wage income is the most important thing in household income, capital income is another source of income that accounts for a significant proportion. In particular, considering the reality that most of the capital is held by high-income households rather than low-income households, changes in capital income can directly affect household income inequality.

According to the OECD (2018), the proportion of capital income among the total household income in the top quantile has increased sharply over the past 20 years compared to the lowest quantile. The decrease in the proportion of capital income in the top quantile of the United States is presumed to be a result of tax reform. In the above, the change in market income inequality was examined. The impact of capital income inequality cannot be ignored, but wage income inequality is the most important factor in market income inequality. It is important to see how much previous income has contributed to alleviating income inequality. It shows how much income inequality due to market income is alleviated by transfer income from the government.

Recently, various studies have been conducted as interest in asset inequality has increased. As for the asset composition characteristics of Korean households, the proportion of real estate is very high, the distribution of net assets is very concentrated compared to income, and asset holding inequality and polarization are intensifying. It explains the income inequality caused by technological replacement with the hypothesis that as technological progress increases, the share of labor income decreases as the market dominance of companies with a low share of labor in value creation increases. According to them, in the case of Germany, industrial concentration and productivity have increased due to technology replacement (digitalization), and the industry is transformed into labor-saving.

In addition, this replacement of technology can cause income inequality while increasing the capital share of upper income earners. Technology In general, the development of capital-intensive industries can increase the capital stock of specific industries and specific companies. Erik Bengtsson and Daniel Waldenstrom (2015) confirmed that a strong positive correlation between capital share and upper income section was observed in the upper income section, while there was a weak correlation in the lower section. This is due to the strong feedback effect of accumulated capital on the upper income section, resulting in inequality.

This capital stock, or wealth inequality, is a more serious problem than income inequality. According to the first paper, in modern times, the income share in the tenth quantile is 30-50%, while the capital share is 60-90%, which is more serious. Therefore, the problem of inequality arises because the source of higher income comes from more and more capital, and the share of these capital is largely distributed in the upper income segment.

2.3 Contribution of this study

Various studies have examined the relationship between growth and innovation, R&D. This study defines and classifies robot capital as a newly input factor that would replace labor due to technological development. Regarding the new type of robot capital, the replacement has not yet intensified, but many researchers predict that the replacement will intensify in the near future. Therefore, this study aims to examine the impact of robot capital accumulation and substitution on the overall economy and industry, such as capital, labor, and industrial households, and uses a general equilibrium model, which is a macro model, to see the interrelationship between economic entities.

This study uses CGE model in analyzing the economic impact of the economy due to labor replacement. Previous literatures included researches conducted using econometric methodologies and historical data. However, data for robot capital, which is new type of input factor that are observed and expected to replace the labor quickly, has not yet been accumulated. Also, robot capital is not yet replacing labor, rather is expected to expand its area of replacement. Therefore, there is a limitation to examine such impact using the econometric analysis of historical data.

Thus, in order to analyze the economic impact and ripple effects of labor replacement due to technological development, a macro-economic model in which can examine the ripple effects from the exogenous shock is necessary. There is an impact on the entire industry, households, and economy, and they are closely interconnected to each other, affecting one another. CGE model is suitable in this case to examine the economic equilibrium while examining the interactions between each other.

Chapter 3. Social Accounting Matrix Data

This chapter explains how we constructed the social accounting matrix (SAM) data used in this study in detail. The constructed SAM serves as the data-base for the CGE model to depict the baseline of the economy. Accordingly, subsection 3.1 describes how SAM is constructed to depict the economic conditions of the base year and key elements of SAM differentiated for this study.

3.1 Construction of social accounting matrix (SAM)

3.1.1 Concept of SAM

The SAM provides a screenshot of transactions within the economy, depicting the flow of production, consumption, and accumulation activities in a national economy over a period of time. As SAM captures the inter-industrial relationships, transactions between the economic agents, and structure of the economy, the CGE model uses SAM as input data to describe the base-year of the economy. According to such concept of SAM, this study construct a standard form of SAM as in Table 3.1.

The basic structure of the SAM is a matrix with row elements representing income and column elements representing expenditures of related economic institutions. The table shows a macroeconomic framework of an economy with institutions including households, industries, and government. The SAM represents the transaction of the accounts in the cells of table $T(i, j)$. The sum of row elements represents total income (receipt) of the *i-th* account, and includes supplies for the demand of intermediate, factors, final goods and exports. The sum of the column elements T_j represents total expenditure (payment) of the *j-th* account, and includes the purchases of intermediate inputs, factors, tax payments, and imports. Thus, the individual element $T(i, j)$ refers to the expenditure from the *j-th* account to the *i-th* account, as well as the income received by the *i-th* account from the *j-th* account. In other words, sector i receives money (income) from j for providing products or factors, and sector j pays money (expenditure) to sector i for receiving products or factors. In accordance with the principle of the SAM, total income and total expenditure of economic agents should be equal.

Table 3.1. Basic structure of SAM

T(i,j)		Production Activities	Factor Inputs		Taxes		Final Demands			Rest of Worlds	Total
		Commodities	Labor	Capital	Indirect tax	Tariff	Household	Government	Investment	Export	
Production activities	Commodities	T(1,1)					T(1,6)	T(1,7)	T(1,8)	T(1,9)	T01
Factor inputs	Labor	T(2,1)									T02
	Capital	T(3,1)									T03
Taxes	Indirect tax	T(4,1)					T(4,6)		T(4,8)	T(4,9)	T04
	Tariff	T(5,1)									T05
Final demands	Household		T(6,2)	T(6,3)							T06
	Government				T(7,4)	T(7,5)	T(7,6)				T07
	Investment						T(8,6)	T(8,7)		T(8,9)	T08
Rest of world	Import	T(9,1)									T09
Total		T01	T02	T03	T04	T05	T06	T07	T08	T09	

Table 3.2. Structure of the micro-SAM used in this study and sizes of key components (matrices)

T(i,j)		Production Activities	Factor Inputs		Taxes		Final Demands			Rest of World	Total
		Commodities (35)	Labor (3)	Capital (2)	Indirect tax	Tariff	Household (10)	Government	Investment (2)	Export	
Production activities	Commodities (35)	35*35					35*10	35*1	35*2	35*1	T01
Factor inputs	Labor (3)	3*35									T02
	Capital (2)	2*35									T03
Taxes	Indirect tax	1*35					1*10		1*2	35*1	T04
	Tariff	1*35									T05
Final demands	Household(10)		10*3	10*2							T06
	Government				1*1	1*1	1*10				T07
	Investment (2)						2*10	2*1		2*1	T08
Rest of World	Import	1*35									T09
Total		T01	T02	T03	T04	T05	T06	T07	T08	T09	

3.1.2 Main characteristics of SAM in this study

Disaggregation of a specific account in the SAM is conducted in order to represent more detailed sets of transactions and transfers of an economy. In principle, accounts can be disaggregated to some extent without limitation. However, more disaggregation for the increased detail of the SAM comes at a cost. In order to include more detailed transaction activities, identifying origins and destination of data sources is necessary (Round, 2003). The compilation process requires micro-data with detailed information from various sources of data including the household and labor force surveys national accounts, production surveys, statistics data, and a supply-use table. Thus, disaggregating the SAM requires efforts to achieved detailed datasets. Despite that disaggregating accounts in SAM is a non-trivial task, it allows to have extended modeling and analysis for the research purpose.

The size of the micro-SAM is determined by the purpose of study and the degree of disaggregation of each account according to the available data. The main objective of constructing a micro-SAM is to provide an accounting framework and associated dataset that can be utilized to identify the macroeconomic effects of shocks using the CGE model. Before constructing micro-SAM, industrial sectors are classified into 35 sectors to summarize economic transaction between production sectors and institutions. Then, the micro-SAM was constructed in the following manner. First, household institution is subdivided in to ten by income quantiles. Second, labor input factor is subdivided into three by occupational groups with different risk of labor replacement. Third, capital input factor is subdivided into original and robot capital. Fourth, investment part of SAM is subdivided into original and robot investment. Incorporating these features, the newly constructed micro-SAM has detailed accounts that allow to analyze the policy effects in detail. The overall structure of the micro-SAM constructed is shown as in Table 3.2.

3.2 Construction of micro-SAM for household, labor, investment, and capital accounts

3.2.1 Inter-industry transaction composition

Before constructing micro-SAM, this study classifies industrial sectors into 35 sectors as to depict inter-industry transaction composition. By using the Input-Output (IO) table of the year 2015 offered by the Bank of Korea (2019), this study constructs a SAM. In this study, industrial sectors are classified into 35 sectors within the SAM by aggregating industrial classifications listed in the IO statistics as shown in Table 3.3.

Table 3.3. Aggregation of the industrial sectors to construct SAM using IO table of the year 2015

Sectors		Industrial Classifications in SAM Large sized (Medium sized)	Name of Sector
1	Agri	A (01, 02, 03, 04, 05)	Agricultural, forest, and fishery goods
2	Mining	B (06, 07)	Mined and quarried goods

3	Food	C01 (08, 09, 10)	Food, beverages, and tobacco products
4	FiberLeather	C02 (11, 12)	Textile and leather products
5	WoodPaper	C03 (13, 14, 15)	Wood and paper products, printing and reproduction of recorded media
6	CoalOil	C04 (16)	Petroleum and coal products
7	Chemical	C05 (17, 18, 19)	Chemical products (basic chemical products, synthetic resins and synthetic rubbers, chemical fibers)
8	Pharmaceutical	C05 (20)	Pharmaceutical (Medicaments)
9	OtherChemical	C05 (21,22)	Other chemical products (Fertilizers and pesticides, other chemical products)
10	PlasticRubber	C05 (23,24)	Plastic products, rubber products
11	NonMetal	C06 (25, 26)	Non-metallic mineral products
12	PriMetal	C07 (27, 28, 29)	Basic metal products
13	Metal	C08 (30)	Fabricated metal products, except machinery and furniture
14	Computer	C09 (31, 32, 33, 34, 35, 36)	Computing machinery, electronic equipment, and optical instruments
15	Machine	C10 (37)	Electrical equipment
16	ElecEquip	C11 (38, 39)	Machinery and equipment
17	TransEquip	C12 (40, 41, 42)	Transport equipment
18	MissManu	C13 (43)	Other manufactured products
19	IndEquip	C14 (44)	Manufacturing services and repair services of industrial equipment
20	ElecStream	D (45, 46)	Electricity, gas, and steam supply
21	WaterWaste	E (47, 48, 49)	Water supply, sewage, and waste treatment and disposal services
22	Const	F (50, 51)	Construction
23	WholeServ	G (52)	Wholesale and retail trade and commodity brokerage services

24	TransServ	H (53, 54, 55, 56, 57)	Transportation
25	AccomServ	I (58)	Food services and accommodation
26	ITServ	J (59, 60, 61, 62, 63, 64)	Communications and broadcasting
27	FinServ	K (65, 66, 67)	Finance and insurance
28	EstateServ	L (68, 69)	Real estate services
29	ScienceServ	M (70, 71, 72)	Professional, scientific, and technical services
30	BusiServ	N (73, 74)	Business support services
31	Administration	O (75)	Public administration, defense, and social security services
32	EduServ	P (76)	Education services
33	SocialServ	Q (77, 78)	Health and social care services
34	CultureServ	R (79, 80)	Art, sports, and leisure services
35	Miss	S, T (81, 82, 83)	Other services and others

3.2.2 Household division

In order to analyze the differing results of among household groups, it is necessary to divide household accounts by income class. As this study aims to see differing effect of labor substitution on household income, the household account is divided into 10 income quantiles to reflect the heterogeneity of households with different income and consumption structures. In order to distribute types of households (i.e., 10 quantiles of households) the micro data of the '2015 Household Income and Expenditure Survey' published by Statistics Korea has been used (HIE, 2022).

The labor income, capital income, indirect tax, direct tax, and household savings, in which representing T(6,2), T(6,3), T(4,6), T(7,6), and T(8,6) respectively in the macro-SAM should be sub-divided into household income matters. The ratio of the income quantile share for the base year (2015) is calculated from the Household Income and Expenditure Survey data, and is utilized as a bridge matrix as in Table 3.4 and Table 3.5. By multiplying the bridge matrix to the macro-SAM account, micro-SAM is obtained. In the same manner, bridge matrix of household expenditure by industrial sector by household income quantile is constructed from the ‘2015 Household Income and Expenditure Survey’ data.

Table 3.4. Bridge matrix for income, tax, and savings by household income quantile

		Labor Income	Capital Income	Indirect Tax	Direct Tax	Household Saving
		LAB T(6,2)	CAP T(6,3)	IDT T(4,6)	GOV T(7,6)	INV T(8,6)
HOH1	Quantile 1	1.20%	1.87%	3.57%	-8.42%	-1.34%
HOH2	Quantile 2	3.37%	5.14%	5.52%	-4.07%	1.30%
HOH3	Quantile 3	5.25%	6.49%	6.94%	-1.06%	3.21%
HOH4	Quantile 4	6.44%	9.06%	8.06%	1.62%	4.98%
HOH5	Quantile 5	8.52%	8.91%	8.87%	6.90%	7.51%
HOH6	Quantile 6	9.50%	10.78%	10.24%	8.11%	8.11%
HOH7	Quantile 7	11.41%	11.25%	10.82%	12.42%	12.01%
HOH8	Quantile 8	13.63%	12.36%	12.76%	18.33%	12.58%
HOH9	Quantile 9	16.15%	15.14%	14.03%	23.06%	18.94%
HOH10	Quantile 10	24.52%	19.00%	19.18%	43.12%	32.71%
Total		100%	100%	100%	100%	100%

According to the '2015 Household Income and Expenditure Survey' data, consumption expenditure share by household income quantile is as shown in figures. 3.1 and 3.2.

Table 3.5 Household expenditure share in 2015 (HIE, 2022)

	AVERAGE	HOH1	HOH2	HOH3	HOH4	HOH5	HOH6	HOH7	HOH8	HOH9	HOH10
Food and non-alcoholic beverages	13.81%	22.77%	18.15%	16.41%	14.84%	14.56%	14.01%	13.45%	12.35%	12.43%	10.45%
Alcoholic beverages and tobacco	1.29%	1.95%	1.81%	1.74%	1.60%	1.51%	1.30%	1.27%	1.10%	1.08%	0.81%
Clothing and footwear	6.32%	4.16%	4.98%	5.56%	5.95%	6.10%	6.50%	6.48%	6.41%	6.83%	7.21%
Housing, water, electricity, and other fuels	10.83%	17.70%	15.05%	13.86%	12.44%	11.03%	10.77%	10.42%	9.39%	8.94%	8.36%
Furnishings, household Equipment, and routine household maintenance	4.10%	3.88%	3.39%	3.31%	4.03%	3.75%	3.71%	3.98%	3.76%	4.26%	5.42%
Health	6.80%	11.79%	9.25%	8.03%	6.43%	6.88%	6.39%	6.34%	6.80%	6.00%	5.59%
Transport	12.55%	7.57%	10.90%	10.52%	13.00%	11.43%	11.70%	13.44%	14.23%	12.92%	13.96%
Communication	5.76%	6.15%	6.63%	6.81%	6.60%	6.39%	6.03%	5.93%	5.39%	5.48%	4.39%
Recreation and culture	5.85%	4.16%	4.74%	4.87%	5.44%	5.24%	5.88%	5.37%	6.16%	6.34%	7.25%
Restaurants and hotels	11.05%	4.91%	5.91%	8.26%	8.67%	10.97%	11.14%	11.24%	12.75%	12.80%	13.93%
Education	13.24%	8.82%	11.97%	13.01%	13.24%	13.66%	13.56%	13.35%	13.84%	13.93%	13.36%
Miscellaneous goods and services	8.39%	6.13%	7.23%	7.60%	7.76%	8.46%	9.01%	8.75%	7.84%	8.99%	9.27%
Total consumption expenditure	2,563,092	1,031,674	1,533,830	1,899,009	2,195,349	2,332,443	2,712,918	2,799,080	3,249,445	3,482,328	4,390,428

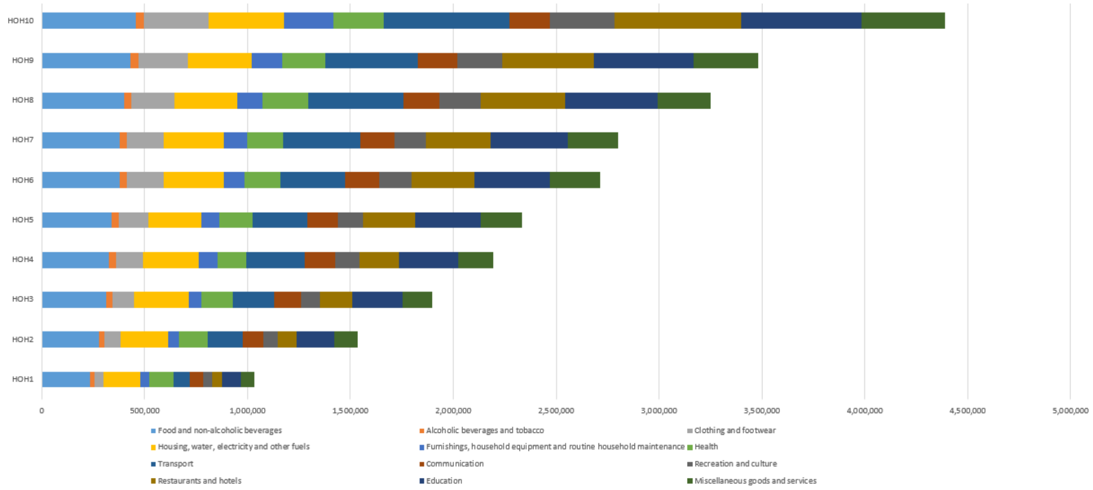

Figure 3.1 Consumption expenditure by households

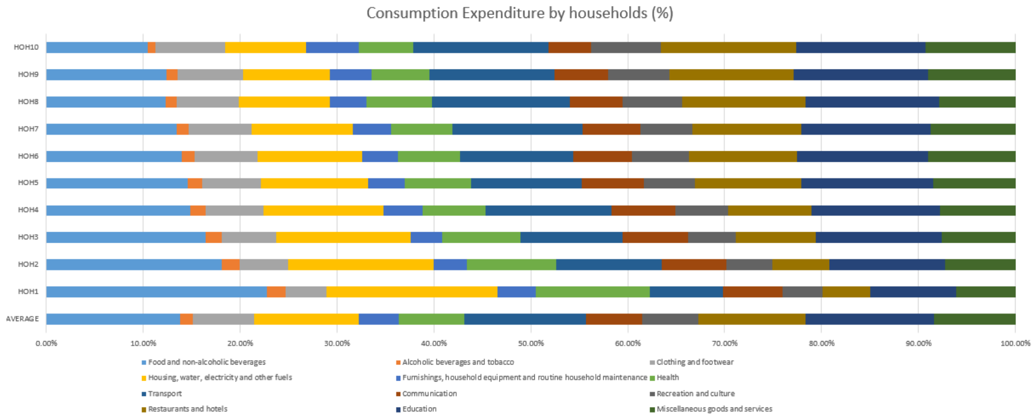

Figure 3.2 Shares of consumption expenditure for each income quantile identified from HIE survey data (%)

This study referenced the detailed category of the household consumption expenditure from HIE survey and matched with the industry classification of this study of 35 industries. Table 3.5 indicates the share of household consumption expenditure for each income quantile matched with the industry classification of this study. This share is used as bridge matrix to be multiplied to macro-SAM.

Table 3.6. Bridge matrix of household consumption expenditure for each income quantile by industrial sector

		HOH1	HOH2	HOH3	HOH4	HOH5	HOH6	HOH7	HOH8	HOH9	HOH10	Total
1	Agri	6.64%	7.87%	8.80%	9.20%	9.60%	10.74%	10.63%	11.34%	12.23%	12.96%	100%
2	Mining	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
3	Food	6.64%	7.87%	8.80%	9.20%	9.60%	10.74%	10.63%	11.34%	12.23%	12.96%	100%
4	Fiber-Leather	2.65%	4.72%	6.53%	8.07%	8.79%	10.90%	11.20%	12.87%	14.70%	19.57%	100%
5	WoodPaper	2.78%	4.39%	6.70%	7.90%	9.42%	10.85%	10.41%	15.85%	14.76%	16.94%	100%
6	CoalOil	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
7	Chemical	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
8	Pharma-ceutical	9.04%	8.26%	9.22%	7.94%	8.76%	9.61%	9.41%	11.07%	12.30%	14.38%	100%
9	Other Chemical	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
10	Plastic Rubber	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
11	NonMetal	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
12	PriMetal	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
13	Metal	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
14	Computer	3.22%	5.69%	7.36%	8.53%	8.16%	11.00%	10.70%	12.86%	16.08%	16.40%	100%
15	Machine	3.86%	5.50%	6.49%	9.88%	8.25%	10.96%	12.63%	11.52%	15.90%	15.00%	100%
16	ElecEquip	3.22%	5.69%	7.36%	8.53%	8.16%	11.00%	10.70%	12.86%	16.08%	16.40%	100%
17	TransEquip	1.63%	4.60%	5.68%	8.84%	8.04%	9.85%	11.90%	15.02%	14.27%	20.16%	100%
18	MissManu	2.29%	4.24%	4.90%	8.00%	8.23%	8.47%	11.71%	12.77%	16.12%	23.26%	100%

19	IndEquip	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
20	ElecStream	7.45%	8.48%	9.21%	9.69%	9.71%	10.40%	10.33%	10.92%	11.48%	12.34%	100%
21	WaterWaste	5.71%	6.95%	8.20%	9.41%	9.82%	10.20%	10.25%	12.51%	12.24%	14.71%	100%
22	Const	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
23	WholeServ	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
24	TransServ	2.43%	5.20%	6.21%	8.87%	8.29%	9.87%	11.70%	14.38%	13.99%	19.06%	100%
25	AccomServ	2.68%	5.41%	7.28%	8.57%	9.39%	10.84%	11.01%	13.25%	14.29%	17.28%	100%
26	ITServ	4.30%	6.89%	8.76%	9.81%	10.09%	11.08%	11.25%	11.87%	12.93%	13.04%	100%
27	FinServ	2.02%	5.09%	7.14%	7.91%	9.89%	11.21%	11.89%	12.27%	14.62%	17.96%	100%
28	EstateServ	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
29	ScienceServ	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
30	BusiServ	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
31	Admini-stration	4.03%	5.99%	7.41%	8.57%	9.10%	10.59%	10.92%	12.68%	13.59%	17.13%	100%
32	EduServ	1.79%	3.20%	5.54%	6.72%	9.04%	10.67%	11.10%	14.62%	15.73%	21.59%	100%
33	SocialServ	6.97%	8.13%	8.75%	8.10%	9.21%	9.94%	10.17%	12.67%	11.99%	14.07%	100%
34	CultureServ	3.03%	4.72%	6.12%	7.73%	7.92%	10.59%	9.71%	13.12%	14.19%	22.87%	100%
35	Miss	2.94%	5.15%	6.71%	7.92%	9.18%	11.37%	11.39%	11.84%	14.56%	18.93%	100%

3.2.3 Labor division

The disaggregation of labor types allows to see noticeable different effects on wages, welfare, and the impacts of policies. The breakdown of labor (by occupation groups, education level, social characteristics, etc.) allows a more detailed analysis of employment issues. This study aims to feature how digitalization and automation have affected the labor market and have diverse impacts on different types of labors. As this study aims to feature diverse impacts on different types of labor due to automation, labor is disaggregated. In order to consider different effects of different occupational groups with different risk of labor replacement by automation, labor is disaggregated into occupational types based on its risk of replacement by automation robots (i.e., labors with low, medium, high replaceable by automation).

This study utilizes the probability of replacement of labor referenced from literature reviews. Frey and Osborne (2013) estimates the probability of replacing future jobs due to technological development, and analyzes jobs that has high probability of being replaced by automation within next 10-20 years using the data from Occupational Information Network (O*NET). They first estimated 702 jobs provided by O*NET for the risk of automation possibilities through focus group interview by experts in machine learning and mobile robotics. In addition, they considered nine additional automation failure factor variables to the estimates of automation possibilities for 70 occupations, and estimated the remaining 632 occupations through the Gaussian process classification. Using the estimated automation probability by occupation estimated in this way, the probability of job replacement by automation in the US labor market was analyzed. Kim (2015) analyzed the probability of job replacement due to automation in Korea (Kim, 2015). This study adopts and references the probability of job replacement from the Kim's literature (2015), which estimated the job replacement probability in the case of South Korea, with the approach of Frey and Osborne (2013).

The labor is classified into three in this study, based on the probability of labor replacement by automation as in Table 3.7. Further, probability of job replacement by industrial sectors are used in this study as in 7.

Table 3.7. Probability of job replacement by the occupation types

Occupational Classification		Probability of Replacement	Number of Employees by Occupation (2015)	Ratio (%)
1. Managers	L1	0.309	358	1.4%
2. Professionals	L1	0.366	5242	20.0%
3. Technicians and associate professionals	L2	0.731	4433	16.9%
4. Clerical support workers	L2	0.518	2763	10.6%
5. Service and sales workers	L3	0.978	3123	11.9%
6. Skilled agricultural, forestry, and fishery workers	L2	0.631	1243	4.7%
7. Craft and related trades workers	L2	0.749	2375	9.1%
8. Plant and machine operators, and assemblers	L3	0.806	3187	12.2%
9. Elementary occupations	L2	0.716	3452	13.2%

Source: Frey and Osborne (2013), Appendix, pp. 57–72; U.S. Bureau of Labor Statistics, Occupational Outlook Handbook and Occupational Employment Statistics

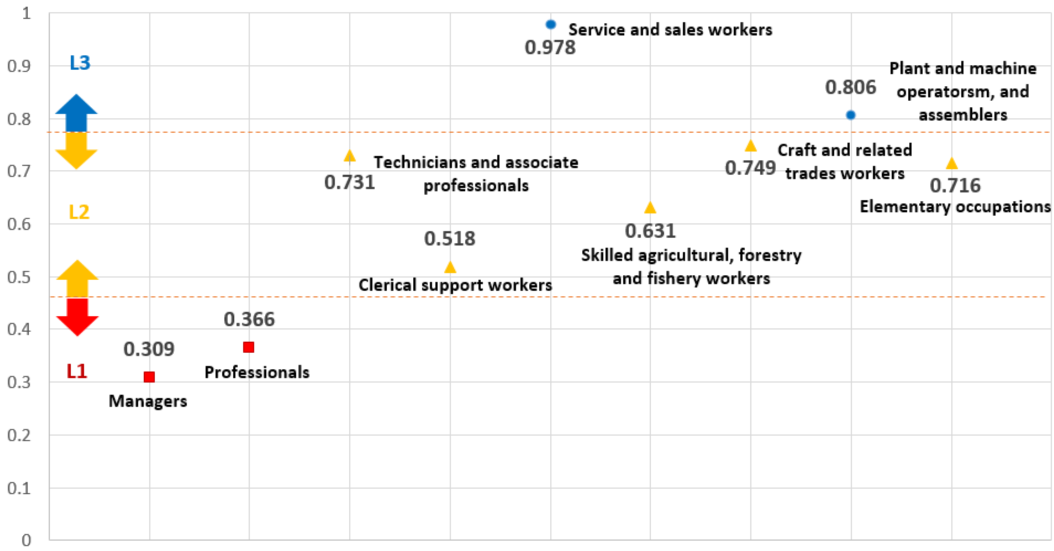

Figure 3.3. Probability of replacement by labor type (Drawn by author using data of Kim, 2015)

Table 3.8. Probability of job replacement by industrial sectors (Kim, 2015)

	Classification	Probability
A	Agricultural, forest, and fishery goods	0.98
B	Mined and quarried goods	0.968
C	Manufacturing	0.561
D	Electricity, gas, and steam supply	0.955
E	Water supply, sewage and waste treatment and disposal services	0.276
F	Construction	0.772
G	Wholesale and retail trade and commodity brokerage services	0.794
H	Transportation	0.837
I	Food services and accommodation	0.806
J	Communications and broadcasting	0.444

K	Finance and insurance	0.878
L	Real estate services	0.975
M	Professional, scientific, and technical services	0.311
N	Business support services	0.547
O	Public administration, defense, and social security services	0.191
P	Education services	0.012
Q	Health and social care services	0.134
R	Art, sports, and leisure services	0.379
S	Other services	0.515
T	Others	0.867
U	International and foreign institutions	0.96

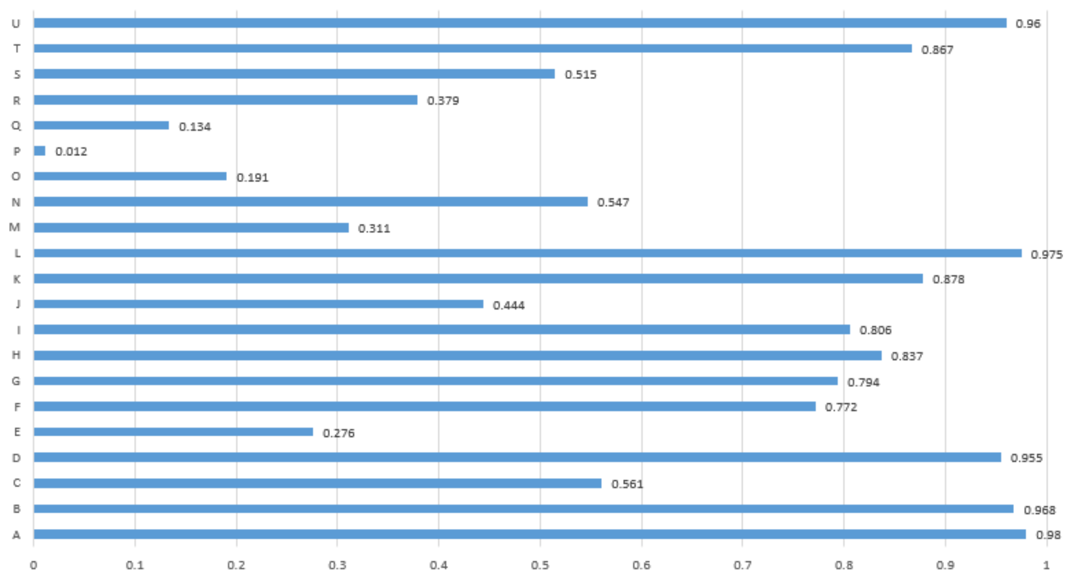

Figure 3.4. Probability of replacement by industrial sectors

Kim (2015) observed that the proportion of jobs in B mining, K finance, and insurance (with a replacement probability of 0.4–0.8) in the middle-level industries such as A agriculture, forestry and fisheries, D electricity, gas, steam and water, H transportation, I accommodation, and restaurants may already be less affected.

Table 3.9. Relative share of each household quantile for the labor composition for the base year of 2015 (Unit: %)

		Low-replaceable Labor	Medium-replaceable Labor	High-replaceable Labor	Total
HOH1	Quantile 1	6.17%	81.48%	12.35%	100%
HOH2	Quantile 2	7.95%	76.16%	15.89%	100%
HOH3	Quantile 3	12.04%	64.23%	23.72%	100%
HOH4	Quantile 4	13.82%	61.62%	24.56%	100%
HOH5	Quantile 5	15.60%	58.32%	26.08%	100%
HOH6	Quantile 6	20.00%	52.88%	27.13%	100%
HOH7	Quantile 7	19.13%	54.39%	26.47%	100%
HOH8	Quantile 8	24.92%	49.45%	25.63%	100%
HOH9	Quantile 9	26.71%	49.37%	23.92%	100%
HOH10	Quantile 10	38.14%	42.98%	18.88%	100%

3.2.4 Capital division

In this study, capital factor is decomposed into two capital types (i.e., original capital and robot capital) by using 'fixed capital formation table', in order to consider the replacement of labor with robot capital due to the development of automation and robot industry. The Bank of Korea publishes the ‘fixed capital formation table’ as an annex to the input output table (IO table). The 2010 data were the most recent data that was available at the time when this study was conducted. Although the 2015 version of data for the fixed capital formation table has been gathered by Bank of Korea, but not released to public yet, the 2010 version of data were used instead. The fixed capital formation table is a table allocating the amount of fixed capital formation by capital goods by industries, and in this study, it was used to classify robot capital and original capital. The ‘fixed capital formation table’ identifies the details of formation (distribution) of each fixed asset formed over a certain period of time and is one of the final demand accounts of the IO table, which is allocated by industry according to the total amount of capital goods in the form of column vectors. Therefore, it is a table in the form of matrix of capital goods x industries so that economic analysis is possible by directly connecting production activities and fixed assets by industry.

The ‘fixed capital formation table’ shows the fixed capital formed in the national economy for a certain period of time (usually one year) in detail by industry and capital goods. It is written in the form of a "capital goods x industry" matrix and is widely used for basic data and productivity analysis of various industrial policies as capital requirements can be calculated according to changes in industrial output. Fixed capital formation is acquired by household and government consumption, transactions, and self-production during the year of production activities and tangible and intangible fixed assets are the targets, including 96 products in the 2010 IO table. Fixed capital can be classified into construction, facility intellectual property products, and others by the asset type.

Of the capital good classes, 100% of industrial robots and 20% of software development supply are included for the robot capital in this study. Software development supply capital goods refer to the goods related to an industrial activity that develops universal application software that automatically processes functions and processes by programming them for specific business processing in a computer. As of 2010, industrial robots and software development supply capital goods can be seen in different industries. Industries with a high proportion of robot capital are in the following order: 23. Finance and Insurance, 25. Specialized, Scientific and Technical Services, 15. Other Manufacturing, 28. Educational Services, 14. Transportation Equipment Manufacturing 22. Information and Communication and Broadcasting, 19. Wholesale and Retail, 18. Construction and 26. Food and Tobacco Manufacturing.

Table 3.10. Capital classification weight between original capital and robot capital

Industrial Sector Classification		Original Capital	Robot Capital
1	Agricultural, forest, and fishery goods	99.89%	0.11%
2	Mined and quarried goods	99.83%	0.17%
3	Food, beverages and tobacco products	97.50%	2.50%
4	Textile and leather products	98.99%	1.01%
5	Wood and paper products, printing, and reproduction of	98.63%	1.37%

	recorded media		
6	Petroleum and coal products	98.87%	1.13%
7	Chemical products (Basic chemical products, Synthetic resins and synthetic rubbers, Chemical fibers)	98.01%	1.99%
8	Non-metallic mineral products	97.88%	2.12%
9	Basic metal products	99.60%	0.40%
10	Fabricated metal products, except machinery and furniture	98.68%	1.32%
11	Manufacturing services and repair services of industrial equipment	98.46%	1.54%
12	Electricity, gas, and steam supply	99.32%	0.68%
13	Machinery and equipment	99.08%	0.92%
14	Transport equipment	96.73%	3.27%
15	Other manufactured products	96.51%	3.49%
16	Electricity, gas, and steam supply	99.51%	0.49%
17	Water supply, sewage, and waste treatment and disposal services	99.74%	0.26%
18	Construction	97.23%	2.77%
19	Wholesale and retail trade and commodity brokerage services	97.19%	2.81%
20	Transportation	99.60%	0.40%
21	Food services and accommodation	99.49%	0.51%
22	Communications and broadcasting	97.17%	2.83%
23	Finance and insurance	91.20%	8.80%
24	Real estate services	99.89%	0.11%
25	Professional, scientific, and technical services	93.95%	6.05%
26	Business support services	97.46%	2.54%

27	Public administration, defense, and social security services	99.90%	0.10%
28	Education services	96.70%	3.30%
29	Health and social care services	97.73%	2.27%
30	Art, sports, and leisure services	98.52%	1.48%
Total		98.69%	1.31%

The share of each household quantile for capital is shown in Table 3.4. Further, how much each household quantile holds each type of capital should be assumed in order to disaggregate the capital into two (e.g. original capital and robot capital). However, there is no data that distinguishes the capital type held by each household quantile group. Thus, this study assumes that each household quantile holds two capital types at the same ratio as shown in Table 3.11 and Table 3.12.

Table 3.11. Relative share of each household quantile in the value-added composition for the base year of 2015 (Unit: %)

		Share of Each income Quantile within the Value added	
		Original Capital	Robot Capital
HOH1	Quantile 1	1.9%	1.9%
HOH2	Quantile 2	5.1%	5.1%
HOH3	Quantile 3	6.5%	6.5%
HOH4	Quantile 4	9.1%	9.1%
HOH5	Quantile 5	8.9%	8.9%
HOH6	Quantile 6	10.8%	10.8%

HOH7	Quantile 7	11.2%	11.2%
HOH8	Quantile 8	12.4%	12.4%
HOH9	Quantile 9	15.1%	15.1%
HOH10	Quantile 10	19.0%	19.0%
Total		100%	100%

Table 3.12. Income structure of each household quantile for the base year of 2015 (Unit:%)

		Income Structure of Each Household Quantile		Total
		Original Capital	Robot Capital	
HOH1	Quantile 1	98.81%	1.19%	100%
HOH2	Quantile 2	98.81%	1.19%	100%
HOH3	Quantile 3	98.81%	1.19%	100%
HOH4	Quantile 4	98.81%	1.19%	100%
HOH5	Quantile 5	98.81%	1.19%	100%
HOH6	Quantile 6	98.81%	1.19%	100%
HOH7	Quantile 7	98.81%	1.19%	100%
HOH8	Quantile 8	98.81%	1.19%	100%
HOH9	Quantile 9	98.81%	1.19%	100%
HOH10	Quantile 10	98.81%	1.19%	100%

3.2.5 Investment division

Accordingly, we distinguished the investment sector into two (i.e., original and robot investment sectors) accordingly with the investment motive by industries with the facility investment amount data from the ‘facility investment plan survey’ published by Korea Development Bank. The proportion of automation and energy consumption was classified into robot investments that invest in automation in investment motivation by industry divided into facility capacity expansion, maintenance, automation and energy-related investment, R&D investment, and others.

3.2.6 Scaling the Social Accounting Matrix

In finalizing the social accounting matrix (SAM) construction, balancing the SAM is necessary, which is to make the sum of the rows equal to the sum of the columns. As mentioned earlier, total income and total expenditure of economic agents should be equal according to the principle of SAM. However, when inputting the actual data, the sum of the rows and columns do not exactly match, because it’s often from diverse sources and different periods of time. Thus, before finalizing the SAM construction for the CGE analysis, it requires a final step to balance the SAM. There are several methods such as RAS and entropy approaches, but this study uses SAM balancing method called SAMBAL approach published by partnership for economic policy (Lemelin et al., 2013).

The SAM balancing program proposed by partnership for economic policy offers a GAMS code to balance an unbalanced SAM. Unlike the other balancing methods, the SAMBAL approach does not require knowledge of the marginal totals. Constraints on the marginal totals can be added optionally if known partially or all. When all marginal totals are known and added as constraints, then the SAMBAL program yields the equivalent solution with RAS balancing method. Further, standard entropy method does not allow negative values. However, by using SAMBAL, it transposes negative values to their counterpart cells before balancing the SAM. Then, reverse transposition is performed after the SAM has been balanced, to restore negative values to their original positions. It should be noted however, that the reverse transposition eliminates the crossflows of opposite signs (Lemelin et al., 2013).

As introduced above, with the macro-SAM, micro-SAM can be constructed in the following way: industry classification through inter-industry transaction composition, household disaggregation by income quantiles, labor disaggregation by replacement probability, capital disaggregation by capital type, and investment disaggregation by investment motivation. Finalize by balancing the SAM. Then, SAM data construction for the CGE analysis is ready for the purpose of this study as shown in table 3.2.

Chapter 4. The Computable General Equilibrium Model

4.1 Overall structure of CGE model

4.1.1 The CGE model

The general equilibrium model allows to capture market interactions. Thus, it is often preferred to the partial equilibrium model in case where the scope of the analysis is large and needs to examine inter-market linkages of the economy. This study uses CGE model to analyze the economic impact from labor replacement. The underlying assumption of general equilibrium analysis is based on Walrasian theory of general equilibrium. Thus, it optimizes rational behavior of the economic agents such as consumers, firms, and governments and clears all markets (De Melo, 1988).

The CGE model is used to simulate the impact of shocks such as taxation policies and changes in policies in the market. In order to simulate the impact of counterfactual policy scenarios depending on the economic variables, CGE model firstly requires to calibrate on the basis of an initial year of SAM to provide a set of consistent initial conditions. Then, the values of the economic variables can be compared after given shocks, which allows to examine the impact of a shock on the economic agents in terms of prices, amount of production or consumption, exports or imports, and welfare.

This study uses the standard CGE model proposed by Hosoe et al. (2010) as a base model to start with. This study changes the production to constant elasticity of substitution (CES) production function to be able to describe different elasticity of substitutions by industries and labor types. Further, the equations are updated accordingly to take consideration of the modified SAM, which classifies households by income quantiles, labors by replacement probability, capitals by types, investment by investing motivation. This study extends to a recursive dynamic model to design a model that describes a dynamic change of economy.

4.1.2 Main features of CGE model equations in this study

This section overviews how CGE model is constructed in this study. Like many other CGE studies, the equation system of this model consists of the conditions for optimization of individual subjects, market clearing conditions, price clearing conditions, and small open economy assumptions. The main features of the CGE model in this study can be summarized as follows. Firstly, this model considers heterogeneous labor (i.e., labors with low, medium, high replaceable by automation) and unemployment in order to consider different effects of different occupational groups with different risk of labor replacement. The unemployment of labors in response to changes in labor prices is considered in the model. Secondly, this model decomposes capital into two (i.e., original capital and robot capital), in order to consider the replacement of labor and robot capital due to the development of automation and robot industry. Thirdly, this model introduces productivity improvements of robot capital to capture automation technology develops over time. Accordingly, we distinguished the investment sector into two (i.e., original and robot investment sectors). Fourthly, this model considers heterogeneous households (i.e., 10 income quantiles) to capture the distribution effects induced by changes in wage and capital income structure, as well as the growth effects. In summary, the methodological feature enables to capture different elasticity of substitution among the input factors (i.e., robot capital and labor with high risk of replacement) and different industries within the CGE framework.

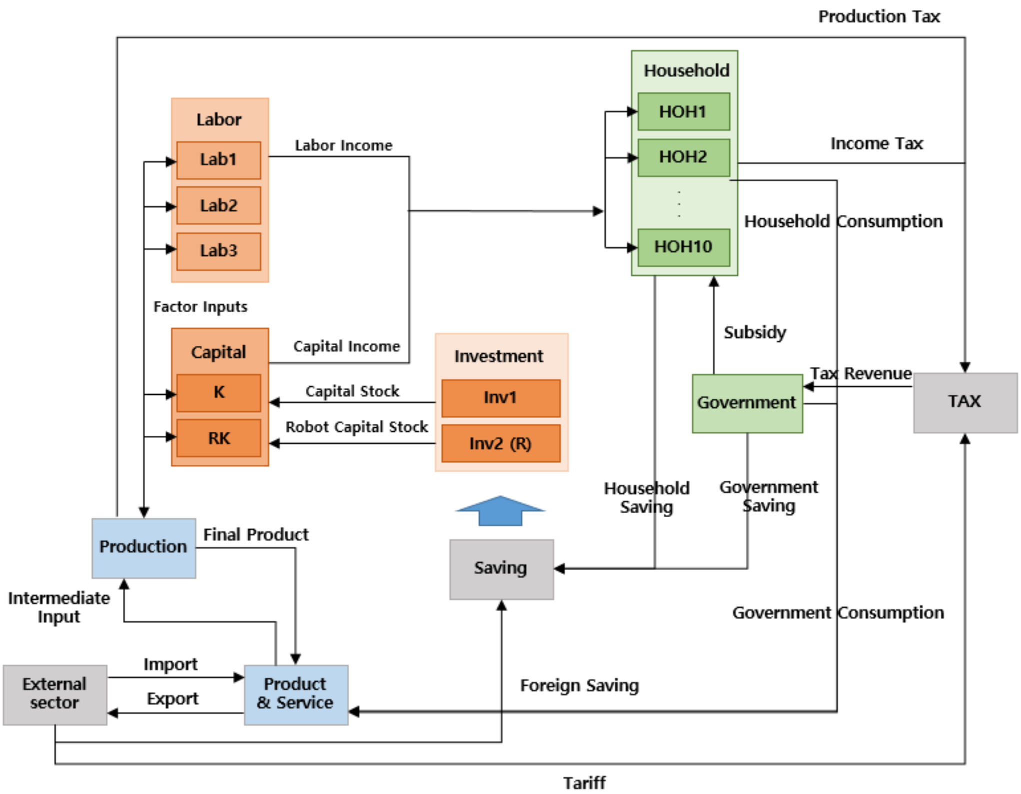

Figure 4.1. Features of the CGE model in this study

Demand is determined from household's utility maximization problem while the supply is determined from producer's profit maximization problem. Market price is determined at point where supply equals demand. Depending on the changing prices, the household's quantile groups react differently to decide the amount of consumption. The features of the CGE model constructed in this study incorporate features mentioned earlier, and the economic transaction relationships are expressed as in Figure 4.1 and Figure 4.2.

The feature, depicting supply and demand side of the CGE model in figure 4.2, is redrawn from the study of Yeo (2019) to better describe the features of the model in this study. The supply side describes how the domestic output are produced as a composite of value-added and intermediate inputs. Further, the value-added composite is produced through production functions with inputs of low-replaceable, medium-replaceable, high-replaceable labor, original capital, and robot capital.

On the demand side of the economy, the produced domestic outputs are partially exported and partially distributed domestically. Comprised with imported goods and domestically distributed goods, domestic demands are formed comprising of private consumption (household consumption), public consumption (government consumption), investment (original and robot capital formation) and intermediate goods.

The behaviors and interactions among each economic agent (i.e., production sectors, households, government, rest of worlds) allows to solve the equilibrium, under the utility maximization and profit maximization behaviors. Each firm behaves to maximize their profit to produce a product good in a competitive market. Each household maximizes utility under the budget constraint.

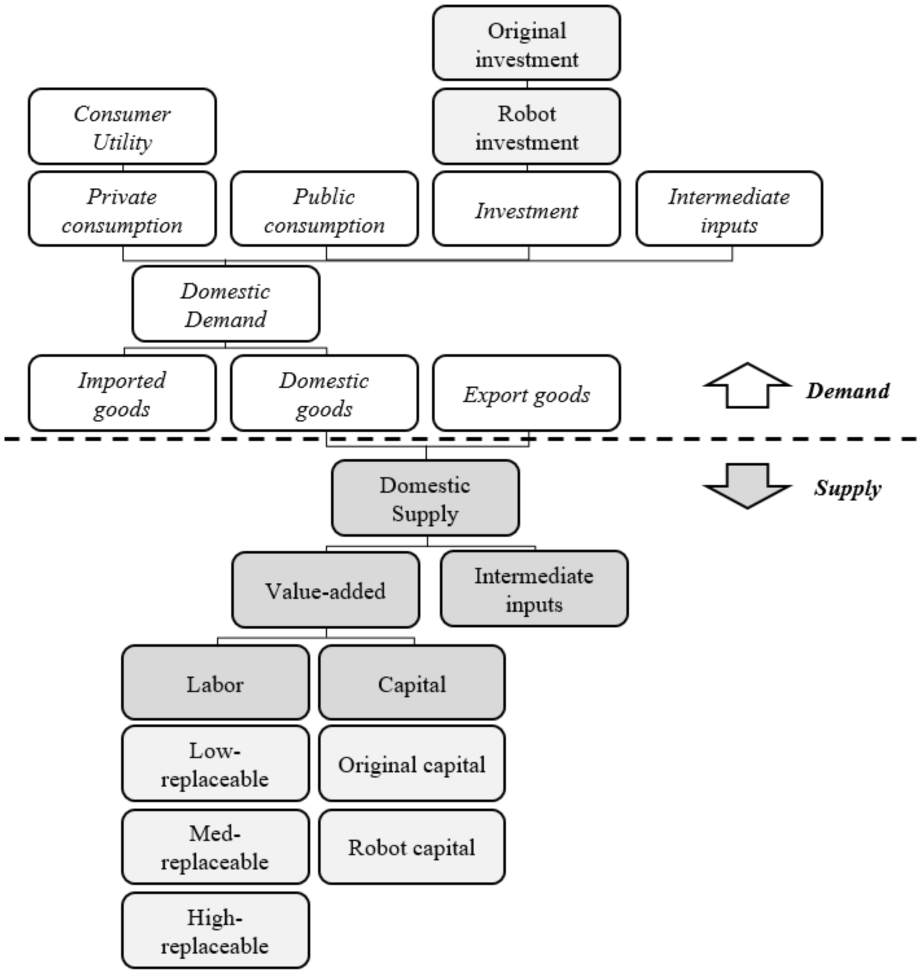

Figure 4.2 Structure of the CGE model of this study depicting supply and demand side

In addition, original and robot capitals are each accumulated and government and households' savings are used to finance investments. For production, three types of labor: low, medium, and high replaceable labor and two types of capitals: original capital, and robot capital are used as input factors. Households earn income through factor incomes (e.g. labor and capital incomes) and government transfer. And government earns revenue taxes (e.g., income tax, corporate tax, indirect tax, robot tax, and import tariffs to households and production sectors), which allows government to consume and save.

Model in this study is assuming a small open economy, that are focused on Korean economy. It is also assumed that production sectors are in perfectly competitive markets seeking to maximize the profits, and all sectors are in full employment.

There are 35 firms that produce one commodity each, maximizes their profits and face a nested production function, with two types of capital (e.g. original capital and robot capital), three types of labor (e.g. low, med, and high replaceable labor) and inter-industry flows as factors of production.

4.2 Production

The producer maximizes its profit by deciding production and input levels in accordance with the relative prices under the given technology. Figure 4.3 indicates the nesting structure of this model, in which a product is produced through aggregation of capitals and labors with intermediate inputs in the following stages.

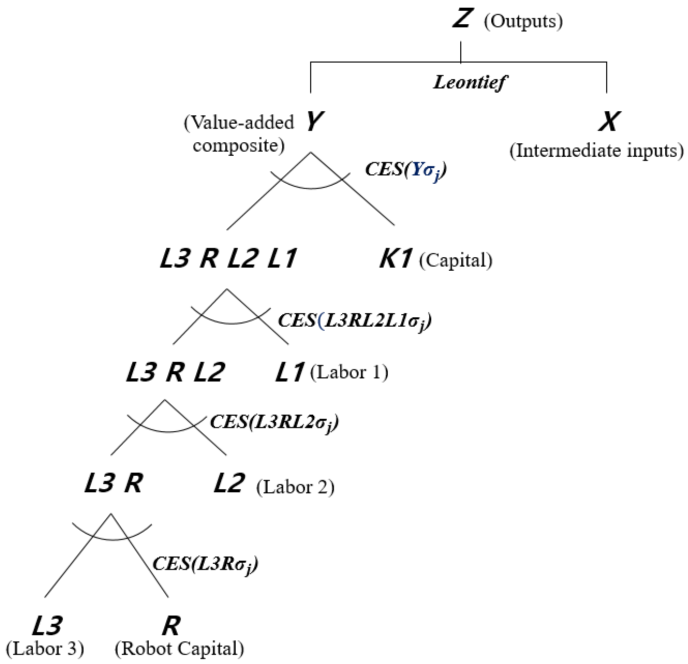

Figure 4.3. Production nesting structure

In order to explain the aggregation process, this section will review production nesting structure from the bottom. In the first nesting, the producer aggregates high replaceable labor ($L3_j$) with robot capital (R_j), which aggregated into the composite factor demand for high replaceable labor and robot capital ($L3R_j$). Here, production nesting is nested with the with CES production function as in , (4.1). Under the CES structure, input factors can be replaced by each other to a certain degree depending on the substitution elasticity value. The substitution parameter ($\eta L3R_j$), that describes substitution between high replaceable labor ($L3_j$) and robot capital (R_j), is calculated as $\eta L3R_j = \left(\sigma L3R_j - 1\right) \big/ \sigma L3R_j$. The higher the value of substitution elasticity the easier to be replaced between the labor and robot capital. The demand for high replaceable labor ($L3_j$) and robot capital (R_j) is determined by the parameters in the CES production function (equation 4.1) and relative price of high replaceable labor ($L3_j$), robot capital (R_j) and composite factor demand ($L3R_j$). The demand equations for high replaceable labor ($L3_j$) and robot capital (R_j) are equations (4.2) and (4.3). This study introduced the improvements in robot capital productivity with the robot capital productivity parameter ($Rprod$).

Following equations are composite factor aggregation and demand functions for the first CES nesting structure:

$$L3R_j = \gamma L3R_j \cdot \left[\delta L3_j \cdot L3_j^{\eta L3R_j} + \left(1 + Rprod\right) \cdot \delta R_j \cdot R_j^{\eta L3R_j} \right]^{1/\eta L3R_j} \quad , (4.1)$$

$$L3_j = \left[\left(\gamma L3R_j^{\eta L3R_j} \cdot \delta L3_j \cdot PL3R_j \right) \Big/ PL_{L3} \right]^{1/\left(1 - \eta L3R_j\right)} \cdot L3R_j \quad , (4.2)$$

$$R_j = \left[\frac{\left(\gamma L3R_j^{\eta L3R_j} \cdot \delta R_j \cdot PL3R_j \right)}{\left(PK_R \cdot \left(1 - KTAXR_R\right) \right)} \right]^{1/\left(1 - \eta L3R_j\right)} \cdot L3R_j \quad , (4.3)$$

$L3R_j$: Composite factor demand of $L3_j$ and R_j for production sector j

$\gamma L3R_j$: Scale parameter for the composite demand $L3R_j$

$\delta L3_j$: Share parameter for the high replaceable labor input ($L3_j$) in the $L3R_j$ composite demand function

$Rprod$: Parameter for the productivity growth of the robot capital

$L3_j$: High replaceable labor demand of the production sector j

R_j : Robot capital demand of the production sector j

$\eta L3R_j$: Substitution elasticity parameter of production sector j for $L3_j$ and R_j

$PL3R_j$: Price for the composite demand $L3R_j$

PL_{L3} : Wage price for the high replaceable labor ($L3$)

PK_R : Price for the robot capital

$KTAXR_R$: Tax rate on robot capital (zero at the baseline scenario)

In the second nesting, composite demand $L3R_j$ and medium replaceable labor ($L2_j$) aggregate into $L3RL2_j$ composite as in equation (4.4). The substitution between composite demand $L3R_j$ and medium replaceable labor ($L2_j$) is determined by the substitution parameter ($\eta L3RL2_j$), which is calculated as $\left(\sigma L3RL2_j - 1\right)/\sigma L3RL2_j$.

Following equations are composite factor aggregation and demand functions for the second CES nesting structure:

$$L3RL2_j = \gamma L3RL2_j \cdot \left[\delta L3R_j \cdot L3R_j^{\eta L3RL2_j} + \delta L2_j \cdot L2_j^{\eta L3RL2_j} \right]^{1/\eta L3RL2_j} \quad , (4.4)$$

$$L3R_j = \left[\frac{\left(\gamma L3RL2_j^{\eta L3RL2_j} \cdot \delta L3R_j \cdot PL3RL2_j \right)}{PL3R_j} \right]^{1/\left(1-\eta L3RL2_j\right)} \cdot L3RL2_j \quad , (4.5)$$

$$L2_j = \left[\frac{\left(\gamma L3RL2_j^{\eta L3RL2_j} \cdot \delta L2_j \cdot PL3RL2_j \right)}{PL_{L2}} \right]^{1/\left(1-\eta L3RL2_j\right)} \cdot L3RL2_j \quad , (4.6)$$

$L3RL2_j$: Composite factor demand of $L3R_j$ and medium replaceable labor ($L2_j$) of the production sector j

$\gamma L3RL2_j$: Scale parameter for the composite demand $L3RL2_j$

$\delta L3R_j$: Share parameter for $L3R_j$ composite input in the $L3RL2_j$ composite demand function of the production sector j

$\delta L2_j$: Share parameter for $L2_j$ composite input in the $L3RL2_j$ composite demand function of the production sector j

$L3R_j$: Composite factor demand of $L3_j$ and R_j for production sector j

$L2_j$: Medium replaceable labor demand of the production sector j

$\eta L3RL2_j$: Substitution elasticity parameter of production sector j for $L3R_j$ and $L2_j$ (where $\eta L3RL2_j = \left(\sigma L3RL2_j - 1\right) / \sigma L3RL2_j$)

$PL3RL2_j$: Price for the $L3RL2_j$ composite factor of the production sector j

PL_{L2} : Wage price for the medium replaceable labor ($L2$)

For the third CES nesting structure, composite demand $L3RL2_j$ and low replaceable labor ($L1_j$) aggregate into $L3RL2L1_j$ composite as in equation (4.7). The substitution between composite demand $L3RL2_j$ and low replaceable labor ($L1_j$) is determined by the substitution parameter ($\eta L3RL2L1_j$), that are calculated as $\eta L3RL2L1_j = \left(\sigma L3RL2L1_j - 1\right) / \sigma L3RL2L1_j$.

Following equations are composite factor aggregation and demand functions for the third CES nesting structure:

$$L3RL2L1_j = \gamma L3RL2L1_j \cdot \left[\delta L3RL2_j \cdot L3RL2_j^{\eta L3RL2L1_j} + \delta L1_j \cdot L1_j^{\eta L3RL2L1_j}\right]^{1/\eta L3RL2L1_j} \quad , (4.7)$$

$$L3RL2_j = L3RL2L1_j \cdot \left[\frac{\left(\gamma L3RL2L1_j^{\eta L3RL2L1_j} \cdot \delta L3RL2_j \cdot PL3RL2L1_j\right)}{PL3RL2_j}\right]^{1/\left(1-\eta L3RL2L1_j\right)} \quad , (4.8)$$

$$L1_j = L3RL2L1_j \cdot \left[\left(\gamma L3RL2L1_j^{\eta L3RL2L1_j} \cdot \delta L1_j \cdot PL3RL2L1_j\right) \Big/ PL_{L1}\right]^{1/\left(1-\eta L3RL2L1_j\right)} \quad , (4.9)$$

$L3RL2L1_j$: composite factor demand of $L3RL2_j$ and low replaceable labor ($L1_j$) of the production sector j

$\gamma L3RL2L1_j$: Scale parameter for the composite demand $L3RL2L1_j$

$\delta L3RL2_j$: Share parameter for $L3RL2_j$ composite input in the $L3RL2L1_j$ composite demand function of $L3RL2_j$ and $L1_j$ the production sector j

$\delta L1_j$: Share parameter for $L1_j$ composite input in the $L3RL2L1_j$ composite demand function of $L3RL2_j$ and $L1_j$ the production sector j

$L3RL2_j$: Composite demand of $L3R_j$ and $L2_j$ the production sector j

$L1_j$: Low replaceable labor demand of the production sector j

$\eta L3RL2L1_j$: Substitution elasticity parameter of the production sector j for $L3RL2_j$ and $L1_j$ ($\eta L3RL2L1_j = \left(\sigma L3RL2L1_j - 1\right) / \sigma L3RL2L1_j$)

$PL3RL2L1_j$: Price for the $L3RL2L1_j$ composite factor of the production sector j

PL_{L1} : Wage price for the low replaceable labor ($L1$)

The fourth CES nesting structure describes the composite demand $L3RL2L1_j$ and original capital ($K1_j$), aggregating into value- added composite (Y_j) as shown in equation(4.10). The substitution between composite demand $L3RL2L1_j$ and original capital ($K1_j$) is determined by the substitution parameter (ηY_j), that are calculated by $\eta Y_j = \left(\sigma Y_j - 1\right) / \sigma Y_j$.

Following equations are composite factor aggregation and demand functions for the fourth nesting structure:

$$Y_j = \gamma Y_j \cdot \left[\delta L3RL2L1_j \cdot L3RL2L1_j^{\eta Y_j} + \delta K1_j \cdot K1_j^{\eta Y_j} \right]^{1/\eta Y_j} \qquad , (4.10)$$

$$L3RL2L1_j = \left[\left(\gamma Y_j^{\eta Y_j} \cdot \delta L3RL2L1_j \cdot PY_j \right) \Big/ PL3RL2L1_j \right]^{1/\left(1-\eta Y_j\right)} \cdot Y_j \qquad , (4.11)$$

$$K1_j = \left[\left(\gamma Y_j^{\eta Y_j} \cdot \delta K1_j \cdot PY_j \right) \Big/ PK_{K1} \right]^{1/\left(1-\eta Y_j\right)} \cdot Y_j \qquad , (4.12)$$

Y_j: Composite factor demand of $L3RL2L1_j$ and original capital ($K1_j$) of the production sector j

γY_j: Scale parameter for the composite demand Y_j

$\delta L3RL2L1_j$: Share parameter for $L3RL2L1_j$ composite input in the Y_j value-added composite demand function of the production sector j

$\delta K1_j$: Share parameter for original capital ($K1_j$)input in the Y_j value-added composite demand function of the production sector j

$L3RL2L1_j$: Composite demand of $L3RL2_j$ and $L1_j$ of the production sector j

$K1_j$: Original capital demand of the production sector j

ηY_j: Substitution elasticity parameter of the production sector j for $L3RL2L1_j$ and original capital ($K1_j$) ($\eta Y_j = \left(\sigma Y_j - 1\right) \Big/ \sigma Y_j$)

PY_j: Price for the value-added composite factor Y_j of the production sector j

PK_{K1}: Price for the original capital ($K1$)

Finally, in the last nesting of the production function, domestic product good (Z_j) is produced with a Leontief composite of value-added composite (Y_i) and intermediate goods (X_{ji}). Assuming a Leontief production function to denote that the composite of the inputs remains at a constant ratio, means that it's not substitutable and so intermediate inputs X_{ji} cannot be substituted with value-added composite Y_i. Thus, each industrial sector seeking to maximize profits are faced with the following optimization problem, as producers seeking to maximize profits under the production function. Faced with the profit-maximization problem, the industrial sector determines the levels of outputs, value-added composites and intermediate goods within production function equations (4.13), (4.14), and (4.15). In equation (4.15), $tauz_i$ indicates the indirect taxes or subsidies imposed to each sector. In addition, PZ_i, PY_i, and PQ_j indicate prices of final goods, value-added composite, and Armington composite, respectively, while ax_{ji} and ay_i denote intermediate goods and value-added composites required in producing one unit of output (i.e., technical coefficients within the Leontief production function that can be calculated from the variable values of base year SAM) in industry i.

$$X_{ji} = ax_{ji} \cdot Z_i \qquad , (4.13)$$

$$Y_i = ay_i \cdot Z_i \qquad , (4.14)$$

$$\left(1 - tauz_i\right) \cdot PZ_j = ay_j \cdot PY_j + \sum_i ax_{ij} \cdot PQ_i \qquad , (4.15)$$

X_{ji} : Intermediate input of commodity j in production sector i

Z_i : Domestic output of production sector i

ax_{ji} : Share parameter of intermediate inputs for the output Z_i (Technical coefficient of Leontief production function)

ay_i : Share parameter of composite Y_i for the output Z_i (Technical coefficient of Leontief production function)

$tauz_i$: Indirect taxes or subsidies imposed to sector i

PZ_j : Price of the domestic output for the production sector j

PY_j : Price of the composite factor for the production sector j

PQ_i : Price of the good for the production sector i

This study adopts unemployment to the model. This study adopts Philips curves concept to the CGE model in order to take consideration of the unemployment (disequilibrium) in the labor market. Phillips (1958) denotes that the rate of unemployment and the rate of inflation are in the inverse relationship to each other, meaning that the decrease in the rate of wages affect negative on employments. In this study, parameter $elasPL$ has been used to refer the real wage changes in response to the variations in the unemployment rate, which in this study is assumed to -0.15. In presence of unemployment in the labor market, that causes the disequilibrium, wage price is not determined where labor supply intersects demand curves. Thus, a new equation is required to determine the wage.

, (4.16) refers to a negative relationship between the rate of change in real gross wage rate, and the rate of change in the unemployment rate with the real wage changes in response to variations in the unemployment rate. The real gross wage rate is defined to be PL^0/CPI^0 in the benchmark, and PL^1/CPI^1, after the proposed change. The unemployment rate is defined to be $UNEMP^0/LS^0$ in the benchmark, and $UNEMP^1/LS^1$, after the proposed change. Then, the wage determination equation is written as equation (4.16).

$$\left(\frac{PL_l^{\,0}/CPI^0}{PL_l^{\,1}/CPI^1}-1\right)=elasPL.\left(\frac{UNEMP_l^1/LS_l^{\,1}}{UNEMP_l^0/LS_l^{\,0}}-1\right) \quad , (4.16)$$

$elasPL$: Changes of initial real wage in variations of the unemployment rate

PL_l : Price of labor (wage) by labor types ($l \in$ low, med, high replaceable labor)

CPI : Consumer price index

Consequently, to take consideration of unemployment to the model, the market clearing conditions for the labor market is as in equation (4.17).

$$L1 + L2 + L3 = LS - UNEMP \qquad , (4.17)$$

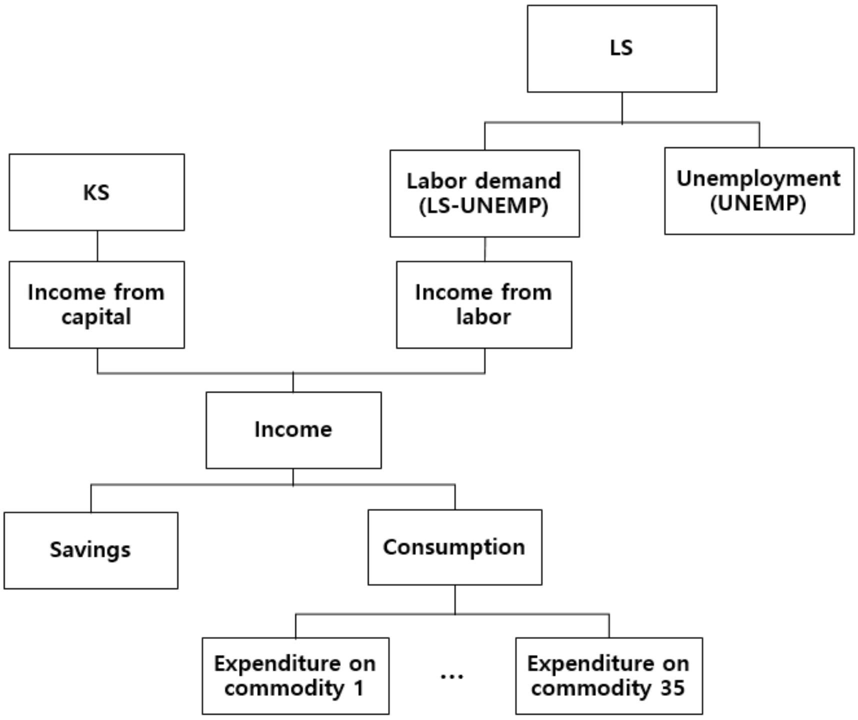

Figure 4.4. Decision of the household to include unemployment in the labor structure (Referenced from EcoMod (2020) and redrawn by the author)

4.3 Households

This study considers ten quantile groups of households in order to take consideration of heterogeneity of households' behavior depending on their income level. Each household are assumed to have consumption behavior of Cobb-Douglas utility function and maximize utility under his or her budget constraints. As in equation (4.18), households in a h quantile group consumes product i is written in households consumption level $Xp_{i,h}$. Households consume each product at Leontief ratio ($\alpha_{i,h}$) of disposable income level minus savings divided by indirect tax and product price. Following equation is for household demand function:

$$Xp_{i,h} = \frac{\alpha_{i,h} * \left(DHI_h - Sp_{i,h}\right)}{\left[\left(1 + tauih_{i,h}\right) * PQ_i\right]} \quad , (4.18)$$

where disposable household income (DHI) is express in , (4.19).

$$\begin{aligned} DHI_h = & \sum\nolimits_c pk_c \cdot KS_c \cdot ror \cdot KHshare_{h,c} \\ & + \sum\nolimits_l \left(\left(LEwUNEMP0_l - UNEMP_l\right) \cdot LHshare_{h,l}\right) - Td_h + gtransfer_h \end{aligned} \quad , (4.19)$$

Disposable income of each household quantile is determined by aggregating the stocks of capital of its type (i.e. original and robot capital) taking into consideration of the price of each capital and rate of return) as well as the labor endowment (after consideration of unemployment), direct tax, and government subsidy given to each households.

$Xp_{i,h}$: Household consumption of the product i by household type h

$\alpha_{i,h}$: Consumption share of household type h for the product i

DHI_h : Disposable household income by household type h

$gtransfer_h$: Government transfer (subsidy) given to each household type h .

PL_l : Wage (labor price) by labor type l ($l \in$ high, med, low replaceable labor)

PK_c : Capital price (original capital and robot capital)

$Sp_{i,h}$: Household saving of household type h on industry sector i

$Td_{i,h}$: Direct tax of household type h on the product i

$tauih_{i,h}$: Indirect tax of household type h on the product i

PQ_i : Price of Armington composite good i

$LEwUNEMP0_l$: Labor endowment including unemployment labors

$UNEMP_l$: Unemployment level by labor type

$LHshare_{l,h}$: Household share by labor type

4.4 Government

The government, like households, has income and expenditure. Government consumes products with tax revenue. Government tax revenue comes from a direct tax which includes capital and labor tax (Td), production tax (Tz_j), an import tariff (Tm_j), indirect tax on household ($TIH_{h,j}$), investment ($TII_{h,j}$), and export ($TIE_{h,j}$). Within the budget of constraints, government consumes (XG_i) and saves (Sg). Equation (4.20) shows government demand function:

$$XG_i = \frac{\mu_i}{PQ_i}\left(Td + \sum_j Tz_j + \sum_j Tm_j + \sum_j TIH_{h,j} + \sum_j TII_{h,j} + \sum_j TIE_{h,j} - Sg\right) \quad ,$$

(4.20)

Following equations represent functions of direct tax revenue, sales tax revenue, import tariff revenues:

$$Td = taud \cdot \sum_j \left[pk \cdot KD_j + \left(\sum_{ul} pl_{ul} \cdot LD_{ul,j} \right) \right] \qquad , (4.21)$$

$$TZ_j = tauz_j * PZ_j * Z_j \qquad , (4.22)$$

$$TM_i = taum_i * PM_i * M_i \qquad , (4.23)$$

Equations (4.24) to (4.26) are for the indirect tax revenue for households, investment, and export:

$$TIH_i = tauh_i * PQ_i * Xp_i \quad , (4.24)$$

$$TII_i = tauii_i * PQ_i * Xv_i \quad , (4.25)$$

$$TIE_i = tauie_i * epsilon * PWE_i * E_i \quad , (4.26)$$

XG_i : Government consumption on commodity i

μ_i : Share of the government consumption on commodity i

Td : Household direct tax

Tz_j : Production tax from the producer j

Tm_j : Import tariff tax from the producer j

TIH_i : Household indirect tax for the commodity i

TII_i : Investment indirect tax for the commodity i

TIE_i : Export indirect tax for the commodity i

Sg : Government saving

$taud$: Direct tax rate

$tauz_j$: Production tax rate for producer j

$taum_j$: Import tariff rate for commodity j

Z_j : Domestic output of commodity j

PM_j : Import price of commodity j in a local currency

M_j : Import demand for commodity j

$tauii_i$: investment indirect tax rate for the commodity i

$tauie_i$: Export indirect tax rate for the commodity i

$epsilon$: Exchange rate

PWE_i : Export price in a foreign currency for commodity i

E_i : Export demand for commodity i

4.5 Investments and savings

This study includes two types of investment and savings as the capital stock is classified into two, original and robot capitals. The investment agent of each household type ($Sp_{v,h}$), government (Sg_v), and foreign sector (Sf_v) saves. Saving amount is decided based on a certain percentage share of expenditure for the product i and the baseline share is maintained. Households saves from their income revenue at the rate of $ssp_{v,h}$ while government saves from tax revenues at the rate of ssg_v. Foreign sector saves its export revenue minus the expenditure amount to import domestic products.

Investment demand function

$$Xv_{i,v} \cdot \sum_i \left(1 + tauii_i\right) \cdot PQ_i = \lambda_{i,v} \cdot \sum_h Sp_{i,h} + Sg_v + epsilon \cdot Sf_v \qquad , (4.27)$$

$$Xv_i = \sum_v Xv_{i,v}$$, (4.28)

$Xv_{i,v}$: Investment demand on each type of investment (e.g., investment on original capital and robot capital).

Xv_i: Total investment demand regardless of the type of investment

Sf_v: Foreign saving in a foreign currency

$Sp_{v,h}$: Household saving by households' type

Sg_v: Average propensity for government saving

$\lambda_{v,i}$: Investment demand share

Households' private saving function:

$$Sp_{v,h} = ssp_{v,h} * \left(\sum_j pk \cdot KD_j + \sum_{ul,j} pl_l \cdot KD_{j,l} \right)$$, (4.29)

Government saving function:

$$Sg_v = ssg_v * \left(Td + \sum_j Tz_j + \sum_j Tm_j + \sum_j TIH_j + \sum_j TII_j + \sum_j TIE_j \right)$$, (4.30)

This study further introduced improvements in robot capital productivity as time goes and the saving propensity of individual would be larger to have more investment in robot industry than other sectors as time goes. For example, $ssp^{t+1}{}_{v,h} = ssp^{t}{}_{v,h} \pm (0.0005)$.

Thus, the saving propensity of household groups are taken consideration as in equations when taking consideration of law of motion for recursive dynamic model.

4.6 Exports and imports (International trade)

A small open economy is assumed in this study. By assuming an open economy model, goods that are domestically produced and consumed are considered slightly different goods compared to those that are imported or exported. This means that the goods that are domestically produced or consumed or goods that are imported or exported are imperfectly substitutable to each other. In order to capture this imperfect substitutability and degree of differences or similarity between them, a parameter to have the constant elasticity of substitution is used. Using the CES function, elasticity of substitution parameter is large (i.e. elastic) when the products are significantly similar to each other. This Armington's (1969) assumption about imperfect substitution allows to take consideration of similarities and differences between imported and domestically produced goods.

Each industrial sector can determine the quantity of domestic and export goods based on equation (4.38).]standard CGE

$$Z_{i,t} = \vartheta_i \cdot \left(\xi e_i \cdot E_{i,t}^{\varphi_i} + \xi d_i \cdot D_{i,t}^{\varphi_i} \right)^{(1/\varphi_i)} \quad , (4.31)$$

Equations. (4.32) and (4.33) is for world export and price equation respectively:

$$PE_i = (1 - tauie_i) * epsilon * PWE_i$$, (4.32)

$$PM_i = epsilon * PWM_i$$, (4.33)

The following equation refers to the balance of payments equation:

$$\sum_i (1 + tauie_i) * PWE_i * E_i + Sf = \sum_i PWM_i * M_i$$, (4.34)

The following equation is for the Armington function:

$$Q_i = A\gamma_i * \left(M\delta_i * M_i^{A\eta_i} + D\delta_i * D_i^{A\eta_i} \right)^{\frac{1}{A\eta_i}}$$, (4.35)

The following equation is for the import and export demand function respectively:

$$M_i = \left[\frac{A\gamma_i^{A\eta_i} * M\delta_i * PQ_i}{(1 + ITR_i) * PM_i} \right]^{\frac{1}{1 - A\eta_i}} * Q_i$$, (4.36)

The following equation for domestic good:

$$D_i = \left[\frac{A\gamma^{A\eta_i} * D\delta_i * PQ_i}{PD_i} \right]^{\frac{1}{1 - A\eta_i}} * Q_i$$, (4.37)

This equation is for the transformation function:

$$Z_i = \theta_i * \left(E\psi_i * E_i^{\phi_i} + D\psi_i * D_i^{\phi_i} \right)^{\frac{1}{\phi_i}}$$, (4.38)

Next equations are for domestic and export good supply function respectively:

$$D_i = \left[\frac{\theta_i^{\phi_i} * D\psi_i * (1 + PTR_i) * PZ_i}{PD_i} \right]^{\frac{1}{1-\phi_i}} * Z_i \quad , (4.39)$$

$$E_i = \left[\frac{\theta_i^{\phi_i} * E\psi_i * (1 + PTR_i) * PZ_i}{PE_i / (1 - EITR_i)} \right]^{\frac{1}{1-\phi_i}} * Z_i \quad , (4.40)$$

PE_i : Export price in a local current for commodity i

PWM_i : Import price in a foreign currency for commodity i

Q_i : Armington composite commodity i

$A\gamma_i$: Scaling parameter in the Armington composite function of commodity i

$M\delta_i$: Import share parameter for commodity i

$D\delta_i$: Domestic demand share parameter for commodity i

D_i : Domestic demand for commodity i

$A\eta_i$: Substitution parameter of the commodity i ($A\eta_i = (A\sigma_i - 1) / A\sigma_i$)

PD_i : Price of the domestic demand i

θ_i : Scaling parameter in the transformation function of commodity i

$E\psi_i$: Export share parameter for commodity i

$D\psi_i$: Domestic demand share parameter for commodity i

ϕ_i : Transformation parameter of commodity i ($\phi_i = (ED\sigma_i - 1) / ED\sigma_i$)

4.7 Market and aggregation equilibrium conditions

4.7.1 Consumer price index

In presence of zero-order homogeneity, the CGE model follows the relative price system. This means that the model fixes one price index as a reference. For this study, consumer price index (CPI) is considered as a reference numeraire price and is set to one. CPI measures the weighted average of consumer price for each industry by taking the proportion of household consumption. CPI is calculated a sin equation (4.41).

$$CPI = \sum_i CPIWEIGHT_i \cdot PQ_i \qquad , (4.41)$$

CPI : Consumer price index

$CPIWEIGHT_i$: Household consumption share of product i of total consumption of the household

4.7.2 Market clearing

In CGE model, market clearing conditions set supply equals to demand, so that the price can be determined by the supply-demand theory. The equilibrium conditions for market clearing can be followed by the equations below.

$$Q_i = XP_i + XG_i + XV_i + \sum_j X_{i,j} \qquad , (4.42)$$

The market clearing conditions in the goods market requires supply equals to demand, meaning that the output be equal to the sum of aggregate consumption, investment, and government spending. (eg. supply = demand where aggregate consumption, Gross Investment, Intermediate inputs, Government saving). Considering what mentioned ablove, the market clearing condition is expressed by equations for good market:

$$Q_i = XP_i + XG_i + XV_i + \sum_j X_{i,j} \quad , (4.43)$$

$$\sum_j KD_{c,j} = KS_c \cdot ror \quad , (4.44)$$

Labor factor market clears as follows

$$\sum_j LD_{l,j} + UNEMP_l = \sum_h LEwUNEMP_{h,l} \quad , (4.45)$$

4.8 Recursive equation

This study uses a recursive dynamic CGE model. Thus, model solves static problems, and assumes that capital stock to be updated using the solutions obtained from the previous time period and labor endowment. In the case of the recursive dynamic model, the amounts the investments depend on the values of savings, as in the static model. These investments will form the next-period's capital stocks in the previous period, and this next-period's capital stock affects the production volumes of industrial sectors in the corresponding period.

Recursive equations are as follows.

$$KS_{K,t+1} = (1-dep)*KS_{K,t} + \sum_i Xv_{K,i,t} \quad , (4.46)$$

$$KS_{RK,t+1} = (1-dep)*KS_{RK,t} + \sum_i Xv_{RK,i,t} \quad , (4.47)$$

$$\overline{L_{t+1}} = (1+lprod_{t+1})*\overline{L_t} \quad , (4.48)$$

$KS_{K,t}$: original capital stock at time period t

$KS_{RK,t}$: Robot capital stock at time period t

dep : Depreciation rate

$Xv_{c,i,t}$: Investment demand for the product I at time period t

$\overline{L_t}$: Labor endowment at time period t

$lprod_{t+1}$: Labor productivity growth rate at time period t+1

Chapter 5. Economic impact analysis of labor replacement by robots

The CGE model is widely used tool to analyze the impact of external changes on the economy. Given an exogenous shock, the impact of the scenario can be analyzed through changes in economic growth, household income, production, and household utility level. In order to analyze the impact of policy simulations using on the constructed CGE model, the baseline economy is designed. Using the model constructed as described in the previous chapters, baseline economy of Korea is presented for the year of 2015 to 2050. Business as usual (BAU) scenario assumes that there is no external shock from the base year 2015 to 2050. And, by introducing shock to the CGE model, researcher may examine the policy impacts by comparing the changes in the macroeconomic variables in the model. The projection data that can be obtained exogenously are used to reflect the values to project the phenomenon and future prediction.

The scenario is designed as shown in the table 5.1. The analysis was conducted by setting the scenario as shown in table 5.1, in a situation where additional situations were given step by step by step. In this study, as shown in table 5.1, it is largely divided into three scenarios: BAU scenario, robot capital scenario (e.g., biased distribution of robot capital and labor productivity change scenario), and robot tax imposition scenario. Through the interaction between each economic entity for each scenario situation, the effect of labor substitution on society due to technological change was analyzed in various perspectives.

Table 5.1 Construction of the scenarios in this study

Scenario Type	Detailed Description
5.1 BAU scenario	Labor replacement by robot capital
5.2 Robot capital scenario	5.2.1 Biased distribution of robot capital 5.2.2 Labor productivity biased scenario
5.3 Imposing robot tax	Imposing robot tax of 20%

5.1 Business as usual (BAU) scenario: labor replacement by robot capitals

Figure 5.1 shows the accumulation pattern of original capital and robot capital. The original capital accumulates at a slow rate while the robot capital accumulates rapidly. This characteristics of robot capital stirs the social impacts on the economy.

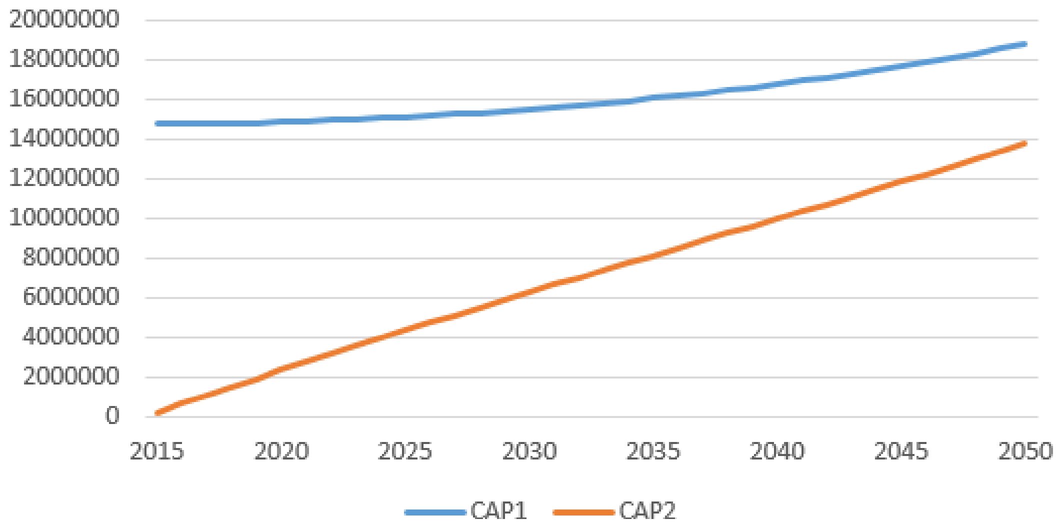

Figure 5.1. Capital accumulation pattern of original (cap1) and robot capitals (cap2)

In this CGE model, different elasticity of substitution by industrial sectors and labor occupations is assumed, in order to take consideration of different of replacement of labor by its industry and occupation. As the estimation value of replacement probability by labor occupations and industries conducted by Kim (2015) are referenced in this study, we normalized the value and used it for the elasticity of substitution. For BAU scenario, this study assumes different elasticities of substitutions for each industry. According to the replacement probability data provided by Kim (2017), shown in table 3.6 in this study, the elasticity of substitution value by industry was used as shown in table 5.2 below.

The replacement rate by industry was normalized by summarizing the computerization possibility data of Kim (2017) in the following way, and reflected in the model as the replacement elasticity value. Kim (2015) calculated and reported the probabilities of computer replacement by job category and industry as shown in tables 3.6 and 3.7, respectively.

The elasticity of substitution between input elements is usually assumed to be 2 in the CGE model (Yeo, 2019; Hwang et al., 2014). Therefore, in this study, the average replacement probability was obtained for labor 1, 2, and 3 (e.g. high, medium, and low replaceable labor), and the elasticity of substitution (EOS) values of labor 1, 2, and 3 were calculated using values relative to the average replacement probability of 2 of the elasticity of substitution, and the values are given in table 5.2.

Table 5.2 Probability of replacement by labor type and normalized elasticity of substitution

	Probability of computerization	EOS
Labor 1	0.362	1.09
Labor 2	0.680	2.05
Labor 3	0.891	2.69
Average	0.663	2

In the same way, the average value of Kim (2015)'s replacement probability by industry was considered as the value of EOS is 2, and the EOS value for each industry was calculated using the relative value, and the value is displayed in table 5.3.

Table 5.3 Probability of replacement by industrial sectors and normalized elasticity of substitution (EOS)

Matching Classification System with Kim (2015)		Probability of Replacement	EOS
Agri	A	0.98	3.13
Mining	B	0.968	3.09
Food	C	0.561	1.79
FiberLeather	C	0.561	1.79
WoodPaper	C	0.561	1.79
CoalOil	C	0.561	1.79
Chemical	C	0.561	1.79
Pharmaceutical	C	0.561	1.79
OtherChemical	C	0.561	1.79
PlasticRubber	C	0.561	1.79
NonMetal	C	0.561	1.79
PriMetal	C	0.561	1.79
Metal	C	0.561	1.79
Computer	C	0.561	1.79
Machine	C	0.561	1.79
ElecEquip	C	0.561	1.79
TransEquip	C	0.561	1.79
MissManu	C	0.561	1.79
IndEquip	C	0.561	1.79
ElecStream	D	0.955	3.05
WaterWaste	E	0.276	0.88
Const	F	0.772	2.46
WholeServ	G	0.794	2.53

TransServ	H	0.837	2.67
AccomServ	I	0.806	2.57
ITServ	J	0.444	1.42
FinServ	K	0.878	2.80
EstateServ	L	0.975	3.11
ScienceServ	M	0.311	0.99
BusiServ	N	0.547	1.75
Administration	O	0.191	0.61
EduServ	P	0.012	0.04
SocialServ	Q	0.134	0.43
CultureServ	R	0.379	1.21
Miss	ST	0.691	2.20
Average	-	0.627	2.00

The EOS value was calculated by multiplying the EOS value by industry and labor type according to the nesting structure of this model by square root and calculating the EOS value of robot capital and labor 3 in order to reflect the high replacement of L3R. table 5.4 shows the elasticity of substitution of the production nesting structure assumed in this model.

Table 5.4. EOS of the industry of the production function in this study

	$\sigma L3R_j$	$\sigma L3RL2_j$	$\sigma L3RL2L1_j$	σY_j
Agri	8.404	2.533	1.849	1.414
Mining	8.301	2.518	1.837	1.414
Food	4.811	1.917	1.399	1.414
FiberLeather	4.811	1.917	1.399	1.414
WoodPaper	4.811	1.917	1.399	1.414
CoalOil	4.811	1.917	1.399	1.414
Chemical	4.811	1.917	1.399	1.414
Pharmaceutical	4.811	1.917	1.399	1.414
OtherChemical	4.811	1.917	1.399	1.414
PlasticRubber	4.811	1.917	1.399	1.414
NonMetal	4.811	1.917	1.399	1.414
PriMetal	4.811	1.917	1.399	1.414
Metal	4.811	1.917	1.399	1.414
Computer	4.811	1.917	1.399	1.414
Machine	4.811	1.917	1.399	1.414
ElecEquip	4.811	1.917	1.399	1.414
TransEquip	4.811	1.917	1.399	1.414
MissManu	4.811	1.917	1.399	1.414
IndEquip	4.811	1.917	1.399	1.414
ElecStream	8.190	2.501	1.825	1.414
WaterWaste	2.367	1.344	0.981	1.414
Const	6.621	2.248	1.641	1.414
WholeServ	6.809	2.280	1.664	1.414
TransServ	7.178	2.341	1.708	1.414
AccomServ	6.912	2.297	1.677	1.414
ITServ	3.808	1.705	1.244	1.414
FinServ	7.530	2.398	1.750	1.414

EstateServ	8.362	2.527	1.844	1.414
ScienceServ	2.667	1.427	1.041	1.414
BusiServ	4.691	1.893	1.381	1.414
Administration	1.638	1.118	0.816	1.414
EduServ	0.103	0.280	0.205	1.414
SocialServ	1.149	0.937	0.684	1.414
CultureServ	3.250	1.575	1.150	1.414
Miss	5.926	2.127	1.552	1.414

Labor productivity was assumed to be 2% (NABO, 2018), and labor elasticity according to wages was assumed to be 15% (Choi & Cho, 2008; Atkeson & Ohanian, 2001). The improvement in robot productivity is considered to increase by 0.5% every year, and accordingly, the proportion of investment in the robot industry is increased.

GDP is predicted using external data of the growth rate of population, GDP, and labor productivity. According to NABO's "2019-2050 NABO Long-term Fiscal Outlook," the average real GDP growth rate until 2050 is predicted to be 2.0%. This study calibrated the last period so that the forecast for 2050 could be similar to the forecast data, and the forecasting of GDP until 2050 for the BAU scenario is shown in figure 5.2 and table 5.3.

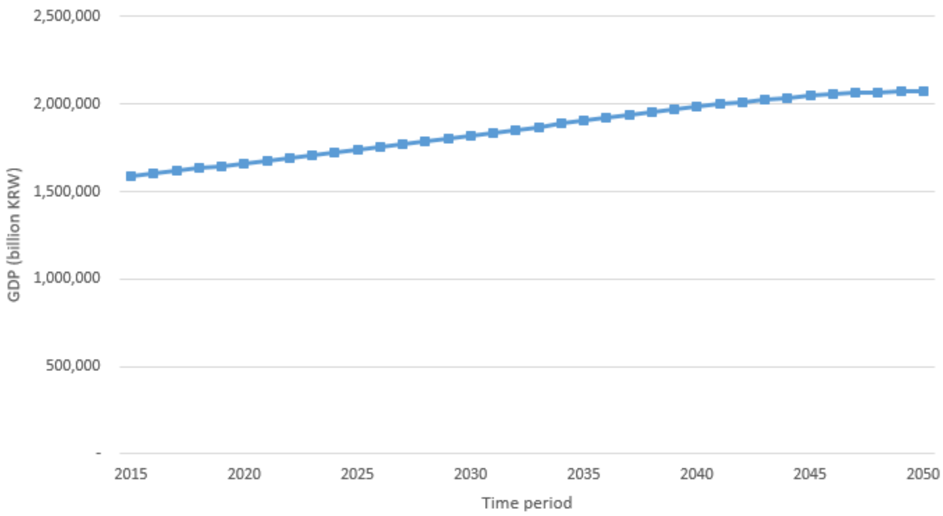

Figure 5.2. GDP forecast from 2015 to 2050

Table 5.5 GDP forecast for BAU scenario (real GDP)

Time	GDP (billion KRW)
2015	1,588,703
2020	1,661,789
2025	1,735,110
2030	1,818,310
2035	1,904,991
2040	1,985,123
2045	2,046,734
2050	2,075,655

In order to compare and analyze the impact of each industry, industrial groups were classified into four categories as shown in figure 5.3 according to the probability of replacement and the degree of capital intensity, and their trends were compared and analyzed. Capital-intensive production indicates the production that require more capital (e.g., equipment and machinery) to produce goods, so more financial investment is required. Labor-intensive production indicates the production that requires higher labor input to carry out production activities compared to the amount of capital required. Since the criteria classified into four are to see trends according to the characteristics of industries, the criteria were divided into relative values between industries. The average probability of substitution for 35 industries classified in this study is 0.532, and the degree of capital intensity is 0.585. If the replacement probability was higher than the average of 0.532, it was classified as a high replacement sector, and if it was lower, it was classified as a low replacement sector. The capital intensive sector is also classified as the capital intensive sector if it is higher than the average, and the Labor Intensive sector if it is lower, based on the average value of 0.585. In this study, it was classified as a relative value to examine the tendency of each cluster.

In Figure 5.3 that is divided into quartiles the first quartile (High, CAP) has a high probability of automation and is a capital intensive industry, including Agri, Mining, ElectStream, EstateServ, and ScienceServ. The second quartile (High, LAB) has a high probability of automation and is a laboratory industry, and Const, WholeServ, TransServ, AccomServ, and Miss industries belong to the quartile. (Low, LAB) is an industry with low automation probability, including Food, Fiber Leather, WoodPaper, Metal, ElecEquip, TransEquip, MissManu, IndEquip, ScienceServ, BusiServ, Administration, EduServices, and Servials. The fourth quartile (Low, CAP) has a low probability of automation and is a capital intensive industry, including Coil Oil, Chemical, Pharmaceutical, Other Chemical, Plastic Rubber, NonMetal, PriMetal, Computer, Machine, WaterWaste, IT Service, and Culture.

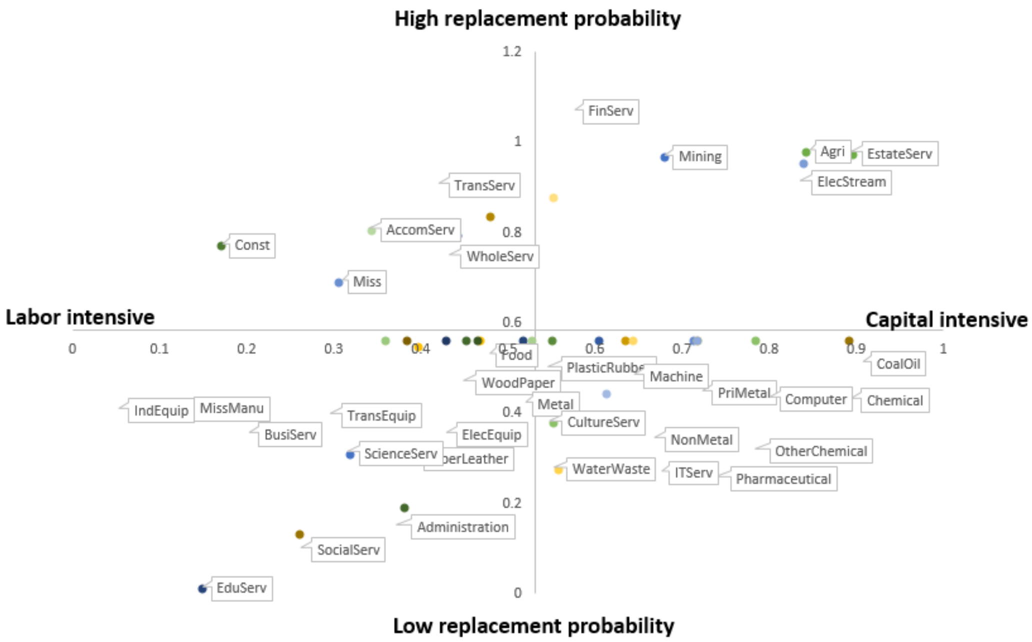

Figure 5.3. Classification of industries by replacement probability and capital intensity

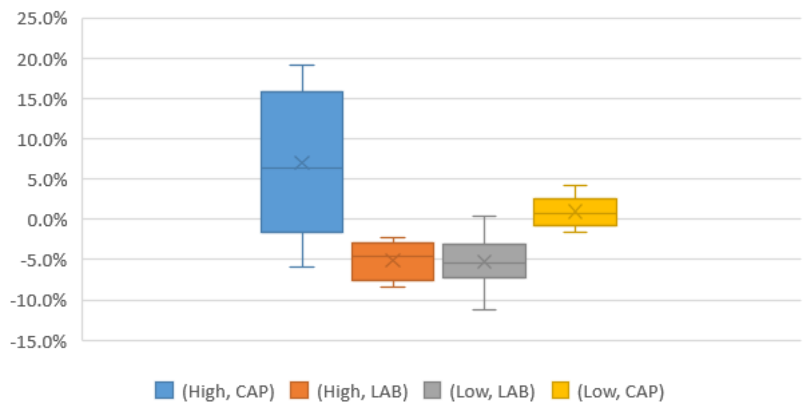

Figure 5.4 Change rate of domestic price (PZ) from 2015 to 2050 for industry types

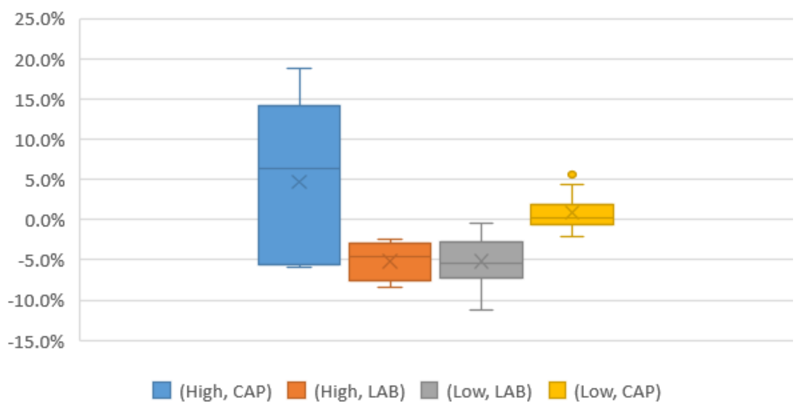

Figure 5.5 Change rate of supply price (PQ) from 2015 to 2050 for industry types

The disposable income of households is used that are in the tenth quantile for each household.

Table 5.6 Changes in household income by income quantile (BAU)

	BAU 2015	BAU 2050	Increase Rate
HOH1	29,282	35,403	20.9%
HOH2	61,687	76,240	23.6%
HOH3	83,343	102,892	23.5%
HOH4	104,890	131,113	25.0%
HOH5	118,908	147,733	24.2%
HOH6	136,430	170,166	24.7%
HOH7	155,411	193,755	24.7%
HOH8	173,016	215,743	24.7%
HOH9	212,640	266,572	25.4%
HOH10	300,706	377,100	25.4%

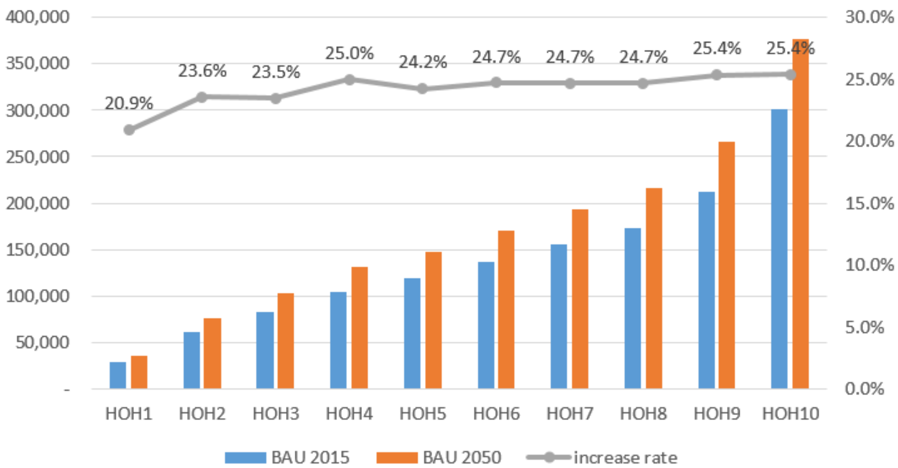

Figure 5.6 Changes in income by household quantile

The rate of increase in disposable income is higher in the high income group and lower in the low income household quantile group. Among household income quantiles, government transfer income accounted for quantile1 (48.8%), quantile2 (25.2%), quantile 3 (18.7%), quantile4 (14.8%), quantile5 (11.06%), quantile6 (10.6%), quantile 7 (8.2%), quantile 9 (6.1%), and quantile 10 (5.1%). The lower the income household, the greater the proportion of transfer income among household income. This is because government transfer income is fixed rather than assumed to continuously increasing. This phenomenon, that income growth rate of low-income group is relatively low, can be explained that the low-income household quantile group lives on transfer income.

Next, labor income is compared. The rate of increase in labor income was the smallest in the 5th to 7th quantiles of households (HOH5-7), which can be seen as a result of the large number of workers in jobs with high labor substitution in the middle and upper income quantile. In other words, the household atmosphere that is most affected by labor income due to labor substitution is households in the fifth, sixth, and seventh quantiles. This is interpreted as a result of changes in the price and demand of input factors (labor 1, 2, 3 and capital 1, 2). Figure 5.3 is a diagram showing changes in the price of labor and capital, and it can be seen that the price of labor 3, which has high elasticity of substitution with robot capital, has fallen the most due to the decline in robot capital prices. Due to the large influx of relatively cheaper robot capital, companies intend to produce it using relatively cheaper robot capital than other input elements. As a result, the prices of labor groups 1, 2, and 3 all fall, and it can be seen that the price drop of labor 3, which is relatively easier to replace, appears more severe.

Table 5.7 Changes in labor income (2015–2050)

	2015	2050	Increase Rate
HOH1	7,756	9,178	18.3%
HOH2	22,587	26,526	17.4%
HOH3	36,609	42,257	15.4%
HOH4	44,366	51,129	15.2%
HOH5	62,404	71,681	14.9%
HOH6	68,716	78,802	14.7%
HOH7	86,039	98,804	14.8%
HOH8	102,798	118,417	15.2%
HOH9	124,446	143,978	15.7%
HOH10	198,503	232,860	17.3%

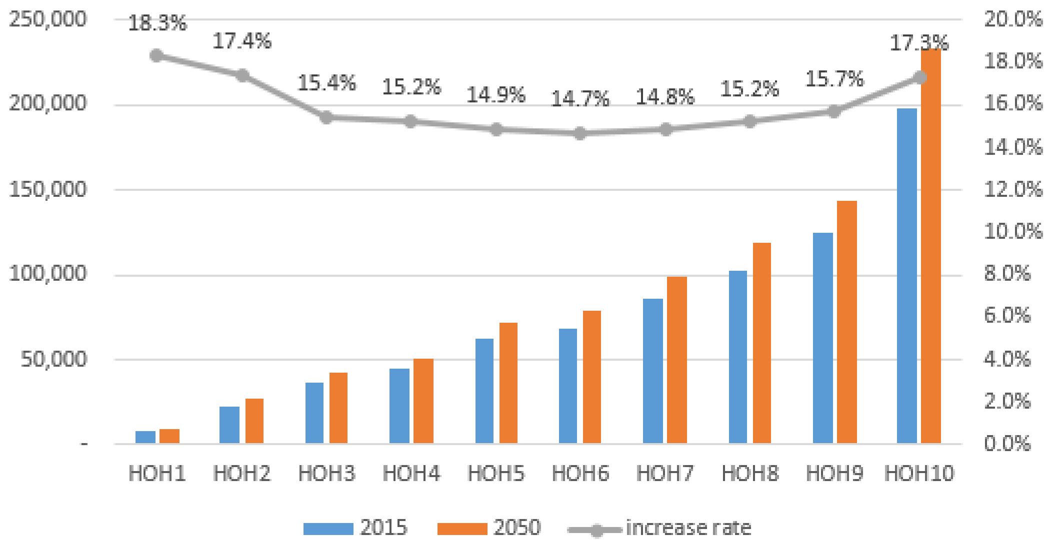

Figure 5.7 Changes in labor income by household quantile group

As robots increase, the price per unit decreases (Figure 5.3). This shows similar results to the existing literature and is the same as the results of an empirical study that industries with large incentives to use robots fall in robot prices due to technological development.

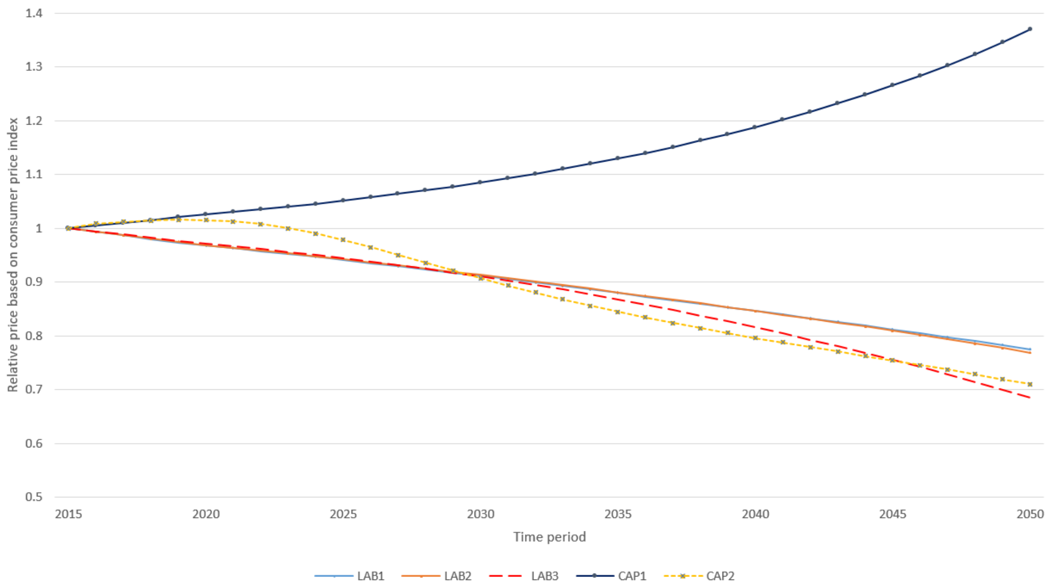

Figure 5.8 Changes in labor and capital price over time (2015–2050)

The quantity and price are affected by labor income, and how prices (wage) of labor 1, labor 2, and labor 3 has changed, quantity changed, unemployment changed, and HOH classified. As shown in figure 5.7, the labor change rate varies according to the replacement probability by industry. The employment rate

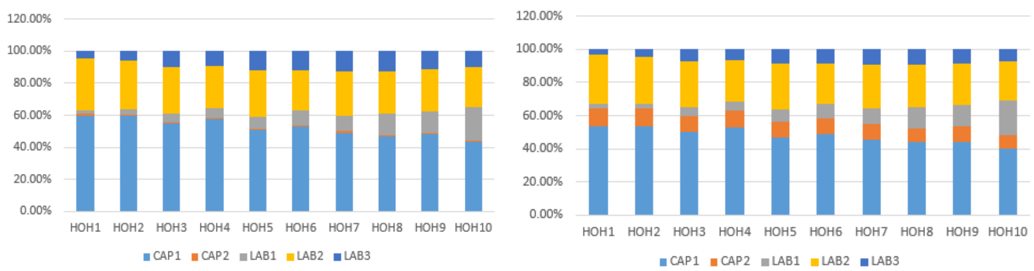

Figure 5.9. Labor income change by households (2015 → 2050)

As seen in figure. 5.8, the probability of replacement by industries show negative relationship with labor type (e.g., low, medium, high- replaceable labor with robot capital) and probability of replacement.

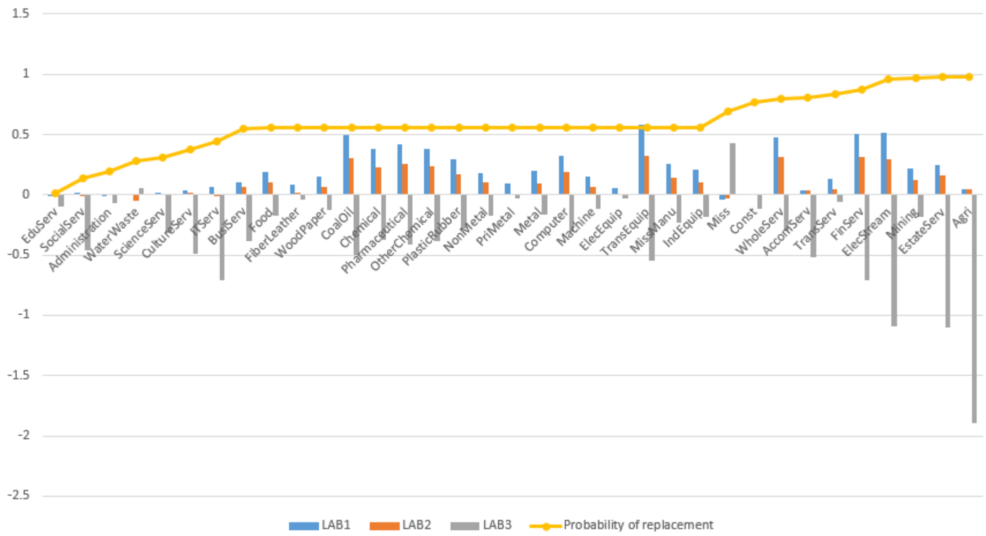

Figure 5.10 Labor demand change and replacement probability by industrial sectors

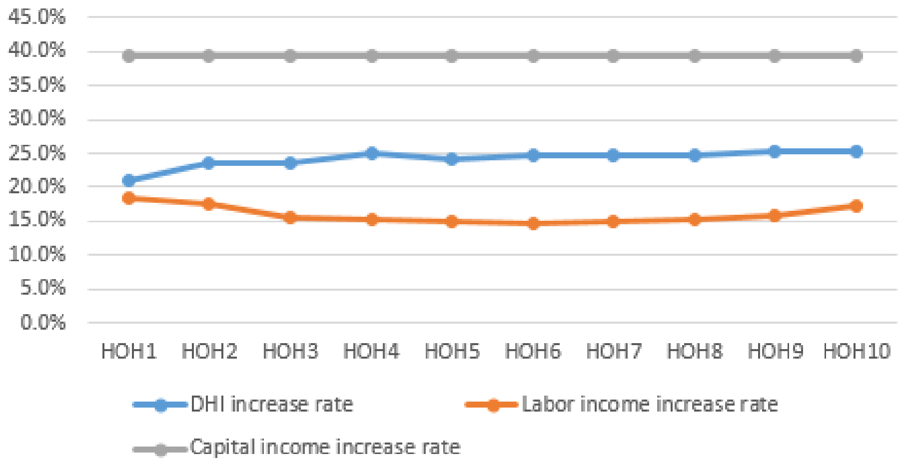

Figure 5.11 Income growth rate

In order to understand this phenomenon, it is necessary to examine the proportion of labor type in each household. In case of low-income quantile, the proportion of labor 3 in the low-income quantile is relatively low. Thus, the damage from labor replacement with robot capital is lower than other quantile group. For the growth rate of capital income, there was no significant difference among the household quantiles, and was similar to the overall household income quantile.

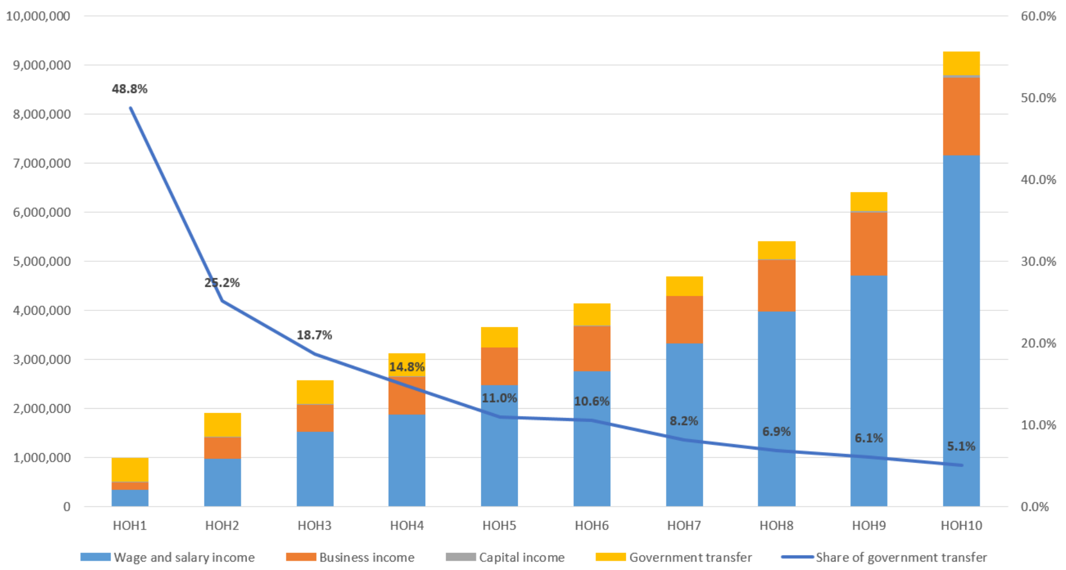

Figure 5.12 Percentage of household income and transfer income

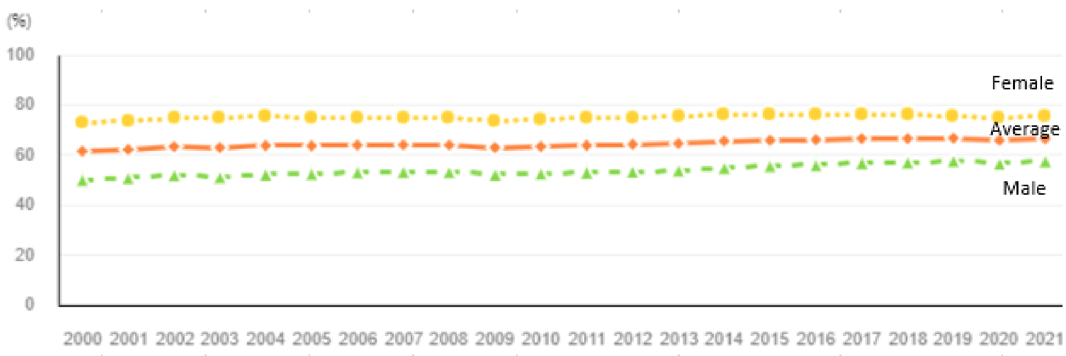

Figure 5.13. Employment rate (Data from National Statistical Office, HIE Survey)

The employment rate is a statistical ratio that measures the ratio of employed workers to the population, calculated as (number of employed people aged 15–64) / (population aged 15–64) x 100. According to statistics from the Korean National Statistical Office, it is shown in figure 5.10. As of 2015, it was 65.9% overall, 75.9% male, and 55.7% female, and as of 2021, it was 66.5% male, 75.2% female, and 57.7% female as in figure 5.10.

In this model, the employment rate for the base year is 71.43%. Therefore, it is intended to examine the rate of change in the employment rate (71.43%) compared to the base year. As a BAU result of the analysis in 2050, the employment rate of workers in the three labor groups decreased further to 61.48% in labor 1, 60.83% in labor 2, and 52.23%. This is determined by the drop in labor prices and the elasticity of substitution labor wages, and the degree of decline in labor prices is more severe in labor 3, which can be interpreted as the largest degree of decline in employment rate. Therefore, it was contrary to the argument of some scholars that the polarization of labor income would worsen due to labor replacement. This is interpreted as reflecting the degree of labor replacement by industry and job group in this study, and the impact on each household is different due to the different proportions of labor and capital income for each household.

The proportion of labor income and capital income among household income is shown in the table 5.8, and it can be understood that capital accounts for a high proportion of low-income households (HOH1-2). The growth rate of capital stock is higher than the labor growth rate, so HOH1-2's capital income growth rate has a figure similar to that of other household units.

Table 5.8 Proportion of labor and capital income by household (base year)

	CAP1	CAP2	LAB1	LAB2	LAB3	Total
HOH1	59.85%	0.85%	2.41%	32.44%	4.45%	100.00%
HOH2	59.45%	0.85%	3.15%	30.76%	5.80%	100.00%
HOH3	54.59%	0.78%	5.41%	29.41%	9.81%	100.00%
HOH4	57.79%	0.82%	5.76%	26.20%	9.43%	100.00%
HOH5	50.58%	0.72%	7.66%	29.23%	11.81%	100.00%
HOH6	52.63%	0.75%	9.42%	25.41%	11.78%	100.00%
HOH7	49.15%	0.70%	9.69%	28.10%	12.36%	100.00%
HOH8	47.10%	0.67%	13.15%	26.62%	12.46%	100.00%
HOH9	47.89%	0.68%	13.86%	26.13%	11.44%	100.00%
HOH10	43.16%	0.62%	21.58%	24.80%	9.84%	100.00%

In classifying households into deciles, capital income is high because it is classified by income quantile, but it does not distinguish households with low and high labor income, but have low capital income. When classifying the 10th quantile based on income, capital income is high but labor income is low, so due to the limitations of these statistics, capital income in the low-income bracket is high, so if the capital return increases, it can be interpreted that the replacement of robots will help the low-income class.

Now, the characteristics of each industry due to labor replacement is examined. Through the rate of change of the proportion of labor and capital by industry, the impact of each industry can be examined through which industry uses less labor and replaces more with capital.

In the case of industries with high elasticity of substitution between labor and capital, production at lower prices is possible due to the increase in robot capital, so robot capital is used more than labor, and production in that industry increases faster than other industries. This makes it possible to consume the industry's products more affordable, increasing demand and increasing the utility of households spending more on the industry.

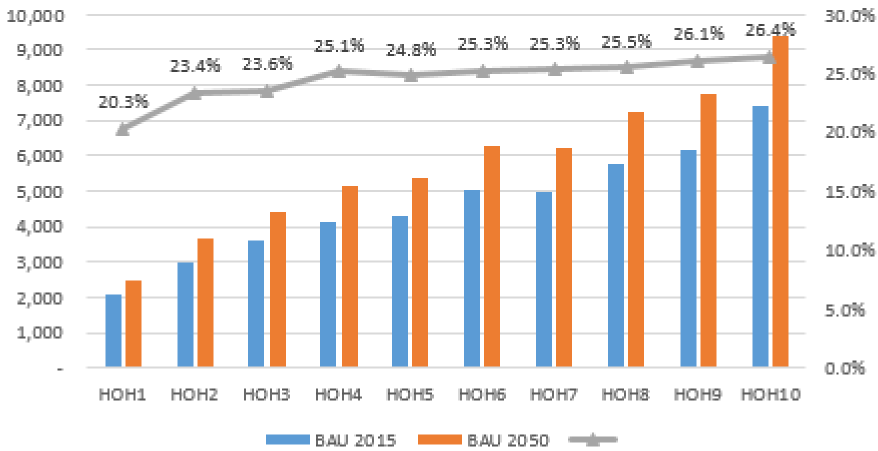

Figure 5.14 Utility change by households

5.2 Robot capital scenario

In this chapter, the impact on households, labor, and companies (household utility, firm production, economic growth, etc.) is analyzed by analyzing situations in which the gap may intensify. There are two scenarios related to the robot capitals: 1) Biased distribution of robot capital and 2) labor productivity biased in technological change. As a scenario of narrowing the gap, the robot tax imposition scenario was analyzed.

5.2.1 Biased distribution of robot capital

According to the OECD (2011), the proportion of capital income among the total household income in the top quantile has increased sharply over the past 20 years compared to the lowest quantile. This scenario assumes a biased distribution of robot capitals. Biased distribution or concentration on high income household is a social issue. The monopoly of the means of production may raise the gap between the households' income group. Robots are both a product of technological development and a product of capital investment. In many previous studies, the replacement of human labor through robots is expected to increase the return of capital and reduce the share of labor, resulting the social impacts due to the characteristics of robot capitals. This scenario analysis assumes a biased distribution of robot capital. Monopoly of factors of production can deepen income polarization. Robots are a product of technology development and capital investment. In many previous studies, the replacement of human labor through robots is expected to intensify the income polarization phenomenon by increasing the return of capital and reducing the proportion of labor. Accordingly, in this study, scenario analysis is conducted on the assumption of the biased distribution of robot capital in which the income portion due to technological development is not evenly distributed, and social phenomena that may be caused are captured.

Table 5.9 assumes that the proportion of general capital and robot capital by household is constant from 2020 as shown in the table below, but the proportion of CAP2 is mostly concentrated on the high-income class (HOH9-10) (Bartels & Jenderny, 2015). The biased distribution of robot capital is assumed to be a phenomenon from 2020.

Table 5.9 General and robot capital ownership by household quantile group

Capital Share before 2020		
	CAP1	CAP2
HOH1	1.60%	1.60%
HOH2	4.57%	4.57%
HOH3	6.05%	6.05%
HOH4	8.37%	8.37%
HOH5	8.76%	8.76%
HOH6	10.48%	10.48%
HOH7	11.39%	11.39%
HOH8	12.53%	12.53%

Capital Share after 2020		
	CAP1	CAP2
HOH1	1.60%	0.10%
HOH2	4.57%	0.10%
HOH3	6.05%	0.10%
HOH4	8.37%	0.10%
HOH5	8.76%	0.10%
HOH6	10.48%	0.10%
HOH7	11.39%	4.40%
HOH8	12.53%	5.00%

HOH9	15.66%	15.66%
HOH10	20.59%	20.59%

HOH9	15.66%	30.00%
HOH10	20.59%	60.00%

As a result of the scenario analysis in which the proportion of robot capital was concentrated in the high-income class, the disposable income of each household is shown in table 5.10 and figure 5.14 for each household in the tenth quantile. Since robot capital is more concentrated in the high-income class, it was found that the income gap between households showed a sharper difference than in the BAU scenario due to the high capital income share of the high-income class.

Table 5.10 Household disposable income in the biased distribution of robot capital scenario and compare with BAU scenario

	KHshare 2015	KHshare 2050	Increase Rate	BAU 2050	BAU Increase Rate
HOH1	29,282	33,044	12.8%	35,403	20.9%
HOH2	61,687	70,309	14.0%	76,240	23.6%
HOH3	83,343	95,088	14.1%	102,892	23.5%
HOH4	104,890	120,168	14.6%	131,113	25.0%
HOH5	118,908	136,611	14.9%	147,733	24.2%
HOH6	136,430	156,734	14.9%	170,166	24.7%

HOH7	155,411	185,393	19.3%	193,755	24.7%
HOH8	173,016	207,030	19.7%	215,743	24.7%
HOH9	212,640	289,548	36.2%	266,572	25.4%
HOH10	300,706	435,894	45.0%	377,100	25.4%

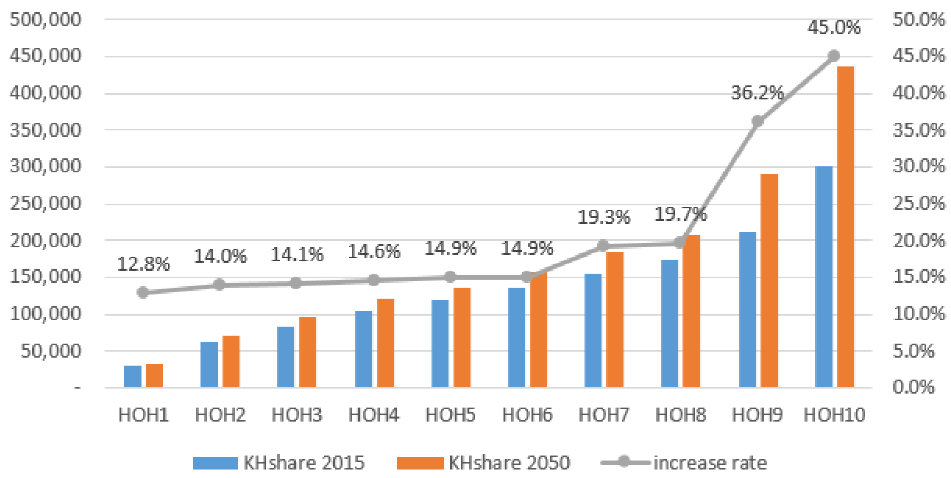

Figure 5.15 Disposable income of household by income quantile (Biased distribution of robot capital scenario)

Labor income by household income quantile was similar to the BAU model. It can be seen that the growth rate of labor income is the smallest in the middle-tier household quantile (5th to 7th quantile), forming a U-shape, because many workers in jobs with high labor substitution are in the middle-tier income quantile for the same reason as in the BAU model. Apart from the robot capital bias of the high-income class, it was confirmed that production using cheap robot capital increased due to the inflow of relatively cheaper robot capital, resulting in a small increase in labor income in the middle-class household quantile (5-7th quantile), where a lot of labor 3 are replaced.

Table 5.11 Labor income by household income quantile (Biased distribution of robot capital scenario)

	KHshare 2015	KHshare 2050	increase rate	BAU 2050	BAU Increase Rate
HOH1	7,756	9,282	19.7%	9,178	18.3%
HOH2	22,587	26,826	18.8%	26,526	17.4%
HOH3	36,609	42,730	16.7%	42,257	15.4%
HOH4	44,366	51,700	16.5%	51,129	15.2%
HOH5	62,404	72,480	16.1%	71,681	14.9%
HOH6	68,716	79,679	16.0%	78,802	14.7%
HOH7	86,039	99,904	16.1%	98,804	14.8%
HOH8	102,798	119,736	16.5%	118,417	15.2%
HOH9	124,446	145,586	17.0%	143,978	15.7%
HOH10	198,503	235,475	18.6%	232,860	17.3%

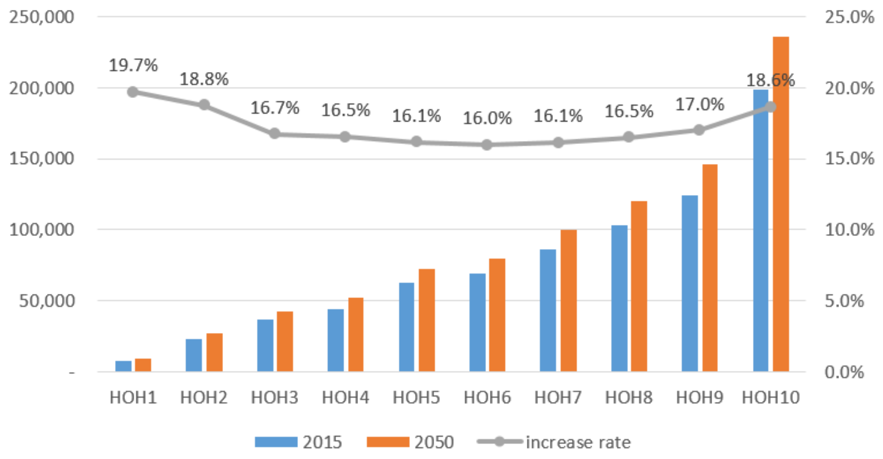

Figure 5.16 Labor income by household quantile group (Biased distribution of robot capital scenario)

Capital income assumes an exclusive form of robot capital (biased distribution to the high-income households), so it can be seen that the capital income of high-income households increases much faster than other households. This suggests that if robot capital is concentrated on certain households and smooth distribution is not made, polarization within capital income may intensify.

Table 5.12 Capital income by household income quantile group (Biased distribution of robot capital scenario)

	KHshare 2015	KHshare 2050	increase rate	BAU 2050	Increase Rate
HOH1	11,980	14,232	18.8%	16,706	39.4%

HOH2	34,303	40,423	17.8%	47,849	39.5%
HOH3	45,422	53,469	17.7%	63,355	39.5%
HOH4	62,833	73,897	17.6%	87,647	39.5%
HOH5	65,734	77,300	17.6%	91,697	39.5%
HOH6	78,693	92,505	17.6%	109,772	39.5%
HOH7	85,518	108,044	26.3%	119,294	39.5%
HOH8	94,016	119,066	26.6%	131,141	39.5%
HOH9	117,545	190,457	62.0%	163,967	39.5%
HOH10	154,577	286,449	85.3%	215,633	39.5%

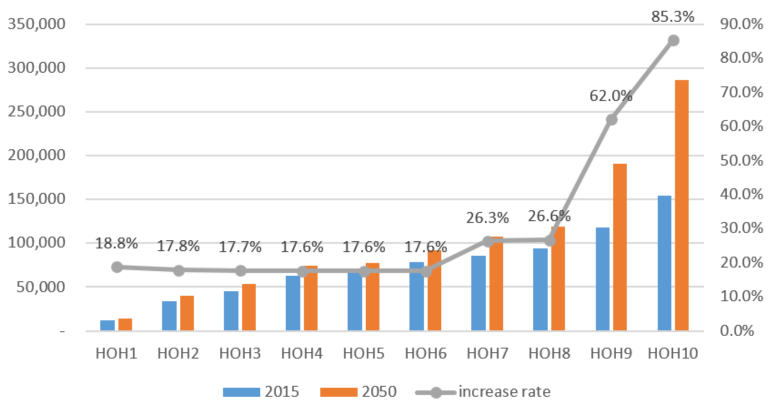

Figure 5.17 Capital income by household income quantile group (Biased distribution of robot capital scenario)

Figure 5.16 shows the growth rate of income by household. Due to the concentration of robot capital in the high-income class, the growth rate of capital income in the high-income class is high in HOH8-10, and it is also reflected in the growth rate of disposable income. The rate of increase in labor income did not show a significant change among households.

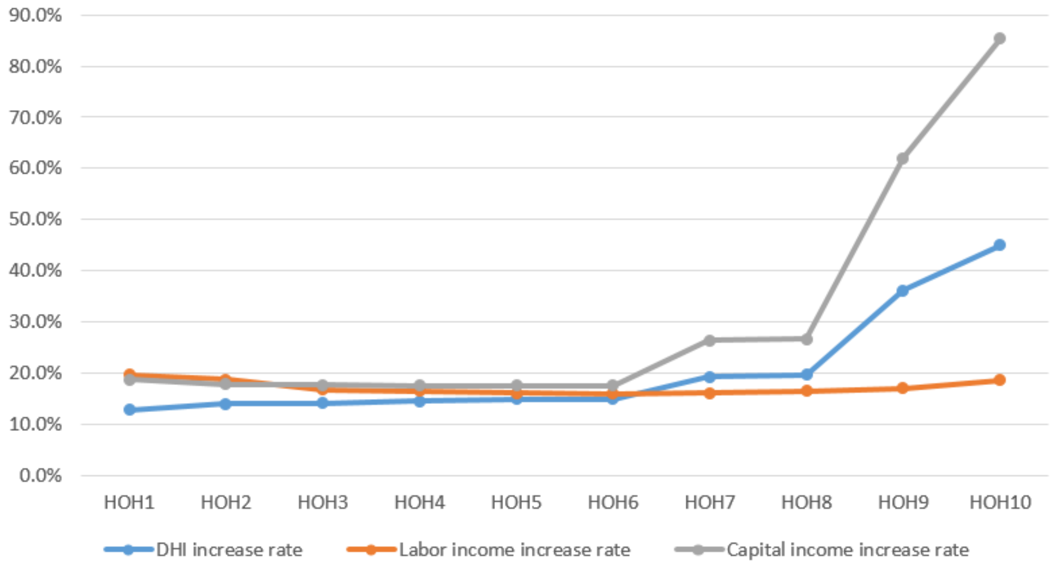

Figure 5.18 A comparison of income growth rate (2015–2050)

In the case of the employment rate, the employment rate of labor 3 fell the most in 2050 compared to the base year (71.43%), in the capital-oriented scenario, to labor 1 (60.66%), labor 2 (58.99%), and labor 3 (36.37%). This was determined by the decline in labor prices and the elasticity of replacement of labor wages, and it can be interpreted that the replacement of labor 3 of Robot 3 was the largest and led to a drop in employment rate.

Compared with the BAU model earlier, it was confirmed that the polarization due to labor substitution intensified in the capital concentration scenario. This is interpreted as having different effects on households due to the different proportion of income from labor and capital (high-income groups own more robot capital).

The impact on the industry was similar to the BAU model. The average employment rate of labor 1 was 61.8%, labor 2 was 61.23%, and labor 3 was 52.52%, down from the initial value of 71.42%. There was also a change in labor demand and proportion by industry. As shown in figure 5.5, the rate of change in the CoalOil, ElecStream, and FinServ industries by industry was relatively higher.

5.2.2 Labor productivity biased scenario

Previously, it was assumed that the labor productivity (lprate) of labor 1, 2, and 3 increased equally every year. As robot capital R increases, the labor group that benefits the most from the increase assumes that the productivity of labor 1 improves relatively further with labor skill (labor 1), and we want to examine the results in the model. The labor productivity biased scenario is designed as in table 5.13.

Table 5.13 Labor productivity assumption for the labor productivity biased scenario

Labor Skill/Type	Labor Productivity Assumption (lprate)
Labor 1 (low risk of replacement by robot capital)	3%
Labor 2 (medium risk)	2%
Labor 3 (high risk)	2%

Labor productivity refers to the added value obtained by injecting labor for a certain period and is viewed as the efficiency or efficiency of labor. Previously, it was assumed that labor 1, 2, and 3 all had the same labor productivity, but in this scenario, it was assumed that the productivity of labor 1 was higher. In this scenario analysis, to reflect the labor productivity bias in the model, the labor productivity of labor 1, which has the least substitution, was assumed to be higher than that of other labor. We would like to examine whether this results in labor productivity biased form of incoming quality.

First, it can be seen that the polarization of labor income has worsened. As shown in table 3.8, the specific gravity of labor 1 is high in the order of HOH10 (38.14%), HOH9 (26.71%), HOH8 (24.92%), HOH6 (20.00%), and HOH7 (19.13%). Therefore, the household group that benefits the most from the improvement of labor 1's labor productivity is the high-income group. As a result, the growth rate of income in the household quantile group increased significantly compared to other household groups. For this reason, it can be seen that the polarization of labor income has intensified, as shown in figure 5.7. The increase in labor 1's labor income was also reflected in the increase in household disposable income, indicating that the income growth rate of the high-income class increased more than that of other households, such as figure 5.12.

Table 5.14 Household disposable income in the labor productivity biased scenario and compare with KHshare scenario

	Labor Productivity Biased 2015	Labor Productivity Biased 2050	Increase Rate	KHshare 2050	Increase Rate
HOH1	29,282	34,432	17.6%	33,044	12.8%
HOH2	61,687	73,626	19.4%	70,309	14.0%
HOH3	83,343	99,856	19.8%	95,088	14.1%
HOH4	104,890	126,351	20.5%	120,168	14.6%
HOH5	118,908	144,004	21.1%	136,611	14.9%
HOH6	136,430	165,204	21.1%	156,734	14.9%
HOH7	155,411	195,768	26.0%	185,393	19.3%
HOH8	173,016	218,821	26.5%	207,030	19.7%
HOH9	212,640	306,247	44.0%	289,548	36.2%
HOH10	300,706	461,629	53.5%	435,894	45.0%

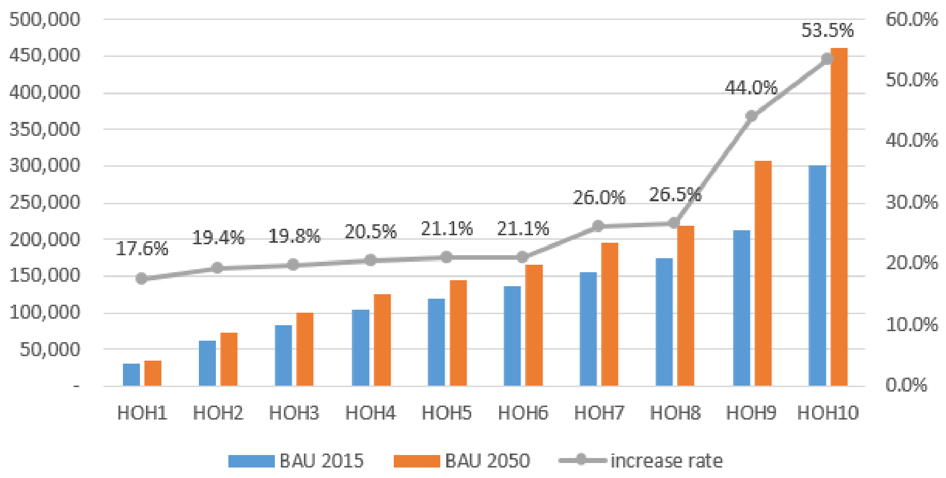

Figure 5.19 Disposable income by household income quantile (labor productivity-biased

scenario)

Table 5.15 Labor income in the labor productivity-biased scenario and compare with KHshare scenario

	2015	2050	Increase Rate	KHshare 2050	Increase Rate
HOH1	7,756	9,922	27.9%	9,282	19.7%
HOH2	22,587	28,670	26.9%	26,826	18.8%
HOH3	36,609	45,649	24.7%	42,730	16.7%
HOH4	44,366	55,230	24.5%	51,700	16.5%
HOH5	62,404	77,425	24.1%	72,480	16.1%
HOH6	68,716	85,115	23.9%	79,679	16.0%
HOH7	86,039	106,723	24.0%	99,904	16.1%
HOH8	102,798	127,927	24.4%	119,736	16.5%
HOH9	124,446	155,566	25.0%	145,586	17.0%
HOH10	198,503	251,736	26.8%	235,475	18.6%

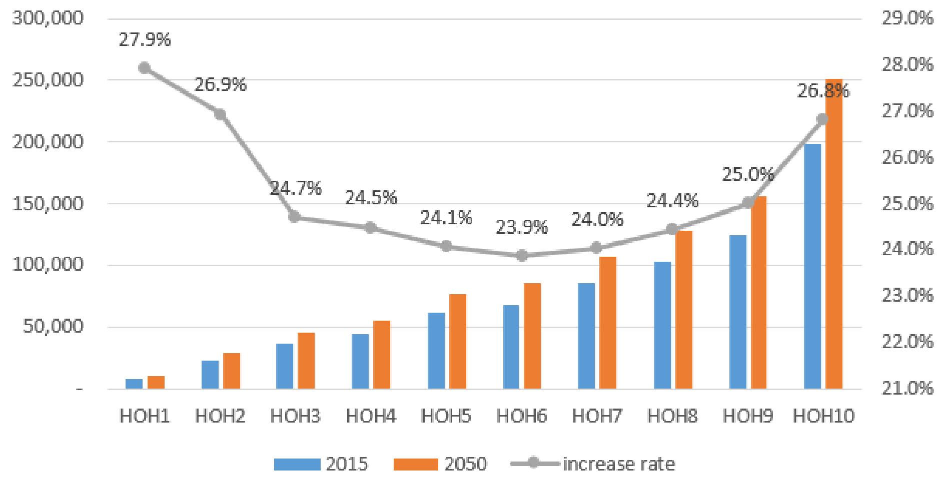

Figure 5.20 labor income by household income quantile (labor productivity-biased scenario)

In the case of capital income, the entire household group increased, assuming that only labor 1 productivity was improved in addition to the previous scenario, it can be interpreted that the increase in labor 1 productivity increased overall production and the positive effect spread to the entire household. Labor 1, 2, and 3 relative price comparison refers that labor 3 has a more negative impact.

Table 5.16 Capital income by household income quantile in robot capital scenario

	2015	2050	Increase Rate	KHshare 2050	Increase Rate
HOH1	11,980	14,986	25.1%	14,232	18.8%
HOH2	34,303	42,564	24.1%	40,423	17.8%
HOH3	45,422	56,301	24.0%	53,469	17.7%

HOH4	62,833	77,811	23.8%	73,897	17.6%
HOH5	65,734	81,395	23.8%	77,300	17.6%
HOH6	78,693	97,405	23.8%	92,505	17.6%
HOH7	85,518	113,817	33.1%	108,044	26.3%
HOH8	94,016	125,430	33.4%	119,066	26.6%
HOH9	117,545	200,900	70.9%	190,457	62.0%
HOH10	154,577	302,331	95.6%	286,449	85.3%

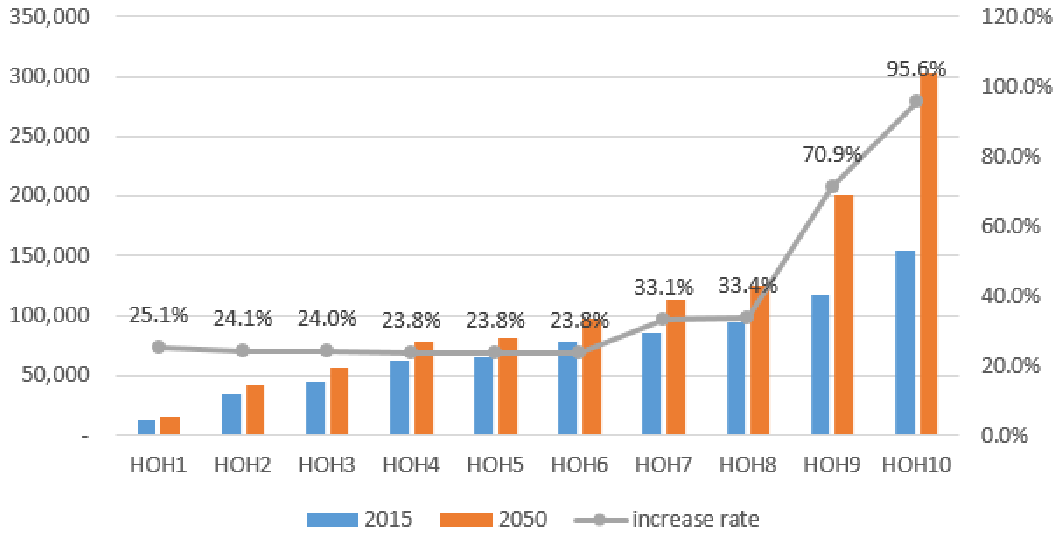

Figure 5.21 Capital income by household income quantile (labor productivity-biased scenario)

5.3 Imposing tax on robot capital scenario

This chapter analyzes the impact of imposing a robot tax on robot capital on the economy. As a result, equity is mitigated but appears to have an adverse effect on economic growth (GDP loss of -0.1%).

Table 5.17 Household disposable income in imposing tax scenario and compare with robot capital scenario

	KTAX 2015	KTAX 2050	Increase Rate	Labor Productivity-Biased 2050	Increase Rate
HOH1	29,282	34,362	17.3%	34,432	17.6%
HOH2	61,687	73,506	19.2%	73,626	19.4%
HOH3	83,343	99,710	19.6%	99,856	19.8%
HOH4	104,890	126,146	20.3%	126,351	20.5%
HOH5	118,908	143,826	21.0%	144,004	21.1%
HOH6	136,430	164,988	20.9%	165,204	21.1%
HOH7	155,411	194,413	25.1%	195,768	26.0%
HOH8	173,016	217,357	25.6%	218,821	26.5%
HOH9	212,640	298,124	40.2%	306,247	44.0%
HOH10	300,706	446,068	48.3%	461,629	53.5%

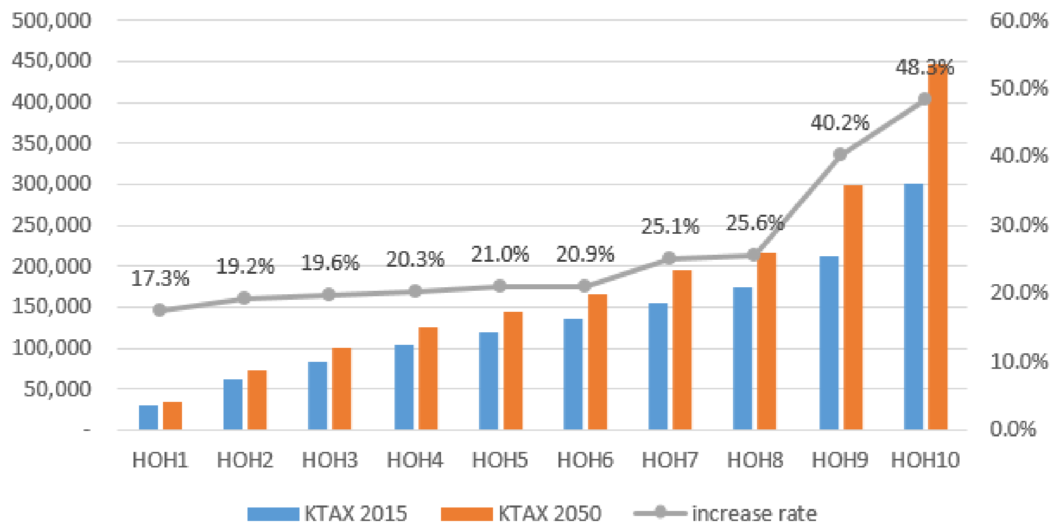

Figure 5.22 Disposable income by household income quantile (KTAX scenario)

Table 5.18 Labor income by household income quantile in the KTAX scenario and compare with robot capital scenario

	2015	2050	Increase Rate	2050	Increase Rate
HOH1	7,756	9,947	28.2%	9,922	27.9%
HOH2	22,587	28,738	27.2%	28,670	26.9%
HOH3	36,609	45,743	24.9%	45,649	24.7%
HOH4	44,366	55,344	24.7%	55,230	24.5%
HOH5	62,404	77,583	24.3%	77,425	24.1%
HOH6	68,716	85,296	24.1%	85,115	23.9%
HOH7	86,039	106,951	24.3%	106,723	24.0%
HOH8	102,798	128,231	24.7%	127,927	24.4%
HOH9	124,446	155,959	25.3%	155,566	25.0%
HOH10	198,503	252,533	27.2%	251,736	26.8%

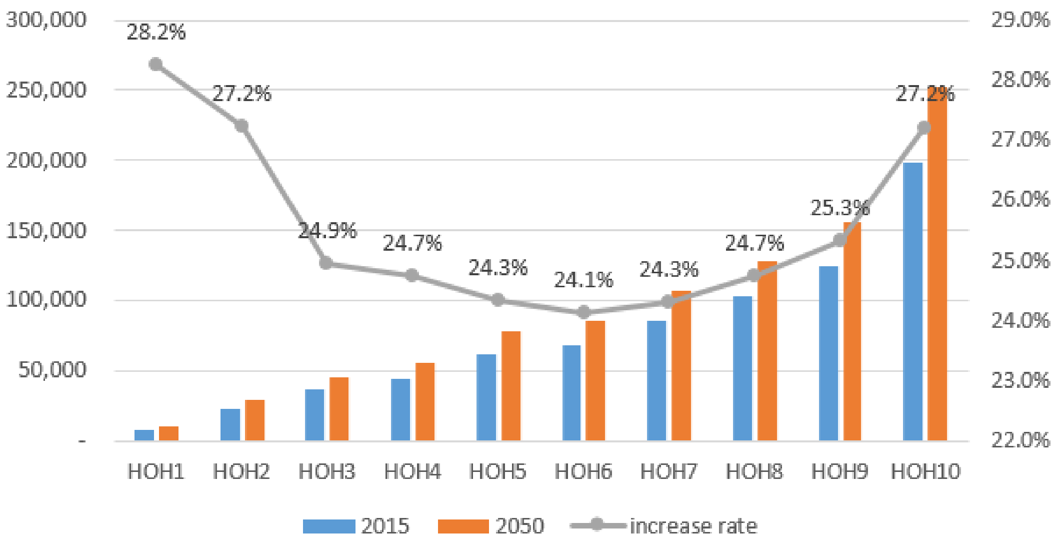

Figure 5.23 Labor income by household income quantile (KTAXscenario)

Table 5.19 Capital income by household income quantile in KTAX scenario

	2015	2050	Increase Rate	KTAX2050	Increase Rate
HOH1	11,980	14,891	24.3%	14,986	25.1%
HOH2	34,303	42,353	23.5%	42,564	24.1%
HOH3	45,422	56,031	23.4%	56,301	24.0%
HOH4	62,833	77,450	23.3%	77,811	23.8%
HOH5	65,734	81,018	23.3%	81,395	23.8%
HOH6	78,693	96,961	23.2%	97,405	23.8%
HOH7	85,518	111,945	30.9%	113,817	33.1%
HOH8	94,016	123,320	31.2%	125,430	33.4%
HOH9	117,545	190,572	62.1%	200,900	70.9%

HOH10	154,577	282,098	82.5%	302,331	95.6%

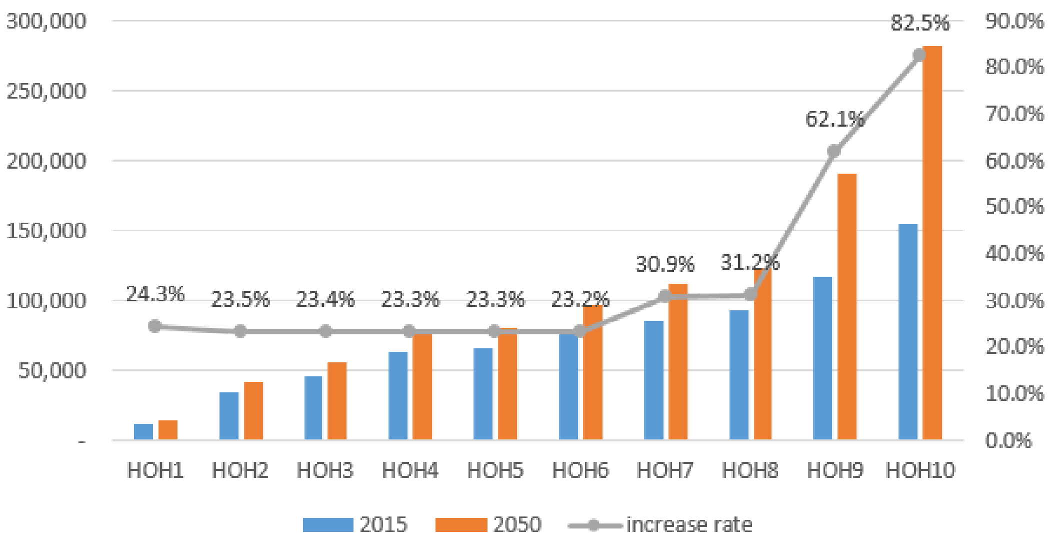

Figure 5.24 Capital income by household income quantile (KTAX scenario)

This study attempted to examine the impact of tax imposition on the industry and economy as a whole through the robot tax imposition scenario. It is assumed that the robot tax rate is 20% from 2020. The imposition of a robot tax causes a contraction in the robot industry, and the resulting decrease in GDP is inevitable. Due to the imposition of robot tax, it was found that GDP decreased by about 0.1% in 2050 compared to the previous scenario. Further, the utility has decreased for the entire households group.

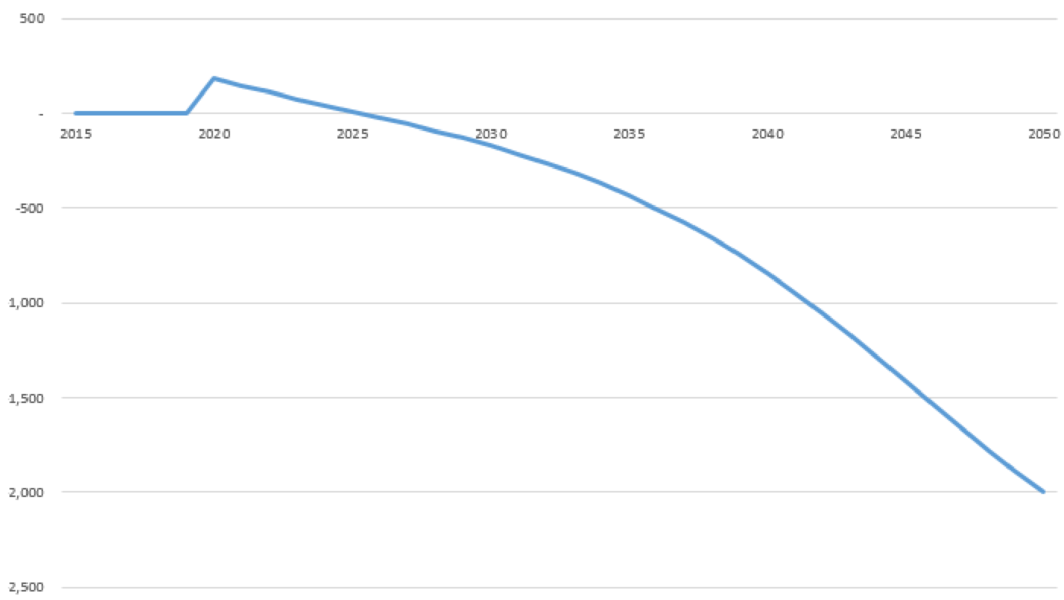

Figure 5.25 Decrease in GDP due to robot tax imposition

Gini coefficient is used to measure income distribution across a population. Thus, it is used to check the degree of inequality represented in a set of values. The coefficient ranges from 0 (or 0%) to 1 (or 100%), with 0 representing perfect equality and 1 representing perfect inequality. A higher Gini index indicates greater inequality, with high-income households receiving much larger percentages of the total income of all households. This study compares the Gini coefficients using households' disposable income distribution as in figure 5.25.

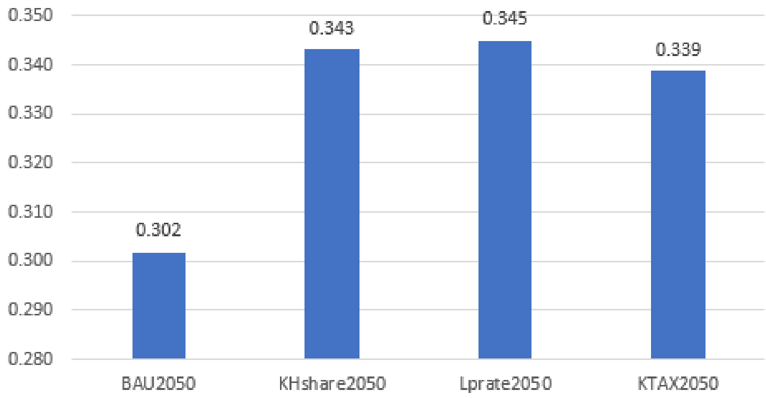

Figure 5.26. Gini coefficient by scenarios

In this way, the ripple effect within the industry can be examined. For the sectoral growth, Household utility by household income quantile group can be measured by the consumption bundle consumed by each household group as in equation (5.1):

$$UU_h = \prod_i XP_{i,h}^{\alpha_{i,h}} \quad . (5.1)$$

Table 5.20 Comparing utility of the households

	HOH1	HOH2	HOH3	HOH4	HOH5	HOH6	HOH7	HOH8	HOH9	HOH10
BAU2015	2,075	2,987	3,587	4,107	4,283	5,022	4,963	5,785	6,139	7,424
BAU2050	2,495	3,686	4,432	5,139	5,345	6,290	6,219	7,259	7,743	9,385
KHSshare	2,329	3,399	4,095	4,709	4,941	5,792	5,949	6,964	8,410	10,849
lprate	2,429	3,559	4,305	4,953	5,219	6,116	6,292	7,381	8,916	11,523
KTAX	2,424	3,553	4,298	4,945	5,212	6,108	6,249	7,331	8,679	11,133

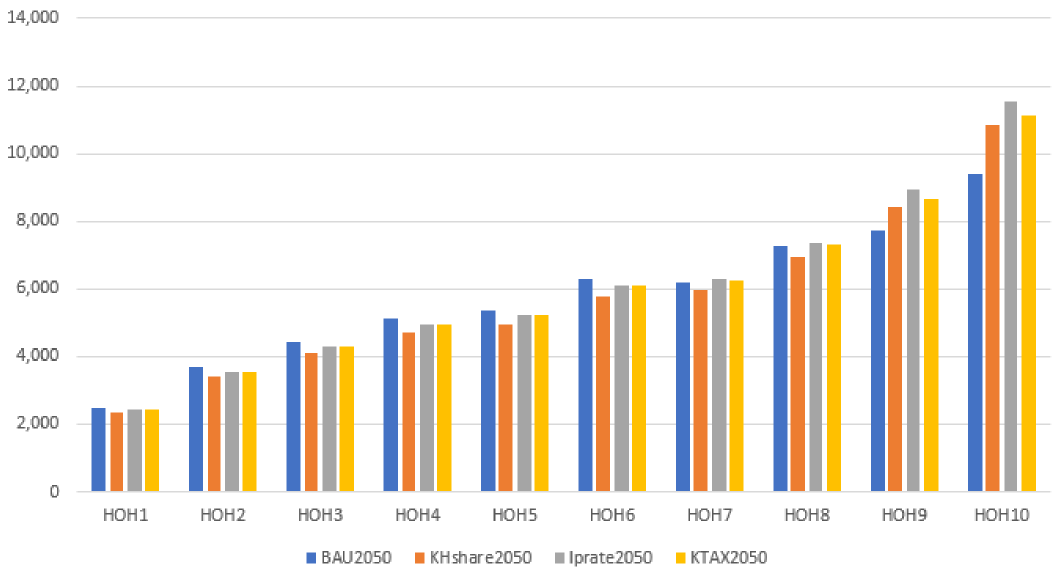

Figure 5.27 Comparing the utility of households by scenarios

5.4 Sensitivity analysis

In order to test the robustness of the model, this subsection investigates whether the simulation results are sensitive to the specification of parameters from external sources. As elasticities of substitution for labor and robot capitals that vary by industries are key element of this study, which determines the level of demand and price of input factors (e.g., labor and capital).

The elasticities of substitution between factors of productions in the value added production function are given new values that are respectively +10, +20, and +30% higher than their original values, as shown in table 5.4. The higher values of elasticities demonstrate the context in which the economy is less flexible.

Basically, the response of the economy is largely different from the original simulation. Especially, the change in production output value and GDP is significantly affected. It is concluded that the simulation results are sensitive to the values of elasticities.

5.4.1 Sensitivity analysis on elasticity of substitution

The EOS used for the analysis is as in table 5.4 in the previous chapter. The sensitivity test will be conducted for +10, +20, and +30% of the value as in tables 5.21 and 5.22.

Table 5.21 Sensitivity test for the elasticity of substitution (+10, 20, 30%)

Sectors	**sigmaL3R(j)**	**sigmaL3RL2(j)**	**sigmaL3RL2L1(j)**	**sigmaY(j)**

	+10%	**+20%**	**+30%**	+10%	**+20%**	**+30%**	+10%	**+20%**	**+30%**	+10%	**+20%**	**+30%**
Agri	9.245	10.085	10.926	2.786	3.040	3.293	2.033	2.218	2.403	1.556	1.697	1.838
Mining	9.132	9.962	10.792	2.769	3.021	3.273	2.021	2.205	2.388	1.556	1.697	1.838
Food	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
FiberLeather	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
WoodPaper	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
CoalOil	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
Chemical	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
Pharmaceutical	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
OtherChemical	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
PlasticRubber	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
NonMetal	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
PriMetal	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
Metal	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
Computer	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
Machine	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
ElecEquip	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
TransEquip	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
MissManu	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
IndEquip	5.292	5.773	6.254	2.108	2.300	2.492	1.539	1.678	1.818	1.556	1.697	1.838
ElecStream	9.009	9.828	10.647	2.751	3.001	3.251	2.007	2.190	2.372	1.556	1.697	1.838
WaterWaste	2.604	2.840	3.077	1.479	1.613	1.748	1.079	1.177	1.275	1.556	1.697	1.838
Const	7.283	7.945	8.607	2.473	2.698	2.923	1.805	1.969	2.133	1.556	1.697	1.838
WholeServ	7.490	8.171	8.852	2.508	2.736	2.964	1.830	1.997	2.163	1.556	1.697	1.838
TransServ	7.896	8.614	9.331	2.575	2.809	3.043	1.879	2.050	2.221	1.556	1.697	1.838
AccomServ	7.603	8.295	8.986	2.527	2.757	2.987	1.844	2.012	2.179	1.556	1.697	1.838
ITServ	4.188	4.569	4.950	1.876	2.046	2.217	1.369	1.493	1.618	1.556	1.697	1.838
FinServ	8.283	9.036	9.789	2.638	2.877	3.117	1.925	2.100	2.275	1.556	1.697	1.838
EstateServ	9.198	10.034	10.870	2.779	3.032	3.285	2.028	2.213	2.397	1.556	1.697	1.838

ScienceServ	2.934	3.201	3.467	1.570	1.712	1.855	1.146	1.250	1.354	1.556	1.697	1.838
BusiServ	5.160	5.629	6.098	2.082	2.271	2.460	1.519	1.657	1.795	1.556	1.697	1.838
Administration	1.802	1.966	2.129	1.230	1.342	1.454	0.898	0.979	1.061	1.556	1.697	1.838
EduServ	0.113	0.123	0.134	0.308	0.336	0.364	0.225	0.245	0.266	1.556	1.697	1.838
SocialServ	1.264	1.379	1.494	1.030	1.124	1.218	0.752	0.820	0.889	1.556	1.697	1.838
CultureServ	3.575	3.900	4.225	1.733	1.890	2.048	1.265	1.380	1.495	1.556	1.697	1.838
Miss	6.519	7.111	7.704	2.340	2.553	2.765	1.708	1.863	2.018	1.556	1.697	1.838

5.4.2 Sensitivity test results

The results are as follows. Firstly, GDP trend are in the increasing trend as in figure 5.27. The increasing rate, however, is larger when elasticity of substitution increase at a higher rate. This is because higher elasticity of substitution refers that labor is more easily replaced by robot capitals. As the price of robot capital gets lower than that of other inputs (e.g., Labor 3, labor 2, labor 1, and original capital in ordinals). Thus, more outputs are produced when there is higher value for the elasticity of substitution.

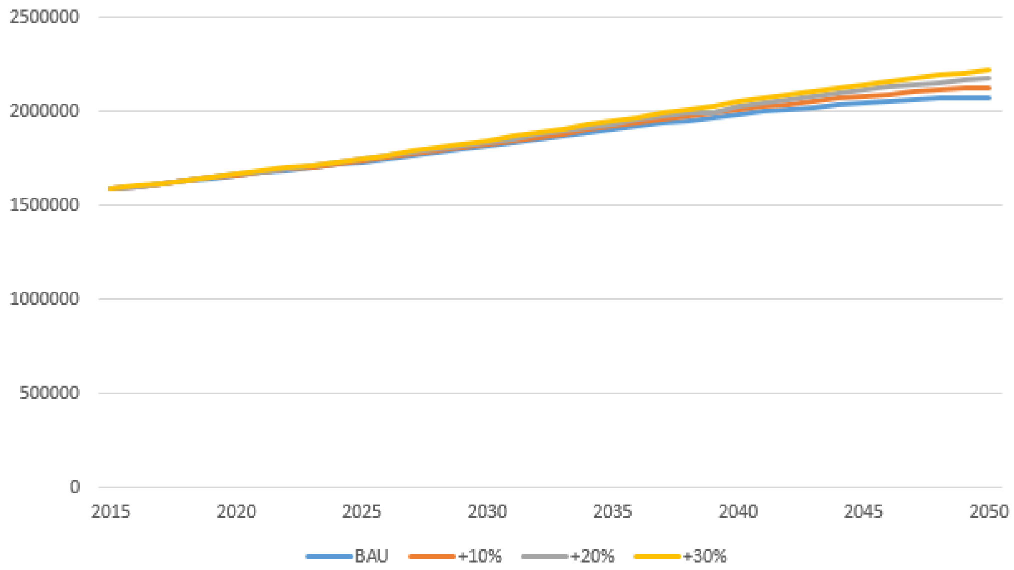

Figure 5.28 Changes in GDP at 10%, 20%, and 30% increase in elasticity of substitution

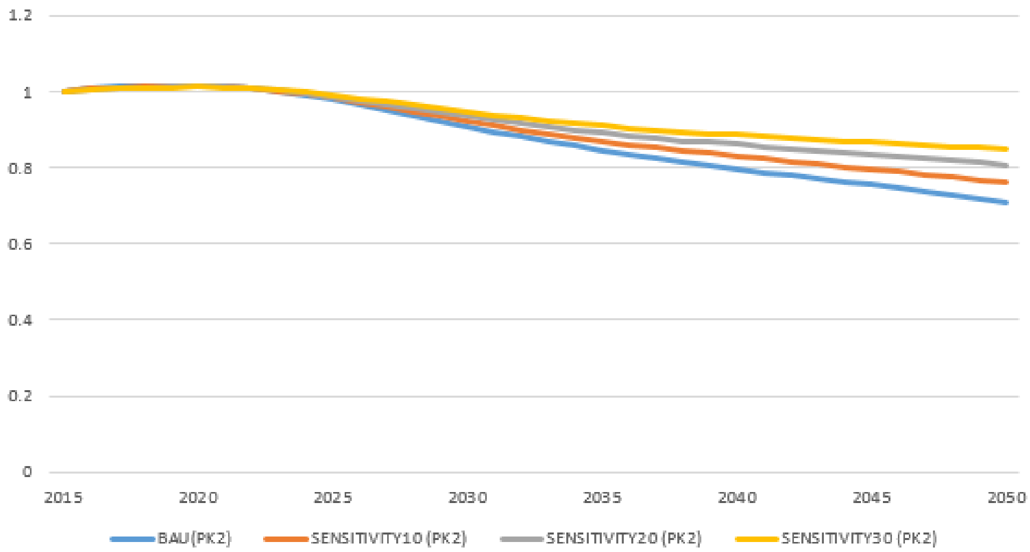

Figure 5.29 Changes in price of robot capital at 10%, 20%, and 30% increase in elasticity of substitution

Chapter 6. Conclusion

Using a CGE model that can analyze economic ripple effects, this study analyzed the social phenomenon and economic impacts caused by labor replacement by robot capital. To summarize the results of this study, labor replacement by robot capital affect industries and households differently. This section reviews the results and the mechanism in which the economy reacts to the increase in robot capitals that replaces labors. Further, this section concludes with the contribution and limitations of this study.

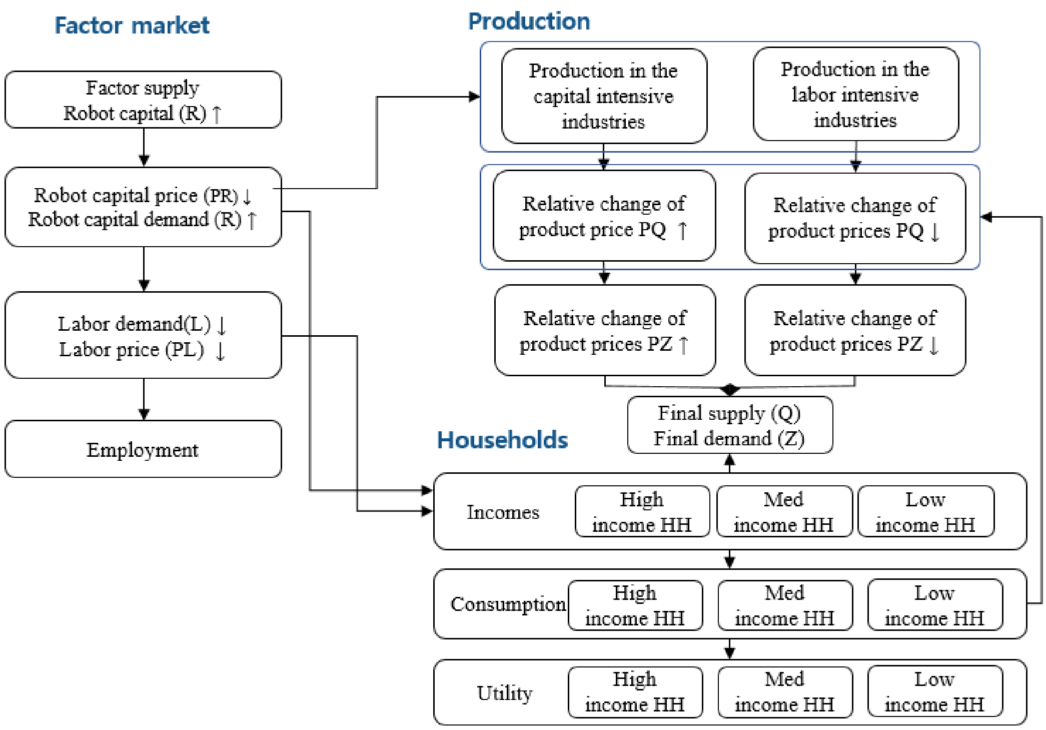

Figure 6.1 Causal chain mechanisms of labor replacement by robot capitals in this CGE model

Figure 6.1 shows the mechanism of how economy reacts to the introduction of robot capital. In accordance with the characteristics of robot capital, the productivity and quantity of robot capital rapidly increases. With rapidly increased supply of robot capital, the price of robot capital decreases. Lower capital prices decrease the labor demand due to its possibility of replacement between labor and robot capital, because firms prefer to use the factor that is cheaper for their cost minimizing behaviors. The labor price decreases as demand in robot capital increases rapidly. Such changes affect to the employment rate. It lowers the employment rate as the labor demand decreases, and relatively the labor demand for the highly replaceable labor (L3) decreased the most, having the employment rate also decreased the most.

The increase in robot capital and its labor replacement affect the industries differently. In order to capture this difference, this study classified the industries into four groups by using the capital intensity and replacement probability. Here, the change rate of the prices from 2015 to 2050 is compared. The change rate of product price (PQ) of the capital intensive industries is relatively higher than that of labor intensive industries. This is because the price of robot capital is lowered, while price of original capital became higher. Thus, the industries that are capital intensive does get less advantage of a lowered price of robot capitals. Among the capital intensive industries, the product price of the industries with higher probability of replacement are relatively higher. This affect to the demand price (PZ) in the same direction, which then affect the final demand (Z).

Households are classified into ten income quantile groups. For the convenience of interpretation, we recalled it with high-, medium-, and low-income households by grouping into three or four quantile groups.

Depending on the factor price and demand, labor and capital income of the households are determined. This study compared the increase rate of households' income from the base year 2015 to project year 2050 by households' income quantiles. Thus, the change in income of the households depends on the change in factor price and demand. As explained above, the labor demand is decreased and labor price is decreased. These changes affect households' labor income. The result indicates that the labor income increase rate is the smallest in the middle income household quantile groups (HOH5-7). This is because they are the households group whose composition of labor with the most highly replaceable labors (L3). On the other hand, there was no significant difference among household income quantile groups for the increase rate of capital income from 2015 to 2050. This is interpreted to be due to the fact that capital income accounts for a higher proportion of the income of households (HOH1-4). Further, disposable household income is compared, in which the government transfers and direct taxes are taken into consideration.

The utility differences widen more than the income differences by household quantiles. Households' purchasing power changes due to changes in product and demand price (PQ and PZ). The price of goods gets relatively higher for the capital intensive industries with high probability of replacement (High, CAP), that are heavily consumed by low-income households. On the other hands, the price of goods of the capital intensive industries with low probability of replacement (Low, CAP), that are consumed more by high-income households. Thus, the high-income households get better purchasing power than the change in income. These changes are reflected in the utility level of the households. Utility increases the most in the high income household group. Further, this study compared the Gini coefficients in order to see if the income gap among households gets larger. In the base scenario, Gini coefficients increase from 0.299 in 2015 to 0.302 in 2050 (increase rate of 1.0%).

This study provides following contributions to the literature. First, it provides methodological contribution as it defines robot capital that are differentiated from original capital. By doing so, this study enables to analyze the impact of labor replacement caused by rapid accumulation of robot capital. Further, this study considers the differences between industries, labor, households due to the labor replacement of robots, industry, labor, household, capital, and investment were classified, and other elasticities of substitution were assumed in consideration of the probability of automation by industry.

Second, it provides theoretical contribution as robot replacement is a critical social issues, and is concerned for causing unemployment and inequality issue. By examining the economic impact using CGE model, this study examines the ripple effects on the economy to see whether the researchers' opinion aligns with the results of this studies. Many scholars bring arguments regarding the impacts on society whether inequality issue are intensified due to technology development. With the model developed in this study, it enabled to examine the impacts on labor, households, and sector vary. Further, we examined how the economic impact may differ in the case when inequality is intensified and alleviated through robot tax.

Third, this study provides policy contribution. As the inequality is a critical issue concerned in this economy, this study examines policy assessment that may alleviate the inequality problems, and the following consequence effects to the economy and growth. Labors at the high risk of replacement due to the technology development are the most influenced labors with increasing unemployment from labor replacement by robot capital. The most impacted household groups were the middle-income class households (HOH 5-7). Thus, this study makes policy implication that it requires to consider different impacts to each economic agents when proposing policy shock to the economy.

This study proposes policy alternatives to solve social problems caused by technological development. The recursive dynamic CGE model is developed to evaluate the effect of labor replacement. The robot tax scenario, in which considered to alleviate the income inequality gap from labor replacement, lessens the inequality gap; however, it may not be the best solution alternative as it dampens industrial development.

There are following limitations of this study. Firstly, this study conducts a scenario analysis on robot tax imposition, however, does not deal with the redistribution of tax revenue. An important area of taxation analysis is the redistribution effects. However, as this study does not cover redistribution of tax revenue, it may be covered in the further research. Secondly, there is no specific consensus on the concept, scope, and definition of robots among scholars, research institutes, and stakeholders. Thus, the result and implication of this study is only subject to robot capital defined in this study, and with different scope for the definition of robot, the results may not result same.

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Abstract (Korean)

로봇의 등장 및 확산은 산업, 노동, 경제성장 등 경제에 많은 영향을 미치며 사회경제적으로 많은 긍·부정적 변화를 예고하고 있다. 로봇의 등장으로 인해 생산환경이 바뀌고 있으며, 로봇이 노동자에게 미치는 영향은 노동직군에 따라 다를 수 있다. 이 같은 배경 하에, 본 연구는 노동대체 현상이 산업, 직군, 그리고 가계 별로 어떻게 다르게 나타나며 경제성장을 포함한 가격, 수요, 공급, 효용 등 경제 요인 간에 어떤 상호 작용을 불러 일으키는지 살펴보고자 한다. 이를 바탕으로, 산업 및 직군 간 다른 노동대체율을 반영하여 연산가능 일반균형 (Computable General Equilibrium; CGE) 모형을 설계하고 제안할 수 있도록 한다.

연산가능 일반균형 모형은 다양한 정책의 파급효과를 체계적으로 분석 가능하다는 장점이 있어, 경제성장과 혁신정책 등 다양한 분야에서 활용되고 있다. 본 연구는 CGE모형을 이용하여 최근에 크게 사회적으로 우려가 되고 있는 로봇자본에 의한 노동대체 문제와 사회·경제적 영향을 이해하는 것을 목표로 한다. 특히, 노동대체 이슈는 사회적 영향이 클 것으로 우려되어 경제성장에 미치는 파급효과 및 메커니즘에 대한 면밀한 연구가 요구된다.

구체적으로, 이 연구는 다른 산업간 노동의 이질적인 특성에 따라 노동대체에 의해 다르게 미치는 영향을 반영하기 위하여 사회계정행렬 (Social Accounting Matrix; SAM) 자료체계 내 노동 및 가계 계정을 세분화하였다. 또한, 로봇자본이라는 새로운 유형의 자본 개념을 새롭게 정의하고, 이에 따라 투자

와 자본을 일반과 로봇으로 구분하였다. 이를 통해, 경제 혹은 정책 충격에 따라 경제주체에 미치는 상이한 효과를 분석할 수 있는 모형 및 자료체계를 구축할 수 있었다. 이처럼 설계된 연산일반균형 모형을 바탕으로, 본 연구는 실증연구를 통해 상이한 노동대체가 경제에 미치는 상이한 효과와 각 주체의 상호작용이 파급되는 경제체제 내 경로를 식별하고자 하였다.

본 연구에서는 recursive dynamic CGE모형을 이용하여, 2015-2050년 동안 기술발전에 의한 노동 대체가 사회에 미치는 영향을 분석한다. 가계, 노동, 투자, 자본을 구분한 SAM을 구축하고 산업 및 노동직군에 따라 다른 대체탄력성을 산정하였다. 로봇자본의 노동 대체가 각 산업, 가계, 노동에 미치는 영향을 분석하고, 로봇자본 등장과 관련하여 사회적으로 우려되는 상황에 대한 시나리오를 설정하여 로봇자본의 노동대체로 인한 사회적 영향을 다양한 측면에서 살펴보았다.

분석결과에 따르면, 로봇자본의 생산성 향상과 양의 증가로 인해 로봇자본의 가격이 하락하고 대체가능확률에 따라 노동대체율이 높은 노동일수록 로봇에 의해 많이 대체되는 것을 보여준다. 이때, 노동대체율이 높은 직군의 노동가격 하락폭이 가장 크게 나타났고, 이 때문에 대체율이 높은 노동직군에 해당하는 가계의 노동소득의 증가율이 가장 적게 나타났다. 생산 측면에서의 비교를 위해 35개의 산업을 대체확률(probability of replacement)과 자본집약 정도(capital intensity)에 따라 네 가지 산업종류로 분류하였다. 대체확률이 높고, 자본집약적인 산업의 경우 노동가격의 상대적 하락으로 인해, 2015-2050년도에 대해 생산자 가격과 소비자 가격의 증가율이 높게 나타났다. 이 산업군은 저

소득층의 소비비중이 높은 산업으로 가격증가에 따라 효용감소폭이 크게 나타나는 것을 확인하였다. 반대로 대체확률이 낮고, 노동집약적인 산업의 경우 생산자 가격과 소비자 가격이 하락하였다. 해당 산업 군은 고소득층이 비교적 더 많이 소비하는 산업에 해당하여, 해당 산업 군의 물건 가격이 저렴해진 효과, 즉 물건구매력이 더 좋아졌다고 볼 수 있다. 이는 가계 효용변화로 이어서 해석할 수 있는데, 고소득층의 효용증가율이 더 높게 나타나는 이유가 바로 이 때문이다.

더 나아가 로봇자본의 특성과 관련한 사회적 우려 상황에 대해 시나리오 분석을 진행하였다. 로봇자본의 편중된 분포와 노동생산성 향상으로 인한 노동대체의 사회적 영향 심화 시나리오를 통해 로봇자본이 저소득층과 고소득층간에 소득 양극화를 야기할 수 있다는 점을 확인하였다. 로봇세 부과 시나리오를 통해 로봇자본에 대해 세금을 부과하게 되면, 고소득층의 로봇자본으로 인한 소득을 감소시키는데 일조하여 양극화 정도는 완화되는 것을 확인하였지만, 이는 생산 감소로 이어져 성장둔화를 야기할 수 있다는 시사점을 가진다.

본 연구는 방법론과 실용적인 측면에서 다음과 같은 기여점을 가진다. 먼저, 일반자본과 대체 및 축적의 속도 측면에서 차별화된 특성을 가진 로봇자본을 정의하고 이를 이용하여 산업별 노동직군에 따라 다른 대체율을 반영할 수 있도록 CGE모형을 설계하였다는 점에서 방법론적 측면의 기여가 있다. 또한, 로봇자본의 노동대체가 중요한 사회적 문제로 떠오르고 있는 현 상황에서 노동대체가 가계와 산업에 대해 차별적으로 야기할 수 있는 영향적 측면에서 각 주체간의 상호작용 메커니즘을 이해하는데 실질적인 기여를 한다. 특히, 본 연

구결과는 노동대체로 인한 차별적인 영향을 고려하여 정책입안자가 노동대체라는 사회적 이슈를 고려하여 혁신 정책을 설계할 수 있도록 다양한 시나리오 관점에서 실질적인 방향성을 제공하였다는 점에서 그 가치가 있다.

주요어 : 인적자본, 성장, 혁신, 자본세, 로봇세, 불평등
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