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Research on technology-driven polarization in Korean labor market

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Eunha Kim

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지도교수 황준석

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위 원 장 Jörn Altmann (인)

부위원장 황 준 석 (인)

위 원 오 종 은 (인)

위 원 김 승 현 (인)

위 원 홍 아 름 (인)

Abstract

Research on technology driven polarization in Korean labor market

Eunha Kim
Technology Management, Economics, and Policy Program
The Graduate School
Seoul National University

Technological advancement is the primary growth engine for economic development. At the same time, it has caused growing disparity in the labor market, by increasing the proportions of high and low skilled or high and low paying occupations to the detriment of the middle. To boost economic growth by enhancing productivity and overcoming the reduction of Korea's economically active population, further investment in technology should be consistently promoted. However, to control and stabilize the repercussions of technology implementation, it is necessary to bolster existing institutions and prepare people for this digital transformation. Therefore, policy makers should consider both the positives and negatives of technology to truly, understand the extent and depth of its potential disruption in the labor market.

Studies of polarization have focused on the increasing differential between the earning

potential of high school and college graduates based on wage premiums for higher skills. This has previously been explained as skill-biased technological change (SBTC) wherein technology development has traditionally favored workers with better skills and paid higher wages accordingly. However, recent demand for low-skilled employees has also increased, while occupations requiring middle-level skills have decreased. This polarization is accounted for by routine-biased technological change (RBTC) that is now prevalent in many developed economies. RBTC assumes that technology can substitute routine tasks within occupations, tasks that are simple, repeatable, well-defined, and codifiable. Yet to be determined is whether technology-driven polarization exists in Korea. To date, the literature has failed to find evidence of significant wage premiums based on educational attainment or SBTC. Studies seldom manage to present empirical results demonstrating the effects of technology on inequality until the mid-2000s. There have been various attempts to explain polarization in Korea, but they rarely considered RBTC based on a task-oriented approach.

Task-oriented analysis allows us to determine which tasks have increased demand and those that have become obsolete in the workplace, thereby suggesting to workers the skills they must strengthen or acquire. In this study, occupations are defined as a set of tasks performed by the employee holding that position. There are three kinds of tasks: analytic, routine (cognitive or manual), and non-routine manual tasks. Among them, routine or repetitive tasks are more vulnerable to replacement by technology as computers or robotics can perform most simple, specific, and repeatable tasks that are easily programmed. To

measure the combined task intensity of each occupation, the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (ONET) database developed in the United States were used to construct cross references between the Korean Standard Classification of Occupations (KSCO) and the U.S. Standard Occupational Classification (SOC). The measurement system for task intensity was tested against the co-occurrence of effectively utilized tasks within occupations using network community analysis.

In this study, rather than try to guess the impact of technology on the labor market, the employment changes of routine and non-routine labor were first tested to see whether they were affected by the reduced costs of information and communications technology (ICT) through different stages of technological advancement at the industrial level. With this theoretical framework indicating the relationship between the decline of ICT costs and labor demand, it can be empirically estimated that ICT capital is complementary with analytic and high-skill occupations but serves as a substitute for routine and manual workers. Next, RBTC related to industrial occupation levels in Korea was explored. The results imply that over the last two decades there has been a collapse in the middle-income job market while employment for more routine occupations has grown slower than others. Finally, Korean labor panel data was used to trace the career changes of mid-level or routine workers and the consequential impact on their wages after these individuals were displaced from their jobs. This study indicates that middle-income workers usually transition to lower paying occupations and have no choice but to accept reduced wages in their new workplaces, while workers who continue in routine occupations tend to experience wage

growth.

This research offers a measurable and quantitative index to capture the technological impact on the labor market by bridging the tasks required in the workplace (demand side) with the skills that workers should possess (supply side). It clarifies the importance of human capital investment through education and stresses the demand for enhanced skills related to creativity, interpersonal communication, problem solving, information analysis, and various soft skills. It also supports actions to develop new ways of investing and educating people to excel in new skills rather than continue to generate human capital with skills that are either already obsolete or will be in the near future. Polarization in skill demand is commonly witnessed in developed countries but this is not predestined to raise labor income inequality. Countries differ in level of inequality depending on their policies. The depth and width of technological advancement and the following socioeconomic changes are determined by not only technological side like technological feasibility, regulation on technology or cost but demand and supply of skills from the labor market. Based on this study, a meticulous consideration on the labor market is expected help solving problems of both polarization and cultivating human capital.

Keywords: Employment Polarization, Routine-biased technological change (RBTC), Task-oriented analysis

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Chapter 1. Introduction

1.1 Research background and problem description

1.1.1 Socioeconomic changes brought by technological advances

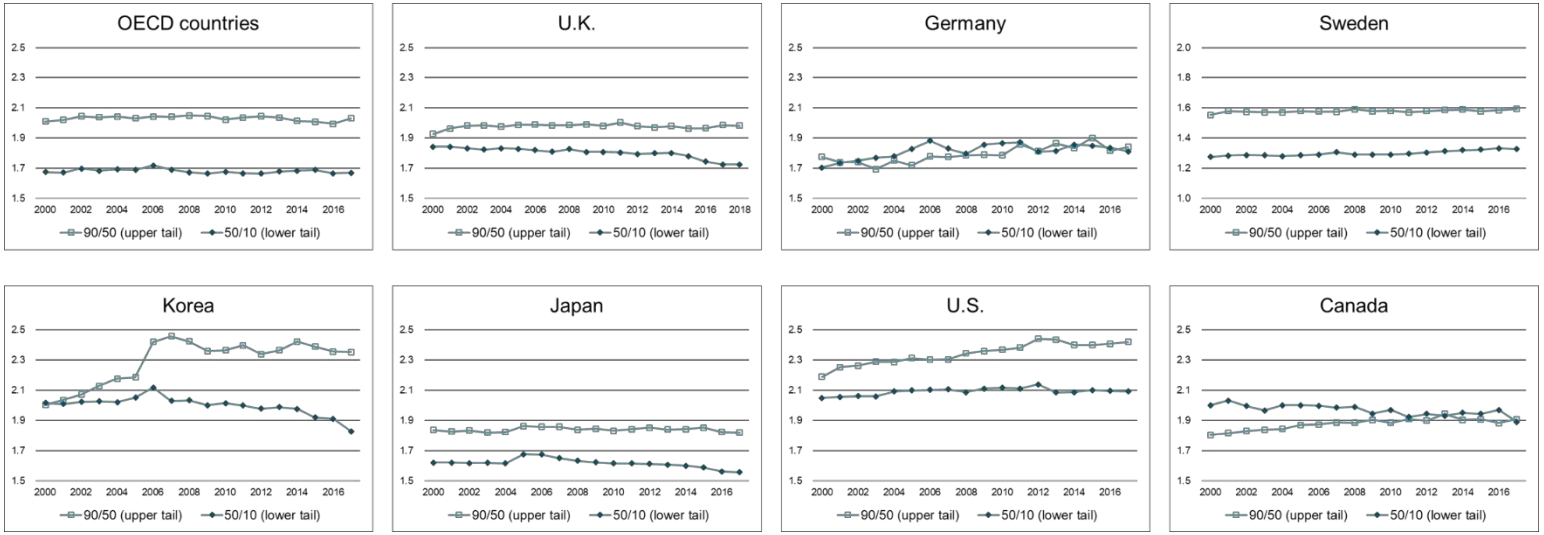
The nature of work has rapidly changed as a consequence of technological development, specifically information and communications technology (ICT). It is expected that most occupations for today's children when they eventually enter the workforce as young adults will be newly created positions that do not even exist today(WEF, 2016). The advent and rapid deployment of artificial intelligence (AI), big data, and automation technology suggest that many jobs will be replaced by machines and computers even though the extent and potential impact of this replacement remains highly controversial. Without doubt, with the aid of technology in workplaces, the skills required for many occupations will need to evolve as some tasks will be replaced. New types of employment are being created by utilizing digital technologies. For instance, ICT-based mobile work has transformed the way workers perform their tasks. Job sharing platforms allow employers to offer casual work that they are not obliged to provide regularly or continuously. Instead, they have the flexibility of soliciting short-term help on demand only when required (Degryse, 2016). One example is a platform called Upwork. Any employer can post a project and connect with top talent worldwide. Interested parties can be interviewed, collaborate, and be paid

for completing authorized projects.[1] Internet-based platforms reduce transaction costs and barriers to finding appropriate jobs. They open new opportunities for people who have been isolated geographically or have had limited access to information. Immediate benefits have been seen through the inclusion of more women in the workforce as well as persons with disabilities. However, there is tradeoff. Many of these project-based workers cannot be protected under regular social security legislation because most platform companies refuse to regard themselves as employers. This is somewhat alarming considering Upwork alone offers its services to more than ten million workers (Degryse, 2016).

Remarkable advances in ICT have brought both dividends and division simultaneously (World Bank, 2016). Technology has long been regarded as the principle growth engine for economic development by expanding opportunities and participation in labor markets, creating new jobs and business, and increasing productivity of the existing workforce. However, it has also been criticized for its significant role in polarizing labor markets and creating income inequality in several developed countries. Income inequality has been treated as normative with concerns about escalating conflicts and violence that damage social trust and cohesion. It is time to seriously reconsider socioeconomic levels after recent studies demonstrated that there is no evidence of trickle-down effects and that inequality can negatively impact economic growth, consumption, productivity, etc. (Cingano, 2014; Lee, 2018). For instance, certain types of temporary work and self-employment that have

[1] https://www.upwork.com/ (Accessed on 29th May, 2019)

been enabled by digital technology can create job opportunities for all, but these workers in general often suffer from poor job quality, slower wage growth, and income instability (OECD, 2015). Corrective measures to account for and stabilize inequality should become a critical assignment for economic policymakers. Korea faces the problem of boosting economic growth while easing polarization simultaneously; therefore, it is imperative that policy designers and decision makers understand both the impact of technology and the working mechanisms the lead to technology-driven polarization in the national economy. There are primarily three sources of economic growth: capital accumulation, advances in technology, and increased labor input. The latter infers growth of the working population; however, Korea is thought to be heading over the “demographic cliff” as forecasted by Dent (2014) and remains at risk of losing its growth momentum. This appears to be the right time to build social discourse on technology-driven polarization while keeping the sustainable growth engine activated.



Data source: OECD[2]. All panels have the same scale except for Sweden.

Figure 1 Decile ratios of gross earnings of seven countries, and the average of OECD countries

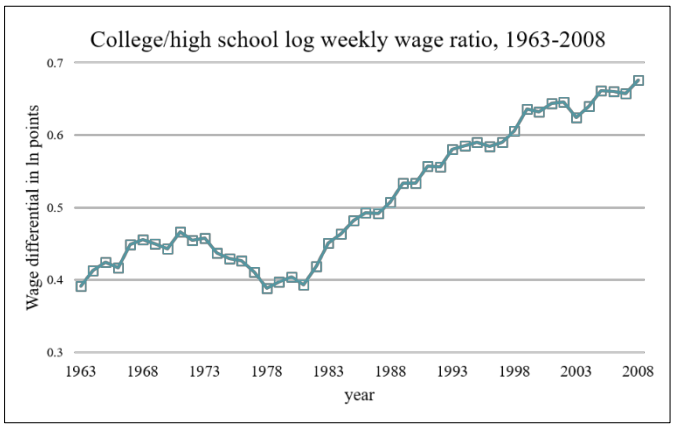
[2] https://stats.oecd.org/Index.aspx?DataSetCode=DEC_I (Accessed on 15th June, 2019). The OECD dataset contains the gross earnings of full-time dependent employees. The data source for Korea is Entreprise Survey (Survey on Labor Conditions by Type of Employment), Korean Ministry of Employment and Labor

1.1.2 Studies on rising inequality in developed countries

Policymakers have important roles to play in the fight against income inequality because the patterns of inequality are determined by policy objectives. A simple and widely used index of income inequality is the decile dispersion ratio that represents the ratio of the average income of the richest 10 percent of the population compared to the average income of the poorest 10 percent. The upper tail 90/50 is the ratio of the income of the top 10 percent to the income of those at the median of earning distribution. The lower tail 50/10 is the ratio of the income of those at the median compared to the bottom 10 percent of the earning distribution. The decile ratio is a straightforward calculation to illustrate the disparity of income distribution. Figure 1 shows the annual decile ratios of gross earnings of some developed countries in North America, Europe, and Asia over the last two decades. The degrees of expanding or narrowing gaps between the upper and lower tails form several different patterns. Compared to the average level of OECD countries, the ratios are significantly higher in the United States and Korea. According to Figure 1, the upper tails of most countries have been stabilized, with the exception of Korea and the United States. Also, the upper half and lower half inequalities diverge, and after 2007, this is primarily derived from the inequality occurring below the median.

It is difficult to isolate precise causes of income inequality based on the complexity of labor markets, but three primary causes arise: technological change, trade globalization, and labor market institutions (Dabla-Norris, Kochhar, Suphaphiphat, Ricka, & Tsounta, 2015). The most prominent is the premium placed on skill that originated from ICT

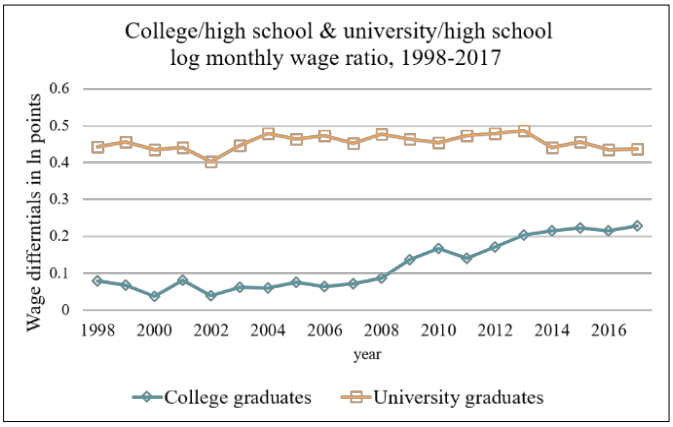
development. Griliches (1969) introduced evidence of the complementarity of skilled labor and capital. As technological advances are usually embodied in new capital goods and their decreased cost over time, “capital deepening” occurs. This has led to the increased demand for skilled labor. In the 1990s, research focused on the role of premium wages for highly skilled or highly educated labor in the surging inequality associated with the development of computers.



Data source: Acemoglu and Autor (2011)

Figure 2 U.S. wage premiums for higher education levels[3]

[3] The wage premium slowdown is known for its relative increase in the supply of college workers. The Vietnam war boosted college enrollment during the late 1960s and early 1970s, but the graduation rate dropped by half in a decade. Also, the decline of wage premiums for higher learning discouraged high school graduates from entering college (Acemoglu & Autor, 2011).



Data source: KLIPS

Figure 3 Korean wage premiums for higher education levels

To understand the context of income inequality and wage premiums in Korea, consider the case of the United States as a comparison that also showed a large disparity in earning distribution. The wage or college premium—defined as the wage differential between those with high school or lower diplomas compared to those with college or higher degrees —played a significant role in the United States job market. With sufficient labor supply of both high school and college graduates, the excess demand for higher-skilled labor aggravated the U.S. wage inequality, a phenomenon explained by SBTC. Figure 2 illustrates the estimated higher education wage premiums in the United States from 1963 to 2008, as presented by Acemoglu and Autor (2011). When compared to high school graduates, the U.S. wage differential monotonically increased for all college and higher education levels. Conversely, the wage differential in Korea between university and high school graduates has exhibited a consistent gap, while that of high school graduates and

college graduates increased relatively fast after 2009, as shown in Figure 3. Considering that the starting points of study in SBTC are rising earnings and returns to college, the analysis of wage distribution in Korea should be interpreted differently as it is not directly comparable to the U.S. situation. Although the share of those with college or higher degrees increased during this period, the wage bill shares and mean wages of these groups did not seem to exhibit severe inequality or polarization.

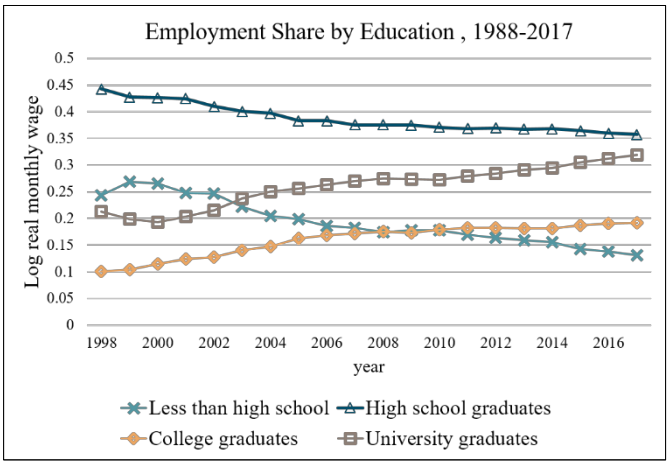


Figure 4 Annual changes in employment share by educational attainment

Figure 4 shows the annual employment share changes by educational attainment between 1998–2017. As the supply of higher-educated labor has been relatively elastic in Korea, it is safe to assume that the polarization of its labor market might be caused by the excess supply of highly educated employment candidates, which in turn increases the proportion of highly paid labor. In Figure 4, the share of those with high school or lower

diplomas was about 70% at one point, but it decreased steadily to less than 50% by 2017. Together with the increased prevalence of highly educated employees, labor costs also increased, thereby clearly demonstrating the effects of continuous demand. This is further supported by empirical analysis showing that the main contributor to the disparity between the levels of educational attainment is demand driven rather than any relative changes in labor supply (Park, 2014). The mean wages of each educational attainment group are depicted in Figure 5. Aside from the Korean financial crisis of 1997 and the global financial crisis of 2007, the mean wage of workers has consistently increased, while the monthly mean wage gap between university graduates and high school graduates has remained stable. Obviously, income inequality has risen in Korea (Figure 1), but the wage differentials related to educational attainment would lead to impetuous conclusions that skill premiums do not exist in Korea. However, the way in which skill is defined can affect the conclusions of this debate; therefore, a more deliberate analysis framework is required to diagnose income inequality relative to specific aspects of skill. Keeping these unique characteristics and the Korean context in mind, this research suggests one method to measure inequality in the labor market through task-oriented analyses rather than educational attainment.

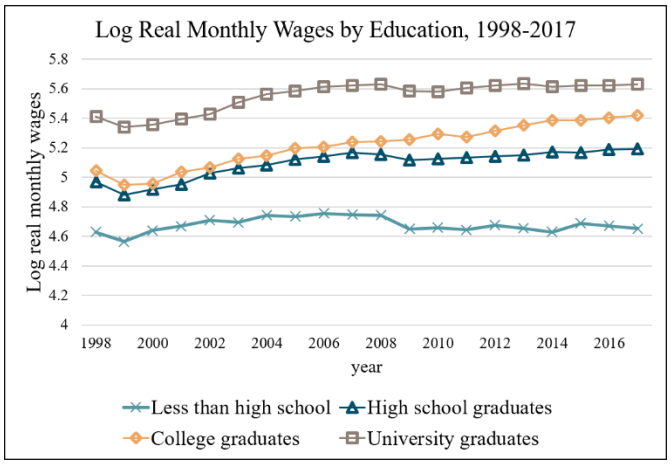


Figure 5 Log real monthly wage change by educational attainment

1.2 Research objective and outline

The scope of technological change is so extensive that devising proper frameworks and variables for analysis is essential for identifying its actual impact on labor markets. Like other developed countries, it was inevitable that Korea could not avoid the polarization of its labor market and the collapse of the middle-income occupations. This study covers the structural changes related to wages and employment caused by technological development at the individual, industrial, and occupational levels with one unified analysis tool featuring a task-based approach. To clarify the scope of terminology utilized throughout the study, income is normally defined as total household disposable income, including employee earnings, income from self-employment, capital or investment income, and public transfers (OECD, 2019). However, for this study we consider only the income from labor of hourly and salaried employees, whole polarization refers to the divergent changes at both ends of

distribution at the expense of middle-income earners primarily in terms of employment opportunities.

Considering and accounting for the impact of technological change on policymaking should be conducted in two coherent ways. The first relates to the preparation of individuals through education and other investments in human capital to serve the upcoming needs and preferences of the labor market. The second involves statutory adjustments related to active labor market policies, social protection, or tax reform. These are all connected to technological and economic development, thus making the problem even more complex. Before beneficial policy decisions can be enacted as law, an accurate diagnosis of the true origin of the current polarization in the labor market is necessary, followed by the implementation of the most appropriate approaches that can lead to timely solutions, one of the main purposes of this research. To analyze labor market changes in accordance with technological evolution, three main questions must be answered: i) define the role of new information technology in the labor market (is it a substitute or complementary with labor), ii) if technology is a substitute for labor, what labor groups have been displaced most often by technology (using an empirical analysis of the polarization of labor demand with a task-based approach), and iii) determine where those who have been displaced have moved and the impact on their wages after these career changes.

During the process of defining the causes and solutions for labor demand polarization in the Korean labor market, this research introduced a task-oriented analysis. Ominous threats presented in previous literature related to the impact of technology on labor markets

have been exaggerated because many of those studies assumed that technology would replace entire occupations rather than only certain tasks performed in those positions (Arntz, Gregory, & Zierahn, 2016; Frey & Osborne, 2013; Lawrence, 2016; WEF, 2016). This led to widespread paranoia that technology would usurp existing jobs and cause "technological unemployment." In some ways, this might be partially true. Advanced computers are now able to perform tasks that until recently had been regarded as the domain reserved for humans; however, one should remember that occupations comprise a complex set of tasks. Technology gradually replaces tasks which are most feasible in terms of technological and economic efficiency. Henceforth, balance between rising and diminishing demands for tasks on the market side and educational preparation on the supply side becomes obligatory.

All three studies in this research reveal polarization in the Korean labor market caused by technological advancement. This polarization accounts for the simultaneous increase at the two extremes of wage distribution at the expense of the diminished middle level. In the first study, the relationship between ICT capital and labor input is examined. Historically, there has been endless debate on whether technology has substituted or complemented labor, from the invention of the steam engine to the IT revolution. This study offers empirical evidence that indicates ICT capital can both substitute and complement labor depending on the characteristics of tasks performed by employees at many workplaces. While firms respond to relative decline in price of ICT based on given wage structures defined by the labor market, the decisions they make will result in changes to labor demand that clearly indicate the kinds of work that are substituted or complemented with ICT

capital. The second study explores the RBTC phenomenon in Korea. It is assumed that the development of technology replaces certain tasks within an occupation rather than the entire occupation. Routine tasks which are simple, repeatable, and easily codifiable are the first to be targeted for replacement by technology. The second article aims to classify different types of tasks within occupations and then ranks these occupations by the "routineness" of their tasks. As mentioned, the overall employment proportion of middle-paying occupations has declined, while the demand for both high- and low-paying continues to increase. The relationship between routine task indices and labor demand changes is estimated from 1993 to 2015.

The third and final study deals with the after-effects of workers formerly employed in routine occupations who were displaced by technology. The direction of job shifts of the ousted middle paying workers and the corresponding impacts on their wages are analyzed. To estimate wages, instead of using existing human capital data that represents skills as years of education, the concept of task-specific human capital is introduced. This alludes to reflect the frequent mismatch between educational attainment and the actual tasks performed in many workplaces which are not fully covering return to education, as well as skills acquired in the workplace within the context of Korea.

1.3 Contribution of this study

To solve the problems caused by technological advances in the labor market, updating the current institutions is essential in order to adopt these dynamic changes while preparing

for future. This research offers task-oriented analysis which provides an important perspective for Korea considering its distinct economic context. This study suggests a framework for policymakers that accounts for the role and influence of technology based on the finer level of specific tasks rather than the base level of occupations. This task-based approach has many advantages; it offers a measurable and quantitative index to capture the technological impact on the labor market. It enables the measurement of task intensity and the classification of occupations according to the characteristics of tasks involved in each. It facilitates inter-occupational comparisons and identifies the most important types of tasks in each occupation as non-routine analytic, routine, and non-routine manual tasks. It can successfully interpret structural employment changes based on technology. Considering that skill premiums occur when the supply of skilled workers cannot satisfy demand—together with the disparity between the tasks now required in the workplace and the skills that employees actually possess—this analysis framework would be an important tool to manage the acquisition and development of appropriate human capabilities for most companies. In particular, workers need to manipulate their career paths based on the skill sets they continue to develop in accordance with the external environmental changes caused by technology.

Regarding the analysis methodology, in addition to the introduction of task intensity, the framework also adopts an evaluation system for task intensity measurement. Using the given task intensities of occupations from either DOT or the ONET database, the system constructs consistent cross references for KSCO. Based on the characteristics of each task,

they are classified as either non-routine analytic, routine, or non-routine manual. This classification system is tested using network analysis of co-occurring tasks that are effectively utilized within each occupation. The test confirms measurements of task intensity and shows the polarization of analytic and manual task types. By adding new variables into the existing measurement system to test the characteristics of certain tasks—or estimating the demand for specific tasks of interest in the labor market—predicting changes is possible within the analysis framework of this study.

In the age of hyperconnectivity, new technologies amplify the impacts of others, such as AI, robotics, machine learning, big data, automation and so on. Considering the impact of each technology, not only the workplace but entire economies experience significant disruption (World Economic Forum, 2016). For instance, digital job platforms have been introduced in the labor market, thereby challenging the traditional forms of employment while contributing to the disintegration of classic work styles into individualized services, fragmentary tasks, and the dismantling of groups working collectively. Work is performed on demand or on call (Meda, 2016). Technology might soon change the fundamental concept of work while still performing its role as a major growth engine for the overall economy. AI is rapidly growing and leading to increases in productivity even though GDP growth has fallen below expectations (Furman & Seamans, 2018). Another promising report is that the implementation of robots contributed 0.36 percentage points to the annual growth in labor productivity without affecting overall employment (Graetz & Michaels, 2015). Revolutionary technology can solve many problems in the economy but cannot

eliminate the residual negative effects on the labor market by itself. To prevent income inequality from hampering forward progress, this research supports a significant framework that can lead to crucial policy solutions.

The development of new technology and the consequential socioeconomic changes are considered to be irreversible progress. Mitigating the inequality of employment and labor income must be approached in various aspects. Education is not the only solution but it is certainly the most important and urgent. Educational reforms should commence immediately. One primary objective should be job training for mid-level workers to help them transition to better occupations and prepare for the paradigm shift facing the next generation. This study suggests certain skills that seem most promising for the future workplace and identifies others that will inevitably decline, thereby providing valuable information that will allow educational institutions to keep pace with technological progress while providing relevant learning opportunities. Understanding these changes in demanded tasks throughout the labor market would be of great value for informing public policies as well as the development of educational or vocational training strategies.

Chapter 2. Literature review: Technology and the labor market

2.1 Technological advances and their impact on the labor market

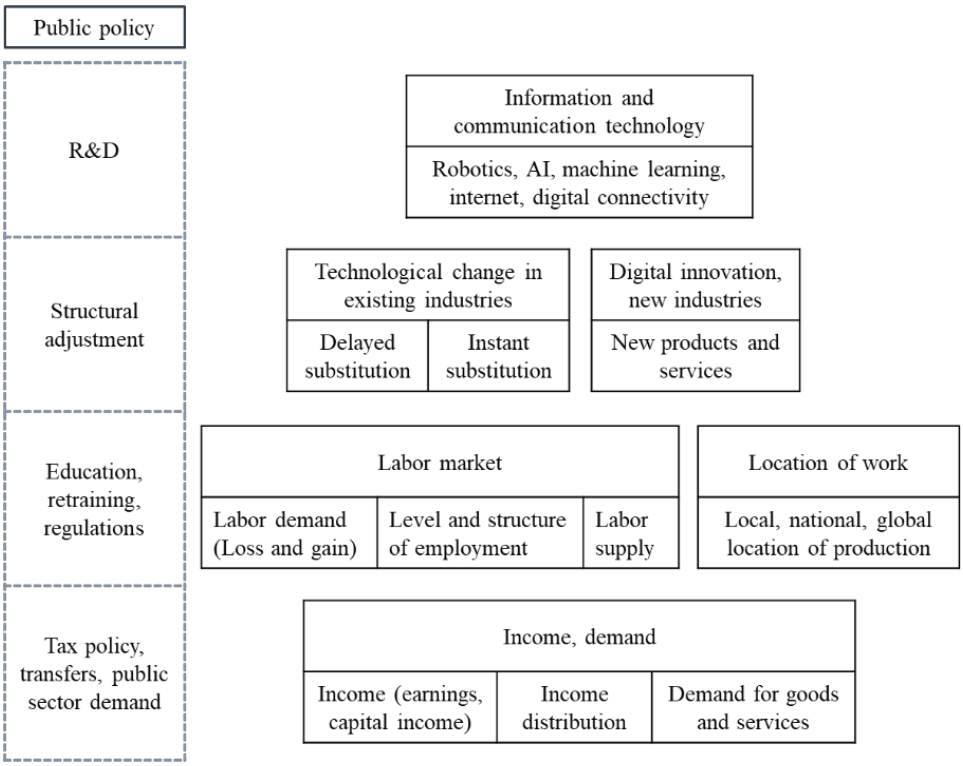
As new technologies such as AI, robotics, and machine learning advance, some papers express expectations of large occupational shifts. One study estimated that by 2030, between 400 million and 800 million people around the world could be displaced by automation, requiring them to find new jobs (Manyika et al., 2017). In 2030, two-thirds of all current jobs may be at risk of automation in the United Kingdom (Lawrence, 2016) and 47 percent of total employment in the United States is at risk of automation(Frey & Osborne, 2013). These statistics raise strong opposition among the public, but fear of job loss due to technological progress is not a fresh phenomenon. In 1930, Keynes (1930) mentioned unemployment due to automation as a temporary phase of maladjustment. Even in the early 19th century, there was the Luddite Movement (1811-1816), a historical period during which English textile artisans resisted the automation of textile production, reflecting their fear of technology. With the introduction of steam engines and factory systems, there was a large displacement of skilled artisans, because the assembly lines were operated by unskilled workers. This process was called “deskilling.” The manufacturing technologies that followed featured more oversight of automated mass production processes, therefore the demand for relatively skilled blue collar workers increased (Goldin & Katz, 1998;

James & Skinner, 1985). This modern pattern of capital-skill complementarity that evolved in the 20th century has been accelerated by the adoption of computer information technology (Frey & Osborne, 2017). In other words, technology has not always substituted workers in favor of skilled labor, but capital and skill are still relative complements.

Advances in technology can affect the labor market in various ways. Technology creates new jobs, and changes the nature of work, encompassing workplace, work schedule, and working style. It also generates new opportunities to access the job market, and creates new and alternative forms of employment, such as on-demand work (EPSC, 2016). Moreover, ICT allows internet-enabled offshoring, creating outsourcing and online work for women in developing countries, which has the potential to change entire societies. Thus, the dividend of digitalization in the labor market is not limited geographically (World Bank, 2016). However, it is difficult to measure the impact of technology quantitatively due to the complexity of the labor market. Substitution and its effects on income occur at the same time, so it is not easy to conclude that the result is either job creation or job elimination. For instance, increased labor productivity will cause a direct decline in labor demand; but will also reduce the price of goods and create additional demand for goods, resulting in an increase in production, which would increase the labor demand. Technological development can also allow for the creation of new products and services, and increase the demand for new technology, which in turn can create more demand and increased production further increasing the market's labor demand.

The Figure 6 shows a simplified outline of the effect of ICT technology on the labor

market, and the related public policy for each stage as suggested by Garcia-Murillo et al.(2018). Each stage cannot stand alone; change in one factor will not affect others in just one way, because all stages are intertwined. The strength of change on some factors will affect others in a nonlinear fashion. Figure 6 shows the broad influence of ICT on employment, yet it is a restricted view. For instance, when focusing on the impact of ICT on job quality, there are three dimensions to be considered: employment relations and employment protection; time and work autonomy; and skills and careers (Rubery & Grimshaw, 2001). Even in one dimension, for example employment relations and protections, there are various factors which affect employment opportunities: ICT could destroy or create work; ICT could lead to fragmentation and undermine collective bargaining systems and employment regulations; or ICT could blur the boundary between employee and employer, changing traditional employment protections (Rubery & Grimshaw, 2001). With the rising interest in inequality caused by technological advances, researchers have tried to explain the relationship between technological change and the labor market, and tried to pin down the extent of its impact, in spite of the complexity of that kind of analysis.



Source: Modified from Garcia-Murillo et al. (2018)

Figure 6 Structure of how ICT influences employment

Throughout history, there have been two competing effects of technology on the labor market. First is the negative effect of reallocating labor, and second is the capitalization effect that expands employment with increased productivity. Although historically the capitalization effect has been predominant, the characteristics of modern technology are far different from those in the past (Mokyr, Vickers, & Ziebarth, 2015). The substitute or complementary status might depend on the characteristics of a particular occupation. But "complementarity or substitution" are just aspects of the impact of technology on the labor market.

2.2 Literature on skill-biased technological change (SBTC) and Canonical model

Income inequality alleviation had been regarded as given after economic growth, ever since Kuznets's hypothesis on an inverted U-shaped relationship between income inequality and development said that after industrialization and development process, inequality would be eased (Kuznets, 1955). But after several decades, the great U-turn was observed, and global concern about income inequality persists. Among the several possible sources of rising inequality, the one with the most impact is technological advance, since higher technology developed more skilled workers, which demanded higher income (Autor, Katz, & Krueger, 1998; Bekman, Bound, & Machin, 1998; Berman, Bound, & Griliches, 1994; Goldin & Katz, 1998; Johnson, 1997; Katz & Autor, 1999; Katz & Murphy, 1992; Machin & Van Reenen, 1998). There are other possible sources of inequality, such as trade, globalization, or offshoring of manufacturing, but the impact of these factors are not comparable to technological advances (Blinder & Krueger, 2009; Bloom, Draca, & Van Reenen, 2016; Desjonqueres, Machin, Reenen, & Van, 1999; Firpo, Fortin, & Lemieux, 2011; Goos, Manning, & Salomons, 2011; Grossman & Rossi-Hansberg, 2008; Jung & Mercenier, 2014). The canonical model based on SBTC (Acemoglu & Autor, 2011) is used to explain relative demand for skilled or highly educated workers. The starting point of the study of this skill-biased technological change (SBTC) is the observation of increasing return to skills, represented as college premium. There are two skill groups performing different and producing imperfect substitutable goods. This model helps explain the

concurrent rise in demand for increased wages for high-skilled workers presented in Figure 7. For simplicity, assume that the relative supply of workers is inelastic. The labor inputs of high-skilled and low-skilled workers are denoted as N_H and N_L, respectively. w_H and w_L indicate the wages of high-skilled and low-skilled workers, respectively. The initial supply S_1 and demand D_1 state that the ratio of wage of high-skilled to that of low-skilled workers is $(w_H/w_L)_1$. When the relative supply increases from S_1 to S_2, the relative wage would decrease to $(w_H/w_L)_2$. But if the relative demand increases sufficiently to offset the supply effect, moving the demand curve from D_1 to D_2, the relative wage will be determined as $(w_H/w_L)_3$.

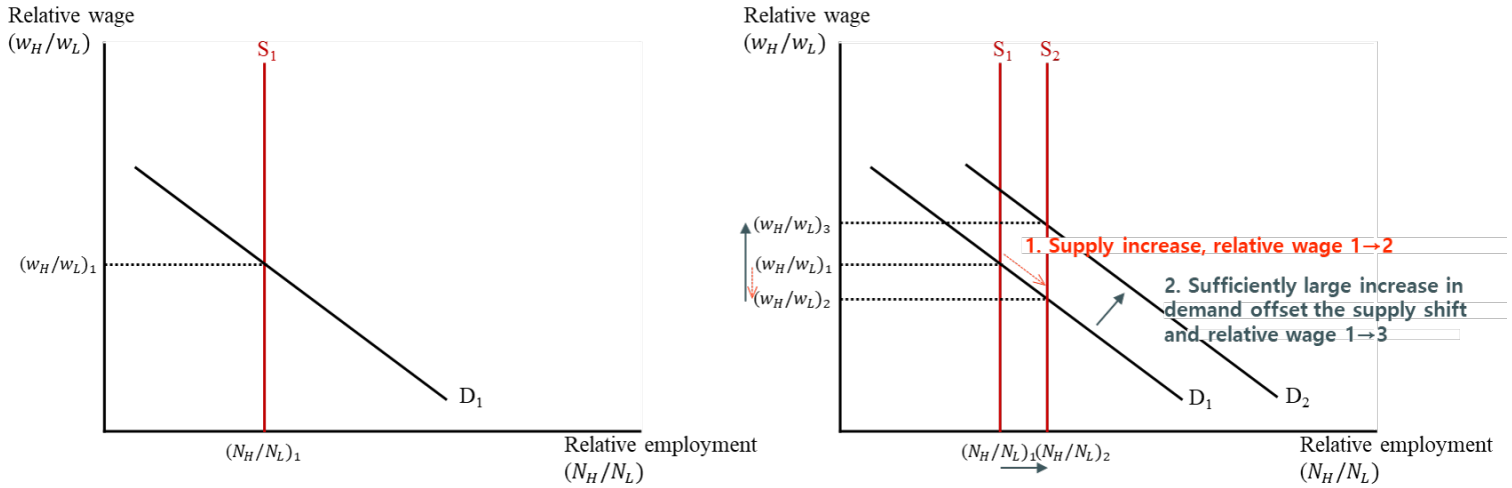


Figure 7 The skeleton of "Skill-biased technological change"

Source: Modified from Van Reenen (2011)

The work done by Katz and Murphy (1992) has measured relative wage to the ratio of college graduates to high school graduates. In the constant elasticity of substitution (CES) technology production function, technology is assumed to be in an exogenously factor-augmenting form, complementing either high- or low-skilled workers. Consider a CES production function with value added Y and elasticity of substitution between college and high school equivalent σ.

$$Y = \left[\lambda N_H^{\frac{\sigma-1}{\sigma}} + (1-\lambda) N_L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \quad \text{Eq. (1)}$$

where the share parameter λ, $0 < \lambda < 1$. Assuming the perfect competition in market of input and production, the first order conditions show the following:

$$\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\left[D - \ln\left(\frac{N_H}{N_L}\right)\right] \quad \text{Eq. (2)}$$

where D is the time series of relative demand shifts measured in log quantity units (Katz & Murphy, 1992), technology is assumed to take a factor-augmenting form in the canonical model. Since this assumption views productivity of workers with low and high skills differently, and induces either a monotonic increase or decrease in wage differentials, the canonical model has successfully explained the wage inequality caused by the gap between two educated or two skilled groups. Changes in competitive skill prices and subsequent

changes in relative wages were observed from 1963 to 1987 in the United States. Katz and Murphy (1992) found this model illuminated within-group and overall wage inequality, using relative wages and quantities of more educated workers. Krueger (1993) estimated that workers receive 10% to 15% higher wage rates as a result of using computer skills; and that the expansion of computers in the workplace accounted for the skill premium. Berman, Bound, and Griliches (1994) also found that labor demand shifted from low-skilled to high-skilled workers in United States manufacturing after the 1980s. This shift could be explained by labor-saving technological changes in production as well as the increased preference for highly educated workers within industries rather than between industries. While most studies take the skill-biased labor demand shift after 1970s as the main stylized factor of rising income inequality, Johnson (1997) said that relative demand for skilled labor had been increasing since the 1940s. Autor, Katz, and Krueger (1998) expanded the time period from 1940 to 1996, in order to analyze the relative supply and wage changes of workers by education. There had been skill upgrading within industries since the 1940s, as Berman, Bound, and Griliches and Johnson mentioned, and after widespread computer usage and computer-related investments in the 1970s, this trend was accelerated. The income distribution of race and gender is also an important area of research, but interestingly, Bartel and Sicherman (1999) found that the skill premium associated with technological change was unrelated to gender or race, and was more relevant in industries with higher rates of technological changes.

However, while advances in ICT continued, wage inequality was stabilized in the 1990s.

The gender and race gaps closed slightly, but remained relatively large, and SBTC failed to explain this (Card & DiNardo, 2002). In the 2000s, researchers began to find that the canonical model failed to fit the real changes in the economy. The model could not explain the real earning declines of less-educated workers in the United States, which had been quite pronounced (Acemoglu and Autor, 2011). The major drawback of the canonical model is that it cannot explain the recent trend of income inequality. Compared to the monotonic rise in demand and wage of high-skilled workers, an increase in employment of high-skilled and low-skilled occupations and a relative decrease in employment in middle-skilled workers have been observed in many developed countries in recent decades. Equation (2) has no interpretation for the cause of the wage trend of polarization. Since it assumes the factor-augmenting form of technology, it does not reflect the mechanism of new technologies such as AI, robotics, and machine learning, and how they affect or replace workers in certain tasks. Skills and tasks may seem similar, yet have different meanings. Hereafter, in this study, the terminology task means a unit of work activity within one's occupation; and skill means a worker's endowment of capability to perform tasks at the workplace. The canonical model does not distinguish between these two, therefore it does not give implications for the systemic changes in the composition by tasks, or explore the simultaneous increase in both highly educated, highly paid occupations, and low-educated, low-paid occupations (Acemoglu & Autor, 2011).

Historically, evidence has shown that technological change predominantly deskilled workers in the 19th century, as introduction of the factory system led to adoption of steam

power and replaced artisans. There's discontinuity of SBTC, although technology has been trending for several centuries, and the nature of technology might not be skill-biased (Katz & Margo, 2013; Van Reenen, 2011). Indeed, it is polarization that is more frequently observed and empirically analyzed in recent years. Although the canonical model is tractable and intuitive and has successfully explained the rising income inequality before the 2000s in the United States, an alternative is required.

2.3 Routine-biased technology change (RBTC) and task-based approach

2.3.1 Routine-biased technology change (RBTC) hypothesis

Despite remarkable studies of SBTC, the role of ICT in the workplace has not been fully explained, and it is a critical source of rising income and labor demand inequality. Autor, Levy and Murnane (2003, hereafter called ALM) suggest a model of how ICT changes task contents within occupations. ALM define the impact of computerization on four categories of tasks as follows:

Table 1 Task model of workplace by ALM (2003)

Task contents	Routine	Non-routine
Analytic and interactive	Substantial substitution	Strong complementarities
Manual	Substantial substitution	Limited opportunities for substitution or complementarity

Source: Autor, Levy and Murnane (2003), p.1286

This framework postulates that ICT capital is more substitutable with routine tasks than non-routine tasks, while routine and non-routine tasks are imperfect substitutes themselves. For formal implications of this assumption, ALM proposed a simple production model that produced Q with two task inputs, routine and non-routine, in the Cobb-Douglas production function at a constant return to scale.

$$\mathrm{Q} = (\mathrm{L_R} + \mathrm{C})^{1-\alpha}\mathrm{L_{NR}}^{\alpha} \quad \cdots\cdots \text{Eq. (3)}$$

where $\mathrm{L_R}$ and $\mathrm{L_{NR}}$ are labor inputs of routine and non-routine tasks, and α is output elasticity. ALM regard C as ICT (computer) capital, and its supply is perfectly elastic at market price, which declines as technology advances. ALM adopt Roy's model (1959) to let income-maximizing workers choose their tasks depending on their ability[4]. Workers have heterogeneous productivity endowments (E_i) in both routine (r_i) and non-routine (n_i) tasks, with $E_i = [r_i, n_i], 0 < r_i, n_i \leq 1$ for all individual workers i. Then, workers will choose tasks to allocate their labor according to their comparative advantages. Hence, the labor of worker i, $L_i = [\lambda_i r_i, (1-\lambda_i)n_i]$, with $0 \leq \lambda_i \leq 1$.

There are two market equilibrium conditions: Given that routine tasks are perfectly substitutable with ICT capital, the wage of routine input (w_{R}) and the price of ICT capital

[4] In his article, he intended to "*combat the existing view that income distribution is an arbitrary one that has developed by the process of historical accident*." In the Roy model, the working population has only two occupations (hunting and fishing). Workers optimize choices of selecting with fundamental distribution of skills, correlations among these skills, and technology available to use these skills (Roy, 1959).

(ρ) is the same $w_{\mathrm{R}} = \rho$. For labor market clearing, workers will choose where to allot their labor: routine or non-routine tasks. If the economy operates on the demand curve, from first order condition,

$$\frac{\partial \mathrm{Q}}{\partial \mathrm{L_R}} = w_{\mathrm{R}} = (1-\alpha)\left(\frac{\mathrm{L_R+C}}{\mathrm{L_{NR}}}\right)^{-\alpha}, \frac{\partial \mathrm{Q}}{\partial \mathrm{L_{NR}}} = w_{\mathrm{NR}} = \alpha\left(\frac{\mathrm{L_R+C}}{\mathrm{L_{NR}}}\right)^{1-\alpha} \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (4)}$$

A decline in price ρ increases the routine task input. The rise in demand for routine tasks will be met by increasing the ICT capital, or adding more routine tasks. But since routine and non-routine tasks are productive complements, the following relation can be derived:

$$\frac{\partial \ln\left(\frac{w_{\mathrm{NR}}}{w_{\mathrm{R}}}\right)}{\partial \ln\rho} = -\frac{1}{\alpha} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (5)}$$

When denoting the ratio of routine to non-routine tasks at the labor market equilibrium state, η^*, the marginal worker performing relative efficiency units is indifferent to routine and non-routine tasks. It means that the individual i supplies routine labor ($\lambda_i = 1$) if $\eta_i < \eta^*$. Then it could be written as:

$$\frac{\partial \ln\eta^*}{\partial \ln\rho} = \frac{1}{\alpha} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (6)}$$

The relative wage paid for non-routine tasks will rise as ρ decreases. The external decline in ICT capital will increase the marginal productivity of non-routine tasks, and

marginal workers with η^* will reallocate their labor from routine to non-routine tasks. Then, the increased demand for routine tasks will be met only by inputs of ICT capital, which might decrease the demand for routine labor input, but compensate by adding more ICT capital. With this model, ALM argue that ICT capital substituted for workers performing routine tasks and complemented those performing non-routine, problem-solving, and complex communications tasks. This task-based analysis could also be translated into education demand; ALM revealed the model explained 60 of the estimated relative demand shift favoring highly educated labor. Yet, they described the rising demand for college-educated workers, or workers with flexibility, creativity, and complex communications while excluding the demand for low-skilled labor. A decade later, Autor and Dorn (2013) proposed features of concurrent polarization of employment and wages in the United States from 1980 to 2005. When ranked by the 1980 occupational mean wage, which is regarded as the skill percentile, the changes in employment share and real hourly wages show a U-shaped relationship. Consistent with the SBTC hypothesis, employment in upper skill distributions rapidly increased, but that in the lowest quartile also expanded sharply. A more striking feature of their study is the distribution of wage changes in terms of skill level. There were non-monotonic wage changes, with the greatest gains in the upper tail, modest gains in the lower tail, and smaller gains in the median. The polarization was assumed to stem from the interaction between two factors, which explain the rapid increase in wage and employment in service occupations. One factor is the decline in the cost of automation technology, which made it more feasible to replace workers performing routine

tasks with ICT capital (but not in-person service tasks), and the other is consumer preferences of variety over specialization, which determines the degree of substitution of workers producing service goods. If consumer preference does not imply close substitutes, non-neutral technological processes would be concentrated in product goods, raising the aggregate demand for service goods, and thus, employment and wages.

This simple model of ALM opens the new era of polarization studies. Following the case of the United States, the polarization induced by routine-task biased technology change is examined over many developed countries, although not recognized before. Spitz-Oener (2006) uses survey data on activities that workers perform at their workplace, and classifies the activities into five categories: non-routine analytic; non-routine interactive; routine cognitive; routine manual; and non-routine manual tasks. The key task measure is defined as the ratio of the number of activities in the task category to the total number of activities in the category. It represents the occupational skill requirements of workers. Routine cognitive tasks are calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature. Routine manual tasks are operating or controlling machines and equipping machines. Spitz-Oener finds that with the development of technology, skilled labor requirements have been rapidly substituted by ICT in Germany. Jerbashian (2019) uses ten Western European countries to provide evidence of the effect of decline in information technologies and their prices on labor demand. He found that the fall in IT prices was associated with higher demand for high-wage occupations, and a lower share of middle-wage occupations, but was not significant for low-wage occupations. The degree

of changes in the share of high- and middle-wage occupations was related to the industries' dependency on IT.

As far as low-skilled or low-paid occupations are concerned, Goos and Manning (2007) point out that SBTC has some deficiencies in explaining recent employment changes in low-wage jobs. They provide the evidence of polarization by RBTC in the United Kingdom. In their follow-up study, Goos, Manning, and Salomons (2014) show the polarization of labor demand in sixteen EU countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom). In this paper, they regarded both technological advances and offshoring as sources of job polarization, and confirmed that RBTC played a more important role than offshoring. They took into account the fact that technological advances accompanied not only employment changes but also product demand changes, in order to account for additional sources of employment changes. RBTC also predicted that industries with routine intensive tasks would reduce employment and see large decreases in relative costs and output prices, which would ultimately influence the product demand in these industries. A study of demographic trends complement argues that RBTC decreases the relative price of goods, and this is associated with increased demand for personal services, with an increasing proportion of seniors. Thus the aging process could complement the rising employment in low-paid occupations, which are mainly service-based (Moreno-Galbis & Sopraseuth, 2014).

The same polarization by RBTC in Portugal is reported by Fonseca, Lima, and Pereira

(2018), where capital accumulation and the share of highly educated workers are relatively low. They sorted routine tasks into manual and cognitive, and found sharp declines in the employment share of routine manual intensive occupations, while modest declines in routine cognitive intensive occupations. In Japan, the input of routine tasks has decreased, while that of non-routine has consistently increased (Ikenaga, 2013). Ikenaga examines empirically the relation between ICT capital and task inputs, and the results show that routine tasks are replaced by technology, and non-routine, analytic, and interactive tasks are complementary to ICT, as ALM assumed.

A study by Fernández-Macías and Hurley (2017) is remarkable because they considered the dynamics of the European labor market, and could not find evidence of the effect of technological changes in the labor market; while Goos et al. (2014) argued RBTC was a pervasive phenomenon in Europe. They found that in the employment structure change, before and after the crisis, the pattern is reversed; most job destruction occurred in the middle quantile of the crisis. Depending on the country, job polarization and the process of structural upgrading varied. There is basic homogeneity of institutional features in the labor market branded as the EU social model, such as minimum wage or collective bargaining system. But institutional diversity remains high, to the extent that institutional forces interact with technology, trade, or employment. This would give the message that understanding the institutional and policy contexts of a country matters when analyzing the patterns of polarization in the labor market.

2.3.2 Task-based view on an occupation

A striking study by Frey and Osborne warns that 47% of total employment in the United States is at risk of computerization in one or two decades (Frey & Osborne, 2013). With emerging interest in the fourth industrial revolution, as suggested by Schwab (2016), related studies have declared the end of work, and sparked the fear of technological unemployment in the public (Autor, 2015). Technology would replace humans, as the combustion engine did to horses, pushing people out of work (Benzell, Kotlikoff, LaGarda, & Sachs, 2015), so children would have newly-created jobs that do not exist now (WEF, 2016). In the OECD report, the share of automatable jobs is 6% in Korea (Arntz, Gregory, & Zierahn, 2016). Robotics or automation technology increase the productivity 10-30% and reduce the labor cost by more than 18% (Boston Consulting Group, 2015). However, these elaborate results could be exaggerated, since they assume that technology will replace certain jobs[5].

Studies on how many jobs will be created or destroyed by technology normally take a holistic view of a job. But technology has heterogeneous effects on tasks within an occupation. In other words, an occupation could be regarded as a complex bundle of tasks performed by each worker at the workplace. This approach is important, because automation is not meant to replace a job but rather replace repetitive and easily codifiable tasks (Autor, 2015). Levy and Murnane (2013) provide a clear example of how technology

[5] In this study, occupation is regarded as a broader concept within the category of jobs. For instance, one has a job as a reporter, but an occupation as a journalist.

changes work by changing how specific tasks are performed. When one washes dishes, she/he would clear and move the dishes from the table, apply detergent, make bubbles, scrub with a sponge, rinse and remove dirt, then dry and finally stack dishes in the cabinet. The machine called the dishwasher cannot complete all functions of actual people when they wash dishes; only part of them. The same principle can be applied to tasks at the workplace. This task-based view is accepted in many studies, including analyses on the polarization of wage structure; employment change; jobless recovery cycle; and skill contents change (Acemoglu & Restrepo, 2018; Black & Spitz-Oener, 2010; Firpo et al., 2011; Jaimovich & Siu, 2012; Spitz-Oener, 2006). Instead of expressing "what percentage of jobs will disappear or be replaced by technology," these studies analyze the effects of technological change on demand for routine or non-routine tasks. There is a great difference, since this distinction is based on the view of occupational composition (Arntz et al., 2016).

With task-based analysis, one can link the tasks required for workers to perform at the workplace with the skills the workers possess. This approach offers a connection between the aggregated demand for skill in the labor market, and the specific skills demanded for the given job activities (Autor & Handel, 2013). One study investigated the evolution of job skills distribution (using UK Skills Survey), concluding that technological advances promoted the use of cognitive and interactive skills; and that the demand for literacy, other communication tasks, and self-planning skills grew fast (Green, 2012), although Green added the importance of employee involvement in the workplace, and emphasized dividing all tasks into either routine or non-routine would be problematic. Technological advances

change the characteristics of occupations; thus, tasks regularly performed in an occupation could be changed. Task-based analysis also can capture the changes in task requirements over time. Hardy et al. (2015) used the 2003 and the 2014 Occupational Information Network (ONET) data[6] to construct the evolution of task content intensities in Poland from 1996 to 2014. They found increasing intensity of both non-routine and routine cognitive tasks, and decreasing intensity of both non-routine and routine manual tasks.

2.4 Literature on the Korean labor market

2.4.1 SBTC studies of Korea

Some studies pay attention to the innovations in information technology, and the corresponding changes to employment structures. Kang and Hong (1999) introduce skill-biased technology change. IT as the source of innovation of technology stimulates SBTC, reduces the share of blue-collar workers, and increases the share of white-collar workers, which in turn results in skill premium, or upskilling, and wage inequality. Kang and Hong use the ratio of R&D expenditures to total sales as a proxy of technological progress, and analyze the relationship of SBTC with the labor market from 1982 to 1997. However, their estimated results turn out to be insignificant. In the early 2000s, researchers tried to find the effects of ICT development in Korea on the labor market at 25 sub-major industry classification levels (Hu, Lee, & Seo, 2003; Hu, Seo, & Lee, 2002). They used wages;

[6] This database contains information on occupations including tasks, skills, education, work activities, etc. They will be dealt with in detail in Chapter 3.

employment; ICT investment; capital; and value-added data to reveal the relationship between ICT intensity (the ratio of real ICT investment to real value-added) and labor demand changes on skilled labor, but they could not provide significant evidence from 1993 to 1999. In the study by Kwon and Kim, they explain the relationship between the share of employment or wage and the share of computer investment at the industry level from 1981 to 1998 (Kwon & Kim, 2001). Although upskilling of labor has a significant positive statistical relationship with computer-related investment, the causality could not be clarified. Additionally, they could not clarify the relationship between ICT intensity and labor demand changes. Serrano and Timmer (2002) also witnessed that the increased supply of skilled and highly educated labor could not reveal the SBTC from 1974 to 1998.

The empirical studies on inequality and SBTC begin to come into force after the late 2000s. Choi and Jeong (2005) demonstrate the relation between technological change and the education wage premium in Korea. They find that the education wage premium from 1983 to 1993 was due to shifts in the supply of college graduates, while the shift from 1993 to 2000 was caused by shifts in labor demand. Using the Korean Labor and Income Panel Study (KLIPS) from 1998 to 2001, they estimated the return to educational and technological change by fixed effect model, and the effect of technology on wages. The latter estimates OLS and the proxy variables for technology are R&D intensity; TFP; ICT intensity; and percentage of scientists and engineers at industry level. But one should be cautious when interpreting the results of Choi and Jeong, since their estimations show that technological development is induced by the increase in skilled labor, showing the reverse

causality of skilled labor demand and technological change.

Hwang (2007) introduces the concept of task-specific skills. His study defines cognitive, physical, and sensory skills according to the common factor analysis from the Korean Dictionary of Occupations. Lee (2017) uses the Korean Occupational Wage Survey, Asia KLEMS data, Korean Input/Output (I/O) Tables, and the UN Comtrade database to demonstrate that rising wage inequality in the manufacturing industry is caused by skill-biased technological changes, and intensified competition on the global trade market. Lee and Kim (2013) use KLIPS from 1998 to 2008. They classify the industry into high, medium-high, medium-low, and low technology, according to the OECD Directorate for Science, Technology and Innovation. Labor demand has increased in industries affected by SBTC, and wage and employment have changed in favor of high-skilled labor, according to their results.

2.4.2 Polarization studies of Korea

Several studies deal with polarization itself, but rarely in view of RBTC or the task-based approach in Korea. Based on SBTC theory, Choi uses the index of technological advances at the industry level, and analyzes the impact of technology on the labor market. He uses the Korean Labor and Income Panel Survey (KLIPS) from 1998 to 2001 to estimate the educational premium, and finds significant results for male workers (Cheon et al., 2005). Some have found that using household total income as the index to measure the degree of polarization results in more severe polarization than using the typical Gini index in Korea

(Cheon, Kim, & Shin, 2006). They analyze polarization on the aspects of earning, employment, and consumption; and set high, middle, and low-paying occupations as thresholds of skill groups. Empirical results show evidence of polarization.

There have been attempts to explain polarization with task-based framework. Kim (2011) defines non-routine cognitive, routine, and non-routine manual tasks by the measure of employment shares of high-skilled, middle-skilled, and low-skilled workers. Skill levels of workers are defined by high-skilled workers (with sixteen years or more of schooling), middle-skilled workers (with twelve years of schooling, including college dropouts), and low-skilled workers (with less than twelve years of schooling). The decreasing price of computer assets raises relative wages of non-routine tasks, and demands for computerization in routine tasks also increases, confirming job polarization. He assumes that the worker's choice to participate in a specific task is dependent on educational attainment, based on Roy's self-selection model. However, this study has limitations: the characteristics of occupation are not defined by its tasks at the workplace, but by the educational attainment of workers.

Kim (2015) divided the occupational classification system of Korea into three skill groups, following Autor and Dorn (2006), based on task framework. According to the occupational classification, this study set non-routine cognitive as high-skilled; routine cognitive and routine manual as middle-skilled; and non-routine manual as low-skilled occupations. It found evidence of polarization and an enormous decrease in the employment share of middle-skilled occupations for three decades.

Chapter 3. Measurement of task intensity

3.1 Construction of measurement variables

3.1.1 Literature using task intensity

One of the purposes of this study is to offer a quantitative tool to measure the impacts of technological changes on the labor market, specifically labor demand based on task requirements. It is assumed that an occupation is a complex combination of various tasks, and that and the effect of the rising penetration rate of computers in the workplace, and the adaptation of robotics or automation for production processes, would be heterogeneous over each task and within each occupation. Hence, accurate and reliable data sources of information on occupations are necessary for this study. This study uses the Occupational Information Network (O*NET), which is the primary source of U.S. occupational information, developed under the sponsorship of the Department of Labor/Employment and Training Administration. The ONET database is a successor of the DOT (Dictionary of Occupational Titles) database, and has been in construction since 2003. The DOT was first published in 1938, and was the largest dataset created in response to the demand for properly matching jobs and workers and in support of job placement activities. Although updated periodically, the economy base shifted from heavy industries to information and services, and in the 1990s, an online database replaced the hard-copy book format of the DOT. The ONET is updated yearly to keep up with dynamic changes in the economy. The sources of the ONET database include job incumbents; occupational experts; analyst

ratings; customer and professional association input; employer job postings; government programs; transactional data; and web research. It contains hundreds of standardized occupation-specific descriptors on almost 1,000 occupations, and is continually updated. It reflects distinguishing characteristics in worker-oriented (worker requirements, experience requirements, and worker characteristics) or job-oriented (occupational requirements, workforce characteristics, and occupation-specific information) aspects. The former contains skills, knowledge, and abilities, among others; while the latter contains general work activities and work context, among others. It is depicted in Figure 8 the ONET content model.

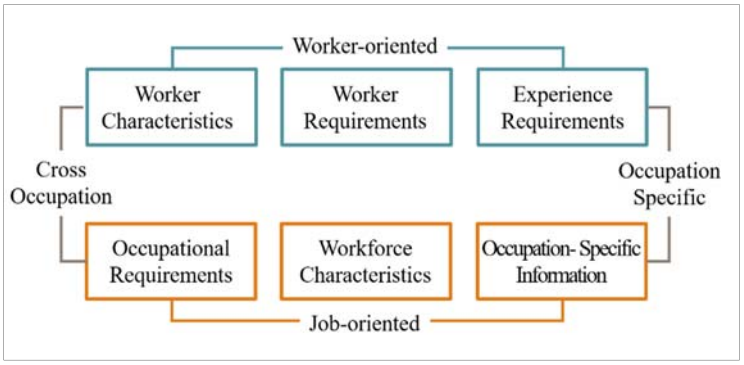


Figure 8 The ONET Content Model

No occupation requires only one task. Since tasks are high-dimensional bundles of work activities, they must be performed jointly to produce output at the workplace (Autor & Handel, 2013). Researchers have used the ONET to characterize the skills and measure the intensity of tasks within occupations, and relate the workplace tasks with skills of workers.

Blinder & Krueger (2009), Goos et al., (2014) and Alabdulkareem et al., (2018) use whole datasets of skills, generalized work activities, work context, ability, workplace skills, and knowledge; while Acemoglu and Autor (2011), Frey and Osborne (2013, 2017), Firpo, Fortin, and Lemieux (2011), Fonseca, Lima, & Pereira (2018b) use specific variables that represent the characteristics of occupations. Most studies that selectively use ONET variables follow Acemoglu and Autor (2011) in their classification. The previous version of the ONET, DOT, also has been adopted in many studies to illuminate the changes in the labor market (Autor, Levy, & Murnane, 2003[7]; Kim, Hong, & Hwang, 2019; Spitz-Oener, 2006). This study uses a selected list of ONET variables following previous studies and introduces the additional verifying process of applying the task classification system using network analysis.

For measuring the task content of occupations, there are two options: one is a pre-established database like the ONET; another is to survey individual workers, asking about the tasks they perform at their workplaces. There would be pros and cons for taking the ONET as the data source, since using ONET data of a certain year would not allow comparison over time. Studies using the ONET assume that the main tasks and characteristics of occupations hardly change, and that workers in the same occupations perform similar tasks. On the other hand, using databases constructed by experts would

[7] Before Autor et al. (2003), researchers already had used DOT to analyze the change in job skill requirement, "*Rumberger [1981], Spenner [1983, 1990], Howell and Wolff [1991], Wolff [1996, 2002], Handel [2000], and Ingram and Neumann [2000]*" quoted in Autor, Levy, & Murnane, (2003) footnote 12, p.1293.

lessen the possibility of measurement bias coming from workers' self-reporting (Sebastian & Biagi, 2018).

3.1.2 Task intensity measurement using ONET variables

To explicate the features of the difference of task importance within occupations, Figure 9 shows the different task intensities required for two different occupations: , "administrative services managers" and "power plant operators." The values of task intensity are from the ONET database. Some tasks are important at similar levels, but others at different levels. Time management and service orientation are highly required for "administrative services managers," while repairing, troubleshooting, and operation monitoring are more important to "power plant operators." The difference in task intensity makes it possible to deduce what the relevant tasks are within occupations, and sort the tasks according to the effectiveness of their usage.

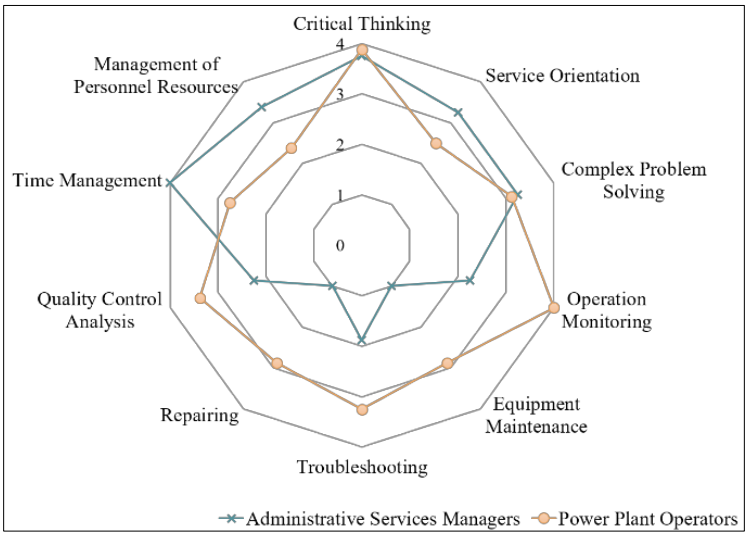


Figure 9 Conceptual feature of task intensities of different occupations

Analysis of the impact of technology on task requirement change is based on the assumption that technologies such as computers, robotics, and AI would replace repetitive and well-specified tasks referred to as routine tasks. In other words, analysis would be dependent on the classification of tasks, and the definition of their routineness. There is some alteration of selected variables among the studies using the DOT or the ONET database, depending on the purpose of their studies, such as computerization or offshoring. However, there is consistency and consensus of using task classification: non-routine analytic or interactive; routine cognitive or manual; and non-routine manual. Classification of tasks into distinctive categories is rooted in the *Handbook for Analyzing Jobs*, released

by the U.S. Department of Labor[8]. The non-routine analytic captures interactive, communications, managerial, and analytic reasoning skills, and represents activities requiring problem-solving and creativity. The ONET variable "Analyzing data or information" for example, which is classified as a non-routine analytic task, requires the understanding of underlying principles by breaking down data. The "Developing objectives and strategies" variable means establishing long-term objectives and the strategies used to achieve them, which is also in the non-routine analytic domain. This task classification would be applied to link the skills of workers. Workers who excel at performing non-routine analytic tasks are expected to be highly educated, and be complementary with ICT capital, usually computers. Measurement of non-routine manual tasks requires coordinated physical movement, interpersonal interaction, or language recognition. Manual and finger dexterity, and the operation of vehicles are examples of variables for manual activities.

[8] It was first published in 1972 and the explanations cited in this paper are from "*The Revised Handbook for Analyzing Jobs*."

Table 2 20 ONET variables description

Category	Description	Types of scales
Non-routine cognitive: Analytical		
4.A.2.a.4	Analyzing data or information	Importance
4.A.2.b.1	Making Decisions and Solving Problems	Importance
4.A.2.b.2	Thinking creatively	Importance
4.A.2.b.4	Developing Objectives and Strategies	Importance
4.A.4.a.1	Interpreting the meaning of information for others	Importance
4.C.1.c.2	Responsibility for Outcomes and Results	Content
4.C.3.a.2.b	Frequency of Decision Making	Content
Routine cognitive		
4.C.3.b.4	Importance of Being Exact or Accurate	Content
4.C.3.b.7	Importance of Repeating Same Tasks	Content
4.C.3.b.8	Structured versus Unstructured Work (reverse)	Content
Routine manual		
4.A.3.a.3	Controlling Machines and Processes	Importance
4.C.2.d.1.i	Spend Time Making Repetitive Motions	Content
4.C.3.b.2	Degree of Automation	Content
4.C.3.d.3	Pace Determined by Speed of Equipment	Content
Non-routine manual		
1.A.1.f.1	Spatial Orientation	Importance
1.A.2.a.2	Manual Dexterity	Importance
1.A.2.a.3	Finger Dexterity	Importance
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment	Importance
4.C.2.b.1.e	Cramped Work Space, Awkward Positions	Importance
4.C.2.d.1.g	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	Content

The tasks which can be performed by machines or computers should be well-defined and specified step-by-step. With the technological revolution of the 21st century, even what has been regarded as an inviolate region for humans is expected to be performed by machine learning, data mining, and artificial intelligence. The extent of automation will expand its influence. Measures of routine cognitive tasks include skills of precise attainment of set limits or standards; repeating the same tasks; or performing accurately. The variables from this category are mainly based on the ONET section “Routine versus challenging work (4.C.3.b)”. Routine manual tasks are represented by the ability to manipulate the rapidity or accuracy of making repetitive motions. Lastly, non-routine manual tasks are represented by the ability to move hands and feet in coordination in accordance with visual stimuli (Autor et al., 2003).

The 20 ONET variables selected for this study are listed in Table 2. Abilities (1.A section) and generalized work activities (4.A section) have two scale types: importance and level. Importance indicates the degree of importance of an ONET variable to the occupation, and level represents the degree to which an ONET variable is needed to perform the occupation. Since importance and level have a high correlation coefficient (0.9689), only the importance scale is used here. Some variables in Table 2 are offered with a scale of content which includes a variety of scales, with some unique and specific work context variables. Since each indicator scale has a different range, from 1 to 5 or from 1 to 7, ONET

also gives information on both the original rating score and the standardized score[9].

In order to apply the measurement system of task content by occupation to the Korean Standard Classification of Occupations (KSCO), several crosswalks of occupational codes are used. The ONET offers the occupational classification as O*NET-SOC Code (n=1110) and the crosswalk with SOC (Standard Occupational Classification) 2010 code (n=841). Since the Korean Statistical Information Service (KOSIS) offers the crosswalk between KSCO (Korean Standard Classification of Occupations) version 06 and ISCO (International Standard Classification of Occupations) version 08, the additional crosswalk between 2010 SOC and ISCO 08 offered by the US Bureau of Labor Statistics is used. Finally, as KLIPS offers the KSCO version 05 revised in 2000, the task contents of the Korean occupational system are constructed using crosswalks between KSCO 05-06. Constructing flawless and constant crosswalks between the ONET database and KSCO is tedious, but a most important part of this research. The crosswalks among KSCO versions are shown in Table 3.

In this study, 20 ONET variables are adopted, following previous studies. To make the variables comparable to previous studies and to ensure the validity more convincing, this research utilized variables which have been proven appropriate for analyzing occupational characteristics[10]. Table 2 shows the ONET variables chosen to represent the characteristics

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[9] https://www.onetonline.org/help/online/scales (Accessed on 3rd March, 2019)

[10] There are studies establishing their own classifications, for example, Blinder (2007) looked at the ONET data on job descriptions, tasks, and work activities of different occupations, and set up the question flow to construct four categories of tasks according to the feasibility of offshoring.

of “non-routine analytic and cognitive,” “routine cognitive,” “routine manual,” and “non-routine manual” (hereafter analytic, routine cognitive, routine manual, and manual, respectively). These definitions are mainly from Acemoglu and Autor (2011) and follow the studies determining complementary and additional ONET variables. Frey and Osborne (2017) defined nine bottleneck ONET variables to computerize. Three indicators of those bottleneck variables are applied here: “1.A.2.a.2, Manual Dexterity," “1.A.2.a.3, Finger Dexterity,” and “4.C.2.b.1.e, Cramped Work Space, Awkward Positions." Some of the variables that Firpo, Fortin, & Lemieux (2011) used as the measures of technological change and automation are in routine cognitive and routine manual categories: “4.C.3.b.7, Importance of Repeating Same Tasks," “4.C.3.b.8, Structured versus Unstructured Work (reverse)," "4.C.2.d.1.i, Spend Time Making Repetitive Motions," "4.C.3.b.2, Degree of Automation," and "4.C.3.d.3, Pace Determined by Speed of Equipment."

Table 3 Crosswalks between KSCO 04-05 and 05-06

KSOC 05	KSCO 04	KSCO 06	KSOC 05	KSCO 04	KSCO 06	KSOC 05	KSCO 04	KSCO 06
2	12, 51	11, 12, 13	41	51	951, 42	813	813	843
3	13	14, 15	42	51	952, 44	814	814	891
11	21, 22, 24	21	43	51	43	815	815	831, 843
12	21	22	44	51	41	816	816	852, 861, 881, 882
13	21	23	51	52	51	817	817	853
14	22	24	52	52	53	821	821, 722, 721	851, 841
15	23,33	25	53	52	52	822	822	832, 842
16	21 ,24, 34	26	61	61	61	823	823	832
17	24	27	62	61	62	824	824	891
18	24, 31, 34	28	63	61	63	825	825	892, 891
21	31, 32, 34	21	711	711	774	826	826	821, 822, 823
22	31	22	712	712	772	827	827	811
23	31	23	713	713	773, 792	828	827	812, 819
24	32	24	714	714	799	829	829	862, 863, 899
25	33	25	721	721	741, 743, 771	831	828	854
26	34	26	722	722	742	832	828	864
27	34	27	731	723	751, 752	833	828	855, 891

KSOC 05	KSCO 04	KSCO 06
28	34	28
29	34	331
311	419	311
312	419	312
314	419	313
315	34, 412, 421	391, 321
316	413	312
317	411, 419	314
318	414	399
32	41, 42	
321	421	321
322	422	392
323	419	399

KSOC 05	KSCO 04	KSCO 06
732	723	753
733	724	753 ,761, 762, 781
741	731	761, 791
742	732	843, 791
743	733	721, 722, 791
744	734	799, 892
751	741	811, 711
752	742	731, 891
753	743	721, 722
754	744	721, 822
811	811	843, 875
812	812	841

KSOC 05	KSCO 04	KSCO 06
841	831	871, 872
842	832	873
843	833	874, 875
844	834	876
911	913,914	951, 952, 941
912	914,915	952, 942
913	915,916	922, 992
914	916	941
915	912	953, 999
92	92	991
93	932	931
941	931	911
942	933	921

Finally, the task intensity for Korean occupational classification is calculated. The score of Analytic for each occupation is derived from the average score of variables of the non-routine cognitive section in Table 2. The result in Table 4 are with respect to KSCO 05, to minimize the loss during crosswalks.

Table 4 Task intensity of occupations (KSCO 05)

KSCO05	Analytic	Routine Cognitive	Routine Manual	Manual
11	1.87	0.25	-0.79	-0.24
12	1.70	-0.63	-0.94	-0.56
21	1.83	-0.20	-1.03	-1.27
23	1.31	-0.17	-1.11	-1.28
24	0.54	-0.17	-0.99	-1.22
27	-0.12	-0.94	-1.20	-0.49
30	1.12	-0.91	-1.33	-1.11
42	0.64	-0.31	-0.91	-0.67
111	0.22	-0.51	-0.46	0.40
112	1.50	0.50	-0.42	-0.56
113	1.17	0.05	-1.13	-1.65
120	0.74	1.41	-0.87	-0.30
131	0.98	0.23	-0.40	-0.29
132	0.71	-0.20	-0.91	-0.79
133	0.87	-0.88	-0.50	-0.63
134	0.51	0.85	-0.07	-0.03
135	1.28	-0.65	-0.84	-0.86
141	1.49	2.24	1.03	1.37
142	1.05	2.19	0.14	-0.35
143	1.09	0.86	-0.51	-0.24
144	-0.58	0.65	0.54	0.64
145	0.85	-0.52	-0.90	-1.25
151	0.75	-0.26	-1.06	-1.39
152	0.76	-0.88	-1.35	-1.24
153	0.65	-1.00	-1.29	-1.09
154	-0.05	-1.43	-1.36	-0.76
155	0.67	-0.24	-1.39	-1.32
156	0.42	-0.42	-1.20	-1.34
157	1.39	-0.58	-1.09	-1.27
161	0.66	-0.26	-0.51	-0.91
163	1.20	-1.01	-1.31	-1.53
164	1.45	0.03	-0.77	-1.28
165	0.73	1.20	-0.62	-1.42
171	1.58	0.39	-0.64	-1.09
172	0.84	0.46	-0.93	-0.95
173	0.54	-1.12	-1.30	-1.07
181	-0.16	-0.01	-0.98	-0.81
182	0.15	0.33	-0.87	-0.60

KSCO05	Analytic	Routine Cognitive	Routine Manual	Manual
183	0.39	-0.17	-0.53	-0.24
184	1.40	1.52	0.30	-0.24
211	-0.44	-0.26	-0.18	0.42
212	-0.47	0.57	0.74	0.10
213	0.75	-0.42	-1.48	-1.55
220	-0.27	0.73	-0.40	-0.31
231	0.82	0.01	-0.52	-0.60
232	0.25	0.06	-0.73	-0.72
233	0.88	-0.91	-0.99	-1.16
235	-0.34	-0.40	-0.10	-0.20
236	0.79	2.27	2.28	2.45
237	0.75	-0.32	-0.82	-0.55
238	0.14	-0.95	-0.52	-1.01
241	1.07	0.04	-1.19	0.02
242	0.47	1.80	2.21	0.98
243	1.10	2.31	-0.02	-0.11
251	0.41	0.02	-1.02	-1.15
252	1.32	-1.18	-1.26	-1.34
253	0.70	-1.69	-1.58	-1.35
261	0.17	0.92	0.30	-0.65
262	0.70	1.16	-0.68	-1.01
263	0.86	0.01	-0.79	-1.09
271	-0.43	-0.57	-0.93	-1.00
281	-0.37	0.43	-0.76	0.37
283	0.19	-0.80	-0.94	0.24
291	1.05	0.15	-0.88	-1.22
292	-0.10	0.08	-1.01	-1.49
293	0.41	1.43	-0.18	-0.63
311	-0.47	0.73	1.40	0.53
312	0.11	1.17	-0.43	-0.62
313	-1.18	1.76	-0.04	-0.69
314	-1.08	1.17	0.01	-0.71
315	-0.47	0.76	-0.75	-1.22
316	-0.02	-0.01	0.05	0.42
317	-2.24	2.72	0.70	0.15
318	0.17	0.27	-0.79	-0.28
321	-0.20	0.29	-0.67	-0.28
322	-1.43	-0.72	0.73	0.05

KSCO05	Analytic	Routine Cognitive	Routine Manual	Manual
323	-0.17	1.40	-0.38	-1.01
411	-0.90	1.00	-0.06	-0.24
412	-1.21	-0.42	-0.03	0.32
413	-1.16	0.08	-0.22	-0.43
414	0.17	-0.33	-0.76	-0.54
415	-1.17	-0.06	-0.24	-0.37
416	0.65	1.22	-0.43	-0.14
421	-0.63	-0.29	0.49	0.38
422	0.05	0.01	0.42	0.07
431	-0.90	-0.63	-0.27	0.23
432	-1.37	0.84	0.68	-0.90
441	0.89	0.49	-0.30	1.07
442	-0.01	0.53	0.15	0.31
443	0.77	0.79	-0.10	0.79
444	0.15	0.22	-0.28	0.08
511	0.55	1.69	-0.46	-1.02
512	1.25	0.88	-0.33	-0.77
513	1.78	-0.07	-1.07	-0.99
521	-1.25	-0.68	0.30	-0.32
522	-2.11	-0.56	0.13	-0.96
530	-3.41	-4.13	-1.55	-1.53
611	-2.27	-0.17	0.98	1.64
616	-0.10	-0.18	0.42	1.68
618	-1.57	-1.57	-1.12	1.36
630	0.26	-0.62	0.47	0.86
711	0.80	-1.30	-1.00	-0.68
712	-0.31	-0.28	0.76	1.29
713	-1.31	-0.04	0.55	0.14
714	-1.02	-1.75	0.51	1.62
721	0.80	0.15	0.30	0.68
722	0.81	0.20	0.82	0.67
731	0.60	0.80	0.32	1.87
732	0.28	1.10	0.24	1.78
733	0.00	0.03	0.29	1.62
741	-1.16	-0.92	-0.83	0.32
742	0.89	1.28	0.08	0.70
743	-0.57	0.94	0.87	0.79
744	-1.64	0.10	0.02	0.80

KSCO05	Analytic	Routine Cognitive	Routine Manual	Manual
751	-0.40	0.99	0.43	0.59
752	-1.07	-1.98	1.92	1.32
753	-0.59	-1.07	1.99	0.79
754	-1.77	0.13	0.16	0.42
811	-0.91	0.53	1.46	1.83
812	-0.34	-1.65	1.45	1.34
813	-0.88	0.69	1.47	0.88
814	-1.03	-2.33	1.67	1.09
815	-0.39	-0.32	1.84	0.65
816	0.17	0.20	1.31	-0.08
821	0.37	0.23	1.52	2.14
822	-0.55	-1.66	1.69	1.07
823	-0.30	-1.64	1.36	1.08
824	-1.15	-1.57	1.49	0.87
825	0.03	0.73	1.71	0.63
826	-2.15	-1.12	2.13	0.01
827	-0.64	0.26	1.87	0.57
828	-0.26	-0.17	2.15	0.80
829	-0.89	-0.17	1.55	0.74
831	-0.39	0.46	1.15	1.18
832	-1.23	0.76	0.89	0.63
833	-1.15	-0.28	1.09	1.39
841	0.27	0.51	1.32	1.94
842	-0.06	0.87	0.00	1.58
843	-2.08	-1.80	1.61	1.71
844	0.15	0.01	1.13	1.78
911	-0.41	-0.35	0.83	0.18
912	0.58	0.31	-0.15	-0.39
913	-0.69	-1.07	0.05	0.71
914	-1.91	-0.62	-0.02	0.29
915	0.66	-0.94	-1.38	-1.21
920	-0.48	-0.67	0.87	1.19
930	-1.45	-0.85	1.88	1.16
941	-0.84	-1.27	1.04	1.53
942	-2.03	0.33	0.15	1.06
981	0.53	1.38	0.88	0.90
982	-1.09	1.05	1.87	1.62

3.2 Confirmation of task classification

Although the classification of tasks follows the *"Handbook of Analyzing Jobs,"* and there is general consensus that measuring the routineness of occupations is the best way to capture the effect of technology (Goos et al., 2014), some studies are suspicious of this classification system (Green, 2012). Previous studies have accepted the classification of tasks constructed by Autor et al. (2003) or Acemoglu and Autor (2011). In this study, by introducing the concept of affiliation network, the classification system of tasks is tested to add accuracy and elaboration. Since an occupation requires a bundle of tasks to produce output, and the expected roles of occupations are different in every workplace, the intensity of utilizing each task would be different depending on the given set of tasks, and the characteristics of the occupations. To construct a network of tasks which are more frequently utilized and more commonly occur together within an occupation, each task of an occupation should be effective.

First, the scale of the importance of a task ($s \in S$) to an occupation ($j \in J$) is normalized to have a value between 0 and 1, $imp(j, s) \in [0,1]$. The measure $imp(j,s)=1$ means the skill s is essential to occupation j, while $imp(j,s)=0$ means s is not a necessary skill to occupation j. Then, to clarify the intensity of tasks utilized by an occupation, then calculated the revealed comparative advantage of each task, $rca(j, s)$, at an occupation as follows, using the importance of a task:

$$rca(j,s) = \frac{imp(j,s) / \sum_{s' \in S} imp(j,s)}{\sum_{j' \in J} imp(j,s) / \sum_{j' \in J, s' \in S} imp(j,s)} \quad \cdots\cdots \text{Eq. (7)}$$

The numerator denotes the relative importance of a skill to an occupation, while the denominator indicates the expected relative importance of a skill on aggregate. The effectiveness of tasks e(j, s) is set with threshold 1 so that

$$rca(j,s) > 1,\ e(j,s) = 1\ and\ e(j,s) = o,\ otherwise \quad \cdots\cdots \text{Eq. (8)}$$

Effectiveness of tasks indicates which tasks are actually useful and important in an occupation. Using effective tasks of each occupation provides information on how the tasks are simultaneously used in the workplace. The relationship between tasks could be defined as their co-occurring importance across occupations (Alabdulkareem et al., 2018).

The affiliation network consists of binary relationships between members of two sets of groups. In Figure 10, tasks are represented as the membership of occupation groups. There are no connecting edges among tasks; they are only connected via occupations, but by introducing biapartite projection, one can generate a social network of tasks based on co-membership in occupations. With one-mode projection on tasks, a network connecting tasks is generated, as shown in Figure 10.

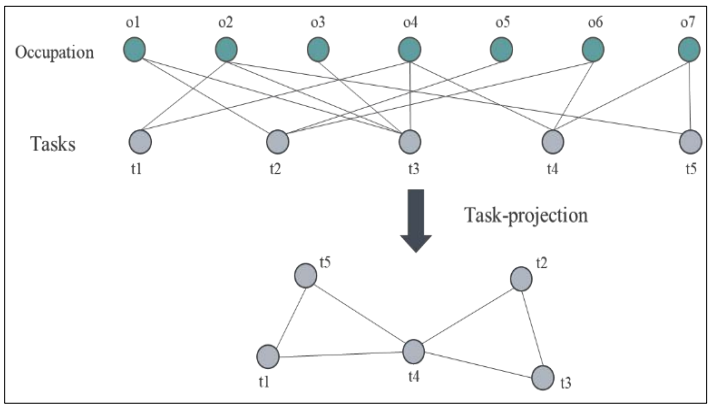

Figure 10 Concept of affiliation network of occupations and tasks

The affiliation network of task projection is generated using 151 occupations in Table 4 and 20 tasks in Table 2. If the classification presented in Table 2 is appropriate, the task mode projection is expected to yield a polarized network with two communities: one of cognitive tasks and the other, manual. As effectiveness of tasks varies within an occupation, the pair of tasks used together effectively within an occupation also varies. Hence, the minimum of the conditional probability of a pair of skills used effectively within one occupation is measured by the following equation:

$$\theta(s, s') = \frac{\sum_{j \in J} e(j,s) \cdot e(j,s')}{\max(\sum_{j \in J} e(j,s), \sum_{j \in J} e(j,s'))} \quad \cdots\cdots \text{Eq. (9)}$$

This similarity of skill pairs is calculated for all the skill pairs effectively used in each occupation. It shows which pair of skills is more frequently used together, and how a pair of skills supports each other. If the value of θ is higher, the co-occurring pairs are key

features across the occupations. The distribution of the value of θ is presented in Figure 11.

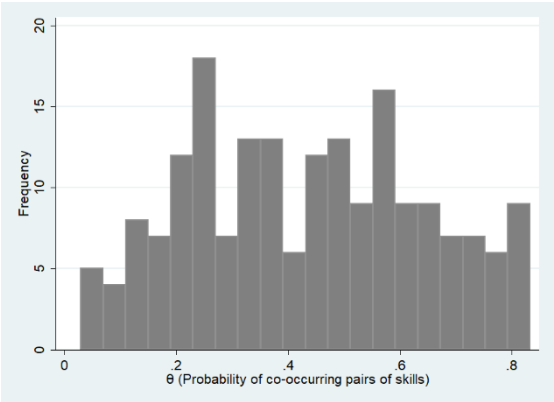

Figure 11 Distribution of probability of co-occurring pair of skills

Networks with total pairs of skills and the evolution of polarized networks with visualization threshold according to θ (zero to 0.5) are represented in Figure 12[11]. The threshold applied network of skill pairs is depicted in Figure 13. The minimum skill similarity (θ) is 0.4, revealing two communities of skill pairs and the derived task classification. To detect the community, it uses the "spin glass cluster method." In this community structure detection, a set of nodes connecting many edges inside the community is defined as a community[12].

[11] Spinglass community detection requires connected networks, and the network with a threshold larger than 0.6 is disconnected into two separated networks.

[12] For community detection, edge betweenness community (based on edge betweenness, detecting which modules are densely connected or sparely connected to other modules) and walk trap community (to find densely connected subgroups it detects shortest random walks tending to stay in the same community) are also considered, giving the same results but 'Structured versus

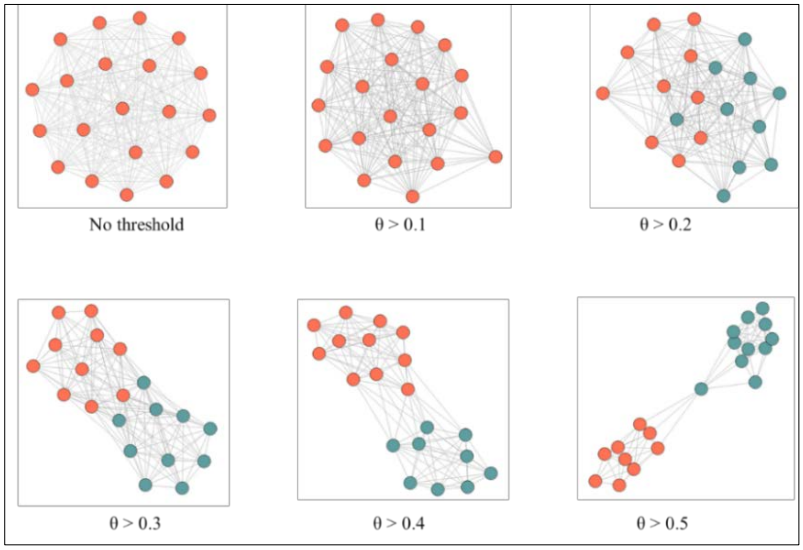

Figure 12 The evolution of skill pair community depending on the threshold

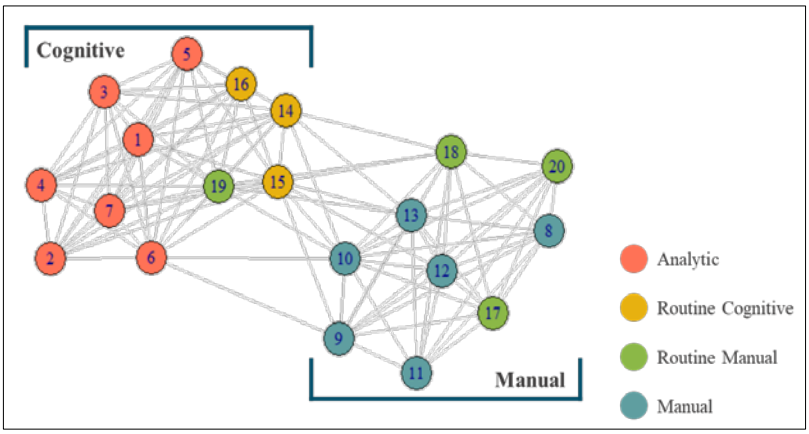

Figure 13 Network of polarized tasks at workplace

Unstructured Work′ (routine cognitive) and ′Degree of Automation′ (routine manual) switched in walk trap community detection.

As expected, the network of co-occurring tasks at workplaces is polarized, confirming that the classification of tasks in Table 2 is suitable to define the characteristics of tasks in the Korean occupational system. Constructing the network of tasks and detecting the polarized communities of tasks would open up opportunities to allow flexibility in selecting the variables of interest when adding new variables into task classification or examining specific task demand changes.

Chapter 4. Substitution or complementarity? The role of ICT in the labor market

4.1 Introduction

With rapid development of ICT, digital technologies have spread worldwide and changed much of people's lives, enhancing overall welfare and fostering the economic development by raising productivity and changing way of business. However, as far as workers are concerned, this digitalization can be a poisoned chalice because this striking achievement have caused the race between technology and skills that workers possess while rising polarization in the labor market (World Bank, 2016). There are also concerns about inequality or polarization issues in the Korean labor market which might have been caused by technological development. For Korea has relatively high competitiveness in information and communication technology (ICT) and experienced ICT-led innovative development (Larson & Park, 2014; Tahir, 2014), the impact of technology might be expected to be relatively considerable.

In late 1990s and early 2000s, the inequality of the labor market of US and other developed countries has been explained by weird simultaneous increase in demand and supply of high-skilled (highly educated) workers, which is confronted existing economic demand supply principle. This wage premium for high skilled labor was explained by skill-biased technological change hypothesis, meaning that technology advanced in favor of high skilled. However, in late 2000s economists witness the polarization labor demand for those

who are in the two extremes of wage distribution increases while that for the middle declines. This phenomenon was described by routine-biased technological change that advances in ICT substitute routine tasks which are repeatable, well defined and specified to be easily replace. Inequality studies with skill-biased technological change approach in Korea have failed to find the significant evidence of ICT until early 2000s but found after mid-2000s (Choi & Jeong, 2005; Hu et al., 2003, 2002; Hwang, 2007; Kang & Hong, 1999; Kwon & Kim, 2001; C.-I. Lee & Kim, 2013; Serrano & Timmer, 2002).

While a number of studies on wage premium is at level of individual educational attainment, this study pays attention to the fact that workers with the same demographic condition such as age, gender, educational attainment, and even occupation earn differently depending on the industry. According to the nature of specific industries, a firm would respond heterogeneously to the external technological shock, so is heterogeneous the degree of adopting or investing in technology which in turn effects a firm's decision for optimizing employment.

In this article, it is assumed that the technological advance appears in the form of decline in the price of ICT. A firm is expected to decide the quantity of inputs with given price of three input factors: labor, ICT and non-ICT capital. Since a firm's decision would be affected by industry's characteristics, using general Mincer equation, industry specific components of wage is assessed in first step. Also the effect of the occupation on wage is tested with respect to the three kinds of occupational characteristics-analytic, routine, and manual. The industry specific wage premium contains the wage differentials among

workers with the same demographic conditions but different industries. Then, accepting industry specific wage premium as instrumental variable which contains the average effect of industry on wage, it explores the labor demand change of the analytic, routine, and manual intensive occupations respectively. Finally, this study would demonstrate whether increasing input of ICT capital would reduce the demand for routine-intensive workers who are in substantially substitutable with ICT capital and would increase the demand for analytic-intensive workers who are in partially complementary with ICT capital. There has been debate on the role of technology in the labor market, whether technology is substitute or complementary with labor. The argue on the degree of these effects also might have been controversial from time to time but in the era of ICT when simple, routine and repetitive tasks can be more easily computerized than before, technology works differently according to the characteristics of occupation. Although firms with higher wage premium have more tendency to reduce the costly input factor in general, the empirical analysis of this study finds that the demand for analytic task intensive occupations earning high income has increased consistently. Meanwhile, the demand for low wage industry workers also has increased at the expense of the middle, causing the polarization in response to decline in price of ICT.

The remainder of this article is organized as follows. Section 4.2 reviews literature on how ICT has affected wage and employment in the labor market in US or other developed countries. The cases of Korean are also introduced. Next, the theoretical model of ICT capital impact on substitution or complementarity and the framework for empirical analysis

will be explained in 4.3. Section 4.4 presents the data used for estimation, and then 4.5 documents the results of empirical analysis. Section 4.6 concludes this study.

4.2 Literature review on effect of ICT on the labor market

4.2.1 Cases of developed countries

Many studies have dealt with the causality between development of ICT and the corresponding labor market structure change. There have been various indices to capture the technological development into empirical researches. Machin and Van Reenen (1998) use R&D intensity as the indicator of technology to suggest the evidence that technical change raised the importance of highly skilled in the United States and several OECD countries (United Kingdom, Denmark, France, German, Sweden and Japan) in 1990s. For similar purpose to explain the increasing demand for high-skilled labor, the investment in computers and R&D or computerization was directly measured by the percentage of workers who reported themselves as users of computers with keyboards at work in U.S. (Autor et al., 1998; Berman et al., 1994). In early stage of studies, computer investment was defined as the sum of firm's expenditure in desktop terminal, personal computers, printers, keyboard and other integrated devices (Autor, Levy, & Murnane, 2003). To construct a variable for computerization, Kim and Hwang (2013) use the total real gross fixed capital of computing equipment, software, and communication equipment for ICT in U.S., offered by EU KLEMS. Atasoy (2013) analyzes the effects of the broadband internet access expansion on the labor market. The author finds that getting access to broadband is

associated with increase in the employment rate since this broadband technology is complementary to highly skilled workers and increases the scale of firms' labor demand. For cross country analysis, the ICT and non-ICT capital is introduced (Michaels, Natraj, & Van Reenen, 2014). This study presents that industries with faster ICT development shifted the labor demand from middle-skilled to high-skilled labor, generating employment polarization.

The argument of effects of ICT is expanding to those of recently outstanding achievement in industrial robots with aid of ICT. Acemoglu & Restrepo (2017) report the negative relation between increasing usage of robots and employment and wages from 1990 to 2007 on the U.S. local labor market. Not all researchers provided pessimistic results. Graetz and Michaels (2015) analyze the relation of the modern industrial robot adoption and labor productivity. In their study, a new instrument variable is introduced that relies on robots' comparative advantage in specific tasks that robots perform. Industrial robots are estimated to increase both value added and labor productivity, raising countries' average growth rates. In German manufacturing industry, there was no evidence of total job loss when exposed to industrial robot, although substantial influence existed in the composition of aggregate employment (Dauth, Findeisen, Suedekum, & Woessner, 2017). In this study, the adoption of robots is assessed to keep the incumbent labor at workplace while forcing them to endure low wage. Instead of destroying existing jobs, robots or the managers who actually decide to adopt the robots choose to reduce the job opportunity for younger people who are outside of the labor market.

One should keep in mind that using R&D intensity, R&D expenditure or computerization as proxy for technology advancement could cause biases as intensity of ICT usage depends on nature of industry (Autor et al., 1998). Any kind of adoption or investment in ICT can be directly related to the industry-specific characteristics.

4.2.2 Literature on Korea

Schneider (2010) analyzed the effect of ICT investments on labor demand of high-, middle-, low-skilled workers in the 14 countries' labor markets, especially from 1977 to 2005 for Korea[13]. The author's estimation result rejected SBTC hypothesis when single country was tested, while impact of ICT in high-skilled workers' relative compensation only before 1995. Kang and Hong (1999) view development of ICT and market-opening as the source of technological innovation which is heading for SBTC, increasing the skill premium and wage inequality. In their study, white-collar workers are defined as skilled labor and the ratio of the expenditure on R&D over sales is used as the proxy of technology advance in manufacturing industry. From 1976 to 1996, the wage bill share of white collar begins to decrease after 1991. This should be understood with distinctive circumstance of Korea in 1980s. In early 1980s, there had been reformation in education and supply of labor with bachelor's degree increased steeply and in late 1980s, the blue collar labor formed unions and insisted improve the labor condition including wage. These two factors might

[13] Due to data availability of 14 different countries, the years of staring vary from 1970 to 1995 but the end of time period is fixed as 2005.

have affected the labor supply and wage bill share in 1990s at the same time. After all, they could not find the empirical evidence of SBTC in the Korean labor market in the period within 1982-1997. Hu, Lee, & Seo (2003) and Hu, Seo, & Lee (2002) use wage, employment, ICT investment, capital and value-added data to reveal relation of the ICT intensity (the ratio of real ICT investment to real value-added) and labor demand change on skilled labor, but they could not suggest the significant evidence during 1993 to 1999. A number of literature that have attempted to explain wage inequality of Korea have failed to present significant result using various indicators including ICT intensity at industry level, wage bill shares and investment in computer related equipment. One of the reason is that because of the unique characteristics of the Korea where a relatively high proportion of tertiary and higher-educated workers makes it difficult to ascertain the actual income dispersion, hindering the measurement of income inequality.

Polarization in the labor market is taking place by replacing the middle-skilled workers who intensively perform the routine tasks which are repetitive, well structured, and easily codified and substituted by computers or ICT capitals (Kim, Hong, & Hwang, 2019). Inferred from previous literature on Korea, the analysis sample from 1977 to 2005 conducted by Schneider may not be appropriate to reflect the context of technology development and penetration in Korea as well as the Korean labor market. It is turned out to be not efficient to use the R&D expenditure as proxy of ICT technology advance to estimate the labor demand change caused by development of ICT. Adopting the direct input of ICT investment data would help reveal the firm's decision to adjust the input of routine-

incentive workers when the price of ICT declines. This is the main assumption of this study.

4.3 Empirical estimation model: Task wage premium

4.3.1 Framework of previous studies

Since 1970s there has been argument about Solow's paradox that computer would not increase productivity as opposed to people's expectation. But now it looks clear that ICT plays critical role as economic growth engine and boosts productivity and innovation activities of firms by increasing the efficiency or opportunity of producing and providing the goods and service (Cardona, Kretschmer, & Strobel, 2013; Colecchia & Schreyer, 2002; Vu, 2011). To define the role of ICT in the labor market, several studies have focused the complementarity of ICT with high-skilled workers and substitution with middle-skilled workers using simple empirical regression (Michaels, Natraj, & Van Reenen, 2014; Van Reenen, 2011b). The framework constructed by Michaels et al. (2014) is introduced as one example of the estimation methodology. They used wage bill share of skill groups as a dependent variable, where wage bill is usually defined as

$$Share_S = \frac{w_s N_s}{\sum_S w_s N_s}, s \in \{H, M. L\} \quad \text{Eq. (10)}$$

N_s is the working hour done by each skill group s and w_s is the hourly wage of skill

group[14]. For the ICT capital or ICT investment data, previous studies have used a data set provided by KLEMS. Empirical analysis successfully explained the impact of ICT in the U.S. labor market (Michaels et al., 2014). When considering the short-run cost function of a firm utilizing high-, middle-, and low-educated workers (denoted as H, M, and L respectively) and ICT and non-ICT capital, the cost function CV(.) can be written as:

$$CV(W^H, W^M, W^L; C, K, Q) \quad \cdots\cdots \text{Eq. (11)}$$

where K is non-ICT capital service, C is ICT capital service, and Q is value added. Using Shepard's lemma, the cost minimization implies the following. The unobserved heterogeneity between industry-by-country pairs (η_{ij}), relative wage differentials between countries (country-by-year effect, ϕ_{jt}), and fixed effects are all considered.

$$Share^s = \phi_{jt} + \eta_{ij} + \alpha_{CS}\ln(\frac{C}{Q})_{ijt} + \alpha_{KS}\ln(\frac{K}{Q})_{ijt} + \alpha_{QS}\ln Q_{ijt} \quad \cdots\cdots \text{Eq. (12)}$$

where *i*=industry, *j*=country, *t*=year. Then key estimating equation is required as following:

$$\Delta Share^s = c_j + \beta_1\Delta(C/Q)_{ijt} + \beta_2\Delta(K/Q)_{ijt} + \beta_3\Delta\ln Q_{ijt} \quad \cdots\cdots \text{Eq. (13)}$$

Before the study of Michaels, Natraj, and Van Reenen (2014), Schneider (2010) also used the similar estimation model, setting the wage bill as a dependent variable and using

[14] Instead of using hours worked, the number of employees also yields consistent result.

ICT investments data of EU KLEMS, however, the results of estimation mostly rejected SBTC. The case of Korea was included in the work of Schneider but revealed to be also insignificant when analyzing from period of 1977-2005.

4.3.2 Alternative framework for theoretical prediction

The following explains the framework of this study to explain the effect of ICT on the labor market, partially based on that of Autor, Levy and Murnane (2003) as well as of Yang and Shim (2014). It assumes the constant return to scale taking Cobb-Douglas production function,

$$Q = (L_R + C)^{1-\alpha} {L_{NR}}^{\alpha}, \alpha \in (0,1) \quad \cdots\cdots \text{Eq. (14)}$$

where L_R and L_{NR} are routine and non-routine labor inputs and C is ICT capital. ICT capital is supplied perfectly elastically at market price *r* where *r* is falling exogenously with time by technological advancement (ALM, 2003).

Consider a profit maximizing firm with input factor of routine and non-routine labor and ICT capital with prices w_R, w_{NR}, and *r*, respectively.

$$\max\{C, L_R, L_{NR}\}\ PQ - w_R L_R - w_{NR} L_{NR} - rC \quad \cdots\cdots \text{Eq. (15)}$$

As the price of ICT capital declines by assumption, the ratio of w_{NR}/r increases. If the polarization arises with decline of *r*, the labor input ratio L_{NR}/L_R would change. The

steady state of it will give $\frac{w_{NR}}{r} = 1$. So keeping the elasticity of substitution between non-routine and total routine (sum of routine intensive labor and ICT capital) inputs as unit 1, let the elasticity of substitution between routine intensive labor and ICT capital as $\frac{1}{1-\mu} > 1$ with $0 < \mu < 1$. Then the equation will be

$$Q = ({L_R}^{\mu} + C^{\mu})^{\frac{1-\alpha}{\mu}} {L_{NR}}^{\alpha}, \alpha \in (0,1) \quad \cdots\cdots \text{Eq. (16)}$$

Without loss of generality, the price of labor is exogenously determined by the labor market and a firm takes it as exogenous factor which is beyond firm's control(Yang & Shim, 2014). One important assumption here is that a firm would have great incentive to replace more expensive input factor with cheaper one (Borjas & Ramey, 2000). With wage differentials across the industries, firms in the different industries would respond differently but all toward change input quantity-employment. With the equation above the polarization of employment responding to the decline of ICT price and increase of $\frac{w_{NR}}{r}$. In higher wage industry, changes in the ratio of employment share between non-routine and routine intensive workers would be greater.

If wage of industry 1 is higher than industry 2 by factor $\lambda > 0$, λ is assumed to be controlled by exogenous factors determined in the labor market. Then wages for routine and non-routine workers in industry 1 and industry 2 are as follows.

$$w_{NR,1} = (1+\lambda)w_{NR,2} \;\; and \;\; w_{R,1} = (1+\lambda)w_{R,2} \quad \cdots\cdots \text{Eq. (17)}$$

In steady state, the first order conditions (f.o.c.) of firm's problem with respect to L_R, L_{NR}, C are as following respectively. The subscript for industry *i* is omitted.

$$\frac{w_R}{P} = \alpha \frac{Q}{L_{NR}} \quad \cdots\cdots \text{Eq. (18)}$$

$$\frac{w_{NR}}{P} = (1-\alpha)\frac{{L_R}^{\mu}}{{L_R}^{\mu}+C^{\mu}}\frac{Q}{L_R} \quad \cdots\cdots \text{Eq. (19)}$$

$$\frac{r}{P} = (1-\alpha)\frac{C^{\mu}}{{L_R}^{\mu}+C^{\mu}}\frac{Q}{C} \quad \cdots\cdots \text{Eq. (20)}$$

Then using the wage relation between industry 1 and industry 2, the followings are obtained dividing each f.o.c. of industry 1 by industry 2.

$$(1+\lambda) = \frac{P_1}{P_2}\frac{Q_1}{Q_2}\frac{L_{NR,2}}{L_{NR,1}} \quad \cdots\cdots \text{Eq. (21)}$$

$$(1+\lambda) = \frac{P_1}{P_2}\frac{Q_1}{Q_2}\frac{{L_{R,2}}^{1-\mu}}{{L_{R,1}}^{1-\mu}}\frac{{L_{R,2}}^{\mu}+{C_2}^{\mu}}{{L_{R,1}}^{\mu}+{C_1}^{\mu}} \quad \cdots\cdots \text{Eq. (22)}$$

$$\frac{P_1}{P_2}\frac{Q_1}{Q_2} = \frac{{C_1}^{1-\mu}}{{C_2}^{1-\mu}}\frac{{L_{R,1}}^{\mu}+{C_1}^{\mu}}{{L_{R,2}}^{\mu}+{C_2}^{\mu}} \quad \cdots\cdots \text{Eq. (23)}$$

Combining the two equations Equation (18) and (19) gives

$$\frac{C_1}{L_{R,1}} = (1+\lambda)^{1/1-\mu}\frac{C_2}{L_{R,2}} \quad \cdots\cdots \text{Eq. (24)}$$

For simplicity, let $\phi = (1+\lambda)^{1/1-\mu} > 1$ and $\kappa_i = \frac{C_i}{L_{R,i}}$ then $\kappa_1 = \phi\kappa_2$.

Combine the last two f.o.c. Equation (22) and (23),

$$\frac{w_R}{r} = {\kappa_i}^{1-\mu} \quad \cdots\cdots \text{Eq. (25)}$$

Assume that the ratio between routine intensive worker wage and the price of ICT capital increases with decline in ICT price with development of technology, and differentiate equations with respect to $\frac{w_R}{r}$.

$$\frac{d\kappa_i}{d\frac{w_R}{r}} = \frac{{\kappa_i}^{\mu}}{1-\mu} > 0 \quad \cdots\cdots \text{Eq. (26)}$$

$$\frac{d\kappa_1}{d\frac{w_{R,1}}{r}} = \frac{{\kappa_1}^{\mu}}{1-\mu} = \phi^{\mu}\frac{d\kappa_2}{d\frac{w_{R,2}}{r}}, \qquad \frac{d\kappa_1}{d\frac{w_{R,2}}{r}} = \phi\frac{d\kappa_2}{d\frac{w_{R,2}}{r}} \quad \cdots\cdots \text{Eq. (27)}$$

Equation proves itself that with decline in the cost of ICT capital, the ICT capital deepens. Since $\phi > 1$, this deepening is more severe in industry with higher wage. This coincident result backs up the argument that firms in higher wage industry have more incentive to reduce labor cost in response to decline of ICT capital rental cost.

For the employment side implication, consider a factor defined as ratio of non-routine over routine intensive workers, $\chi_i = \frac{L_{NR,i}}{L_{R,i}}$ and change of $\frac{w_R}{r}$.

$$\frac{w_{R,i}}{w_{NR,i}} = \frac{1-\alpha}{\alpha}\frac{\chi_i}{1+\kappa_i{}^{\mu}}\frac{d\kappa_i}{d\frac{w_R}{r}} > 0 \quad \cdots\cdots \text{Eq. (28)}$$

The left-hand side of the equation is constant within an industry, meaning that $\frac{\chi_i}{1+\kappa_i{}^{\mu}}$ is also constant. With decline of ICT rental price, capital over routine intensive workers, κ_i increases as $\frac{w_R}{r}$ increases, hence $\frac{\mathrm{d}\chi_i}{\mathrm{d}\frac{w_R}{r}} > 0$ which implies polarization in employment.

$$\frac{\mathrm{d}\chi_i}{\mathrm{d}\frac{w_R}{r}} = \frac{w_{R,i}}{w_{NR,i}}\frac{\alpha\mu}{1-\alpha}\kappa_i{}^{\mu-1} \quad \cdots\cdots \text{Eq. (29)}$$

As $\kappa_1 = \phi\kappa_2$ and $w_{R,1} = (1+\lambda)w_{R,2}$, it is expected that the extent of polarization would dependent on the wage structure of industries.

4.3.3 Estimation of employment share using industrial wage premium

Industry wage premium reflects the unobserved fixed characteristic of an industry. Workers with the same educational attainment, age, gender and occupations would get different wage depending on the industries they belong to. This industry specific differential is captured by industrial wage premium in this study. This study the framework which explains higher initial industry wage would affect the degree of employment polarization. For more effective and efficient estimation, the instrumental variable developed by Shim and Yang (2010) is adopted and adjusted here. The first step is to

estimate the industrial wage premium using general Mincer wage equation for each year.

$$\ln w_{hit} = X_{hit}\beta_t + w_{it} + \varepsilon_{hit} \quad \cdots\cdots \text{Eq. (30)}$$

where $\ln w_{hit}$ is the log wage of worker *h* in industry *i* at year *t*. X_{hit} is the demographic cell, with information of educational attainment (Under high school/high school graduates/college graduates /more than bachelor's degree) –age (15-24/25-34/35-44/45-54/55-64/65+) - gender - occupation (analytic/routine/manual). Then the industry fixed effect w_{it} is estimated as the measure of wage premium of each industry. All wage premiums are acquired as the coefficient of industry dummy in Equation (30) except for one industry omitted[15]. Then the employment share change is estimated as follows:

$$\Delta s_{ijt,t+k} = \theta_j \widehat{w}_{it} + \eta_{ijt} \quad \cdots\cdots \text{Eq. (31)}$$

where $\Delta s_{ijt,t+k}$ is the change in employment share of occupational task group *j* in industry *i*. In the second stage, regression is conducted for three occupational task groups-analytic, routine, and manual separately. To avoid problems accompanied by using estimated value as regressor and reduce the possibility of heteroscedasticity in error term, regression is weighted by sample size of each industry in initial year *t*. Taking the estimated industry wage premium as explanatory variable in Equation (30), this two-step regression will catch

[15] The Agriculture, hunting, forestry and fishing (1) is omitted to make values positive in 1998.

the scene and help understanding the employment share and wage structure evolution over two decades in Korea.

4.4 Data and summary statistics

4.4.1 Data source of ICT capital

The data source of ICT and non-ICT capital data is EU KLEMS. EU KLEMS offers harmonized sectoral dataset for EU countries and other advanced countries such as US, Korea, Japan, and others. Since the purpose of this database is to measure the economic growth, productivity, technological change, and employment at industry level from 1980 onwards[16], to get consistency and compare the results with the previous literature, this study also uses data offered by . For data of Korea, the database is taken from the Korea Industrial Productivity (KIP) database. The data covers from 1980 to 2012. To construct the sample containing industrial information of ICT and labor, the industry classification is integrated into fifteen Korean Standard Industrial Classification (KSIC) 2000. The industry classification crosswalk between KLEMS and KLIPS presented in Table 5. It contains the information on industrial classification used in this study.

[16] http://www.euklems.net/, EU KLEMS is an industry level, growth and productivity research project. EU KLEMS stands for EU level analysis of capital (K), labor (L), energy (E), materials (M) and service (S) inputs. (Last access on 24th April 2019)

Table 5 Information on industrial classification

Author's own classification	Korean Standard Industrial Classification (KSIC)	EU KLEMS classification	KSCO 05	KLIPS Code at two-digit	Manufacturing /Service
1	Agriculture, hunting, forestry and fishing	A to B	A B	01-02 05	Manufacturing
2	Mining and quarrying	C	C	10-12	Manufacturing
3	Total manufacturing	D (15 to 37)	D	15-37	Manufacturing
4	Electricity, gas and water supply	E	E	40-41	Manufacturing
5	Construction	F	F	45-46	Service
6	Hotels and restaurants	H	G H	50-52 55	Service
7	Transport and storage	60 to 63	I	60-63	Service
8	Financial service and insurance activities	J	K	64	Service
9	Real estate activities	70	L	70-71	Service
10	Information and communications	64	J	64	Service
11	Real estate activities and renting and leasing	71 to 74	M	72-5	Service

Author's own classification	Korean Standard Industrial Classification (KSIC)	EU KLEMS classification	KSCO 05	KLIPS Code at two-digit	Manufacturing /Service
12	Public admin and defense; compulsory social security	L	N	76	Service
13	Education	N	O	80	Service
14	Health and social work	N	P	85-86	Service
15	Other community, social and personal services	O, P, Q	Q	8-88	Service
			S	90-93	
			T	95	
			R	99	

For the measure of capital, it uses ICT and non-ICT compensation and value added directly offered by Asia KLEMS[17]. The structure of ICT capital is classified in two categories. First, ICT equipment is asset of computer hardware which had been offered as computing equipment (EU KLEMS description, IT) and telecommunications equipment (description, CT) and second is computer software (Timmer, O'Mahony, & van Ark, 2007). Asia KLEMS offer the capital compensation(CAP) in forms of value added minus labor compensation[18] and the ICT capital compensation(CAPIT) in forms of share in total capital compensation. The unit of capital compensation is in millions of Korean won and all series is put on a 2005 reference year, no further conversion is necessary. ICT capital in log value and the share of ICT capital in total capital by fifteen industry level are presented in Appendix Figure A 1 and Figure A 2, respectively.

In this article, the price of ICT is assumed to be decreased with technological advance. The relative producer price indexes will give hint to this assumption. When the price at 2010 is set to be 100, the price of semi-conductor which is the key component of computer and computers & peripherals shows sharp drops after 1980s and stabilized after 2010. Meanwhile the price indexes of goods, services, and manufacturing products consistently increase by comparison. Figure 14 shows the relative price changes from 1975 to 2018.

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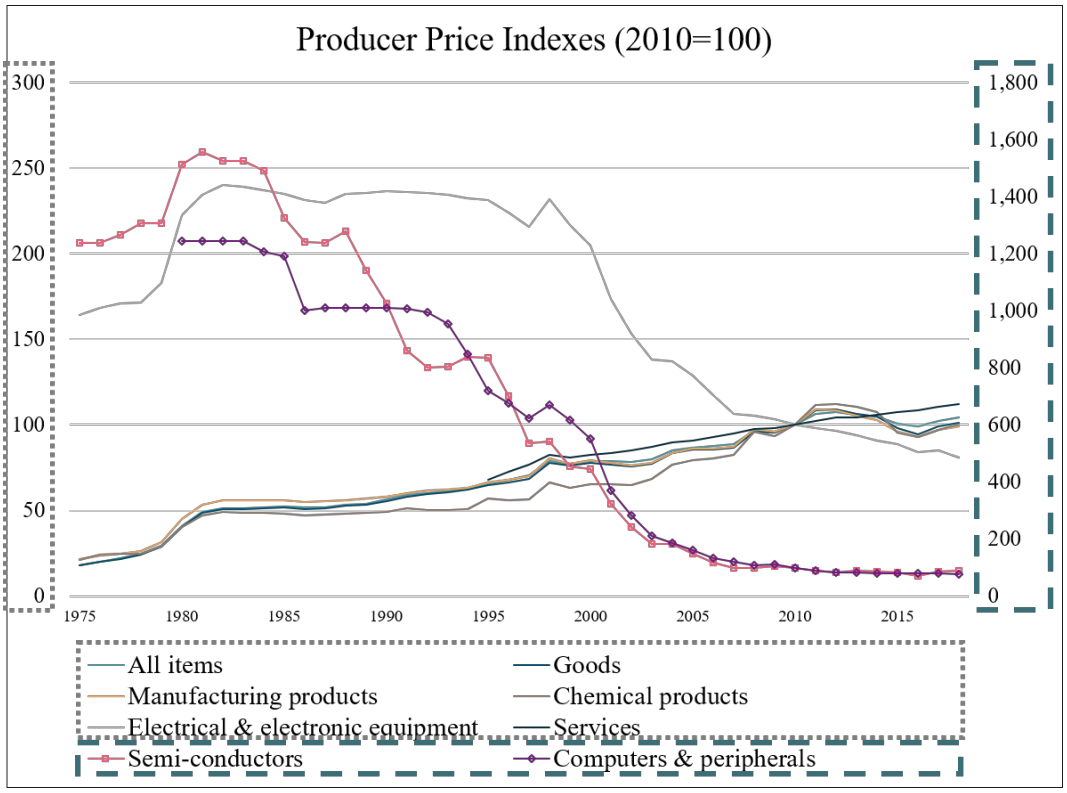
[17] Available at http://www.asiaklems.net (Last access, 29th April 2019)

[18] Labor compensation (LAB) is calculated by applying the ratio of hours worked by total persons engaged to hours worked by employees to compensation, assuming the self-employed receive the same hourly wages as employees (Jäger, 2016).



Data source: The Bank of Korea

Figure 14 Producer price indexes of ICT related and goods and services, 1975-2018

A number of studies use EU KLEMS data to investigate the effect of ICT, non ICT capital, and value added on wage or employment in many developed countries. Hidalgo et al., (2016) analyze the ICT adoption and labor demand of Spain. And they confirm the complementarity of ICT capital with highly skilled labor. Michaels, Natraj, and Van Reenen (2014) and Van Reenen (2011) also use EU KLEMS to describe ICT-based polarization of the U.S. labor market. Schneider (2010) conducts the same analysis on fourteen countries to compare the influence of ICT at 23 industry level from 1970s or 1980s

to 2005 depending on data availability. Yang and Shim (2014) investigate the ICT capital growth rate and the corresponding job polarization and wage differentials in US.

4.4.2 Data of employment and wage

In this article, the data of wage, demographic and educational attainment should be constructed at individual worker's level. The main data source for labor part is Korean Labor & Income Panel Survey (KLIPS), supervised by Korea Labor Institute and supported by the Ministry of Employment and Labor. KLIPS is a longitudinal study of a representative sample of Korean households and individuals living in urban areas. It is conducted annually on a sample of 5000 urban households and the members of the households who aged 15 or order. KLIPS started from Wage1 in 1998 with '1998 original sample' households (n=5,000) and added consolidated original sample of Wave 12 in 2009 to overcome the limit of representability caused by sample attrition. The latest Wave 20 results released in 2018. It contains the information on economic activities, income, and expenditures of households. At individual level, it offers monthly wage data as well as formal schooling, employment type, job satisfaction, and others. It offers four individual weights of both cross-sectional and longitudinal for 1998 original sample (1-20 waves) and consolidated sample (12-20 waves) respectively to adjust the scale by using the projected increase rate in population.

Although KLIPS is available from 1998 to 2017, KLEMS provides data to 2012, therefore the time period for analysis is set from 1998 to 2012. As reviewed in Chapter 2,

most studies on Korean cases which dealt with the effect of ICT on the labor market showed insignificant results when the period was set before 2000s. Therefore, it is reasonable to analyze the effect of ICT investment on wage and employment from 1998 to 2012. The demographic cells are constructed based on age-education-gender-occupation. Four educational groups and six age groups divided by worker's age. The sample analysis only workers with labor income, both regular and non-regular jobs but self-employed workers are excluded because this study deals with the effect of technology on labor income. All missing variables of education, wage, job types and wages with zero value are dropped for accurate analysis, and the numbers of observation samples used for analysis is 65,057.

4.4.3 Characteristics of the occupations

As introduced in Chapter 3, the occupations are classified into three categories according to the values of task intensity in Table 6. In this article instead of dividing four, takes three for occupational level analysis.

Each ONET variable has importance scale that indicates the degree of importance of a variable to the occupation and level represents the degree to which a ONET variable is needed to perform the occupation. The scales of each task content is standardized to have zero mean and unit standard deviation. There are 151 3-digit KSCO 05 occupational code, and for each occupation, the values of analytic, routine, and manual are measured[19]. Table

[19] The calculation is explained in Chapter 3 in more detailed way

6 is the summary of characteristics of major occupational groups. For instance, for major group 5 ‘Service workers’, it rates routine index scores highest among task contents, hence it is assigned as routine occupation.

Table 6 20 ONET variable to measure the task content of occupations

Non-routine analytic and cognitive	Analyzing data or information, Making Decisions and Solving Problems, Thinking creatively, Developing Objectives and Strategies, Interpreting the meaning of information for others, Responsibility for Outcomes and Results, Frequency of Decision Making
Routine	Importance of Being Exact or Accurate, Importance of Repeating Same Tasks, Structured versus Unstructured Work (reverse), Controlling Machines and Processes, Spend Time Making Repetitive Motions, Degree of Automation, Pace Determined by Speed of Equipment
Non-routine manual	Spatial Orientation, Manual Dexterity, Finger Dexterity, Operating Vehicles, Mechanized Devices, or Equipment, Cramped Work Space, Awkward Positions, Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls

4.5 Empirical analysis results

4.5.1 The labor demand change across industries

According to the Economically Active Population Survey, the number of workers and the mean monthly wage have continuously increased from 1993 to 2018 except 1998 employment (Figure A 33.). This instant drop which might be caused by financial crisis in

1997 is fully recovered in1999 and the wage has been increased even in crisis. Figure 15 shows the labor demand changes in fifteen industries are heterogeneous although total employment increased in period of 1998-2012. Industry 1-15 are ranked by their mean monthly real wage in 1998, industry 1 is the lowest and 4 is the highest. Numbering industry follows the Table 5, and analytic, routine, and manual occupations are based on major occupation as classified in Table 7.

Table 7 Task content occupational group

Task group	10 KSCO major group
Non-routine analytic	[1] Administrative, executive and managerial workers [2] Professionals [3] Technicians and semi-professionals
Routine	[4] Clerical workers [5] Service workers [6] Sales workers [9] Craft and related trades workers
Non-routine manual	[7] Skilled agricultural, forestry and fishery workers [8] Equipment, machine operating and assembling workers [10] Elementary workers

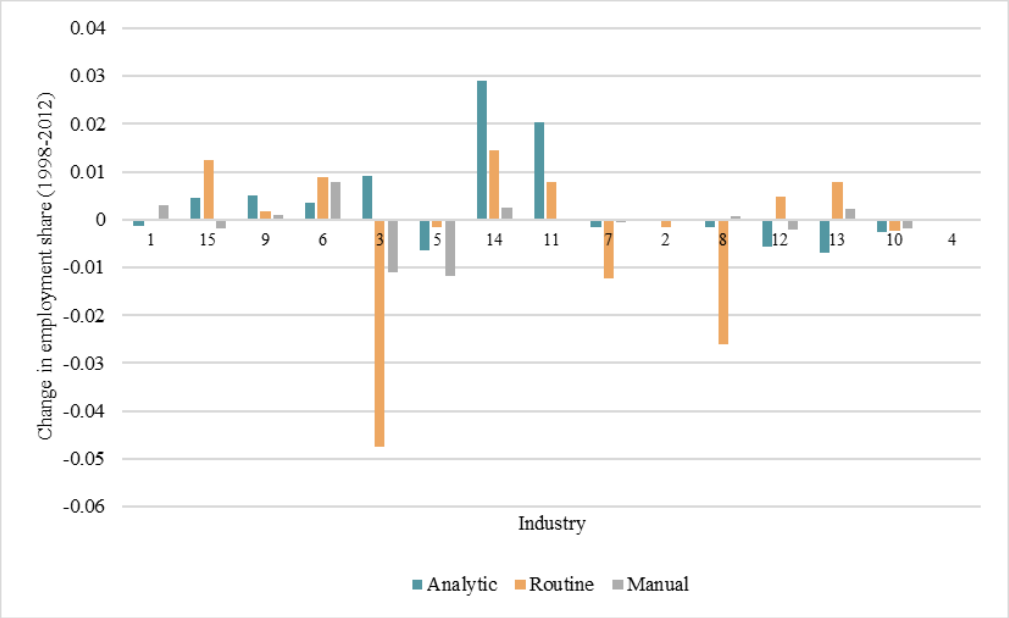


Figure 15 Employment share change at industry level, 1998-2012

The two highest-paying industries reduce employment for all task type labor, and the low-paying industries mostly increase the employment for all task type labor. In industry Total manufacturing (3), Transport and storage (7) and Financial service and insurance activities (8), the labor demand for routine intensive occupations declines exceptionally during 1998 to 2012. It is worth noting that total manufacturing (3) might be affected by technological advance, as routine task intensive occupations can be easily substituted by ICT capital. The Figure 16 shows interesting pattern in employment share change that total employment share decline of routine occupations solely comes from reduced labor demand for manufacturing industry.

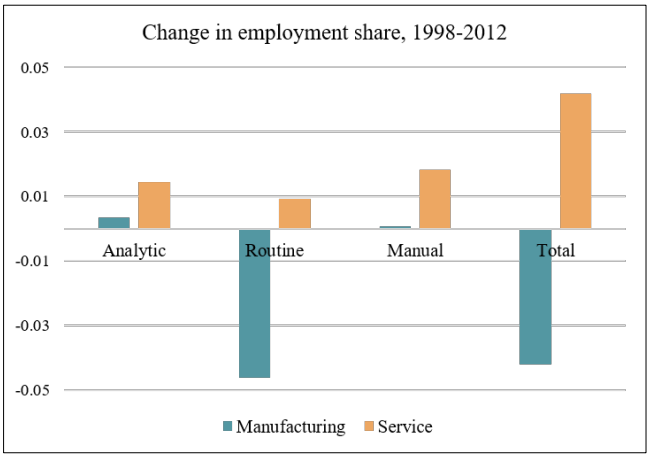


Figure 16 Employment share change in manufacturing and service, 1998-2012

The labor demand change depicted in above Figure 15 might make think the polarization in employment would lead to wage polarization because the labor share increased consistently in lowest paying industries at all occupation groups. Simultaneously, the employment shares of the highest-paying industry. But the role of some mitigating factors should be considered that is: complementarity, demand elasticity, and labor supply. Polarization of employment and wage could happen simultaneously, but the causality between them should be taken into account cautiously.

4.5.2 The result of estimation

Table 8 Estimation results of first stage regression

	log real monthly wage	
Variables	1998	2012
Analytic	0.0844***	0.0722***
	(0.0239)	(0.000372)
Routine	-0.171***	-0.150***
	(0.0219)	(0.000369)
Manual	-0.288***	-0.262***
	(0.0245)	(0.000408)
High school graduate	0.240***	0.228***
	(0.0211)	(0.000421)
College graduate	0.266***	0.368***
	(0.0316)	(0.000507)
University graduate or more	0.441***	0.519***
	(0.0290)	(0.000511)
25-34	0.188***	0.331***
	(0.0252)	(0.000512)
35-44	0.389***	0.506***
	(0.0260)	(0.000511)
45-54	0.435***	0.573***
	(0.0294)	(0.000519)
55-64	0.240***	0.491***
	(0.0367)	(0.000607)
65+	-0.0710	-0.152***
	(0.0719)	(0.000848)
Female	-0.461***	-0.447***
	(0.0167)	(0.000262)
Constant	4.575***	4.681***
	(0.0845)	(0.00133)

	log real monthly wage	
Variables	1998	2012
N	3,914	5,420
R2	0.45031	0.46169

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Analytic, Routine, and Manual is the major occupational groups. For education, 'No schooling & less than high school' is the omitted category. 'High school graduates' includes college/university attending or dropout. For age, age between 15 and 24 is the omitted. Number of observation is number of employee in each year, and the estimation is applied 'Longitudinal individual weights' of panel dataset.

The first stage regression would prove the relationship between whether the wages of workers with the same demographic condition (age, gender, occupation) are affected by the industry. The R square of estimation with only industry fixed effect is 0.0713, without industry fixed effect is 0.434, and with all demographic information and industry fixed effect is 0.454. In all period, including industry fixed effect raise the explanatory power of estimation. When task contents of occupation are test on wage equation, Analytic jobs are positively related while routine and manual jobs are negatively related with wage. This is coincident with wage trend as in all periods, the average wage of analytic occupations is the highest and of manual occupations the lowest at aggregate level, although mean wage of routine occupations is the lowest in several industries. The estimation results of Equation 30 in Table 9 clarifies that task contents of occupation actually have effect on wage as well as the nature of industries. While a number of studies on polarization have been analyzed at aggregate level, the result of this study gives important message that not only the task based approach but industrial characteristics should be considered. As the degree of

computerization or feasibility of automation depends on the task contents of occupations, the extent which ICT capital substitutes the routine intensive labor varies over industries because the shares of occupations also vary within an industry.

Table 9 Estimation of employment share change, 1998-2012

Employment share change,1998-2012	(1) Total	(2) Analytic	(3) Routine	(4) Manual
Industry wage premium in 1998	-0.0278***	0.0118*	-0.0490***	-0.0178***
	(0.00439)	(0.00549)	(0.00709)	(0.00311)
Constant	-0.00389***	0.00172	-0.00747***	-0.00297***
	(0.000894)	(0.00118)	(0.00149)	(0.000554)
N	3914	938	1986	990
R^2	0.010	0.005	0.023	0.032
F	40.02	4.605	47.68	32.57

Standard errors in parentheses, (* p < 0.05, ** p < 0.01, *** p < 0.001) The estimation is applied 'Longitudinal individual weights' of panel dataset.

The theoretical framework in Section 4.3 predicts that labor demand would be more polarized in higher wage industry. The result of employment share change estimation is interesting. During 1998 and 2012, the industry with higher wage have less increased the demand at whole industry level. When the industry wage premium increases 10% then the average rate of routine employment reduces 0.278 %. However, when divided into three occupational groups based on the task contents of the occupations, the labor demand for analytic jobs even increased faster. This supports the skill-biased technological change that

the demand for high-skilled increases while so does the wage of them at the same time which confront the economic principle. This is usually explained by demand effect that demand exceeds increased supply. However, the changes of employment share in routine and manual occupations show negative relation with wage premium and this effect is more critical in routine occupations. This result means that workers in high-paying industry reduced routine intensive occupations which back up the theoretical framework of employment polarization between routine and non-routine (analytic and manual) workers.

Finally, by introducing the industry specific variables of ICT and non-ICT capital, the relation between the decline of price of ICT and substitution or complementarity of labor are tested. Table 10 presents the results of estimation from 1998 to 2012. The results demonstrate the capital and labor substitution relationship at whole industry level, the more capital input the less labor input. Taking account of ratio of ICT and non ICT capital, the effect of ICT is quiet considerable in employment change. Increase of two capitals have negatively correlated to employment share change in all types of occupations except ICT capital in analytic intensive occupations. It means ICT capital favors analytic intensive occupations which has complementary relationship, demanding more highly skilled workers. When compared to the estimation results without industry specific variables, the explanatory power increased in this result and all coefficient related to ICT and non ICT capital turn to be significant at 1% level.

Table 10 Estimation of employment share change with capital investment, 1998-2012

Employment share change,1998-2012	(1) Total	(2) Analytic	(3) Routine	(4) Manual
Industry wage premium in 1998	-0.0375***	0.00484	-0.0734***	-0.00798*
	(0.00400)	(0.00531)	(0.00521)	(0.00309)
ICT capital	-0.00326***	0.00535***	-0.00306***	-0.00442***
	(0.000298)	(0.000462)	(0.000409)	(0.000179)
Non-ICT capital	-0.00857***	-0.00384***	-0.0161***	-0.00113***
	(0.000436)	(0.000590)	(0.000694)	(0.000294)
Constant	0.184***	-0.0113*	0.312***	0.0746***
	(0.00473)	(0.00576)	(0.00771)	(0.00418)
N	3833	938	1986	909
R^2	0.386	0.152	0.618	0.511
F	801.5	55.70	1067.7	315.0

Standard errors in parentheses, (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) The estimation is applied 'Longitudinal individual weights' of panel dataset. N is the number of individuals in 1998.

4.5.3 Estimated wage premium of industry

4.5.3.1 Industry specific wage premium

To test the theoretical framework of high wage premium and employment polarization, the industry specific wage is used. Since the industry wage premium is given by the coefficient of dummy variables in estimation of first stage, one of fifteen industries should be omitted so to make all positive in reference year 1998. Table 11 is the results of first stage estimation in 1998 and Figure 17 displays the wage premium and real monthly mean

wage are highly correlated.

Table 11 Estimated 15 industry wage premium in 1998

Industry	Industry wage premium	Industry	Industry wage premium
1	(omitted)	9	0.099
2	0.161	10	0.402
3	0.183	11	0.176
4	0.407	12	0.209
5	0.174	13	0.218
6	0.176	14	0.291
7	0.131	15	0.011
8	0.356		

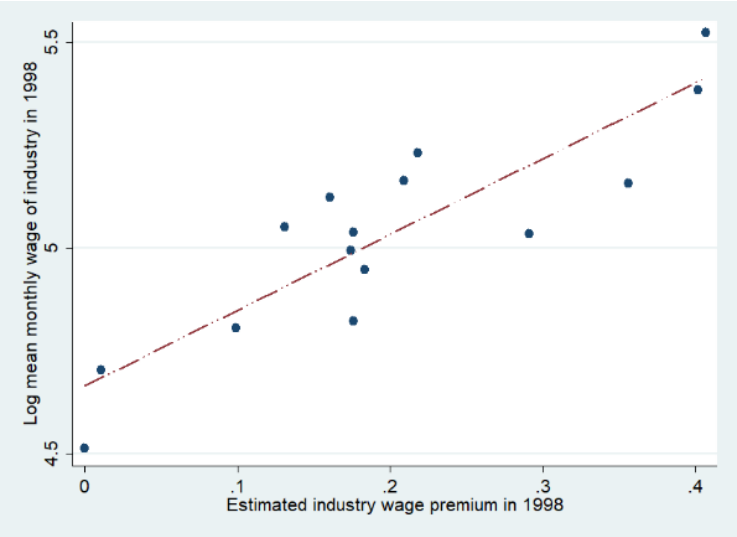


Figure 17 Estimated wage premium and its persistency with real mean wage in 1998

4.5.3.2 Industry-Occupation specific wage premium

This study accepts the assumption that a firm's incentive to reduce input of routine labor in production function is caused by technological development and the corresponding decreased price of ICT. But simply if the wage of routine workers is relatively high compared to other occupations or their labor productivity, this can be another strong factor in determining the employment. Nevertheless, one can expect the employment polarization is mainly driven by ICT capital substitution effect because the mean wage of routine intensive workers is always lower than that of analytic intensive workers. So the industry wage premium is analyzed at industry-occupation specific level and the estimated results are represented in Figure 18. If the price is main driving force of reducing employment, it could not explain the witnessed polarization in this study. Besides, taking industry-occupation specific wage premium into consideration, polarization of employment is definitely driven by replacement of routine tasks since the wage premium of routine occupations is the lowest over most industries, - even lower than manual for some. For those industries whose wage premium for manual occupation is the highest among all, the price effect might act in reducing employment share of manual occupations. Even in the actual mean wage of industry-occupation groups, only one industry pays higher wage to manual workers than routine workers (Figure 19).

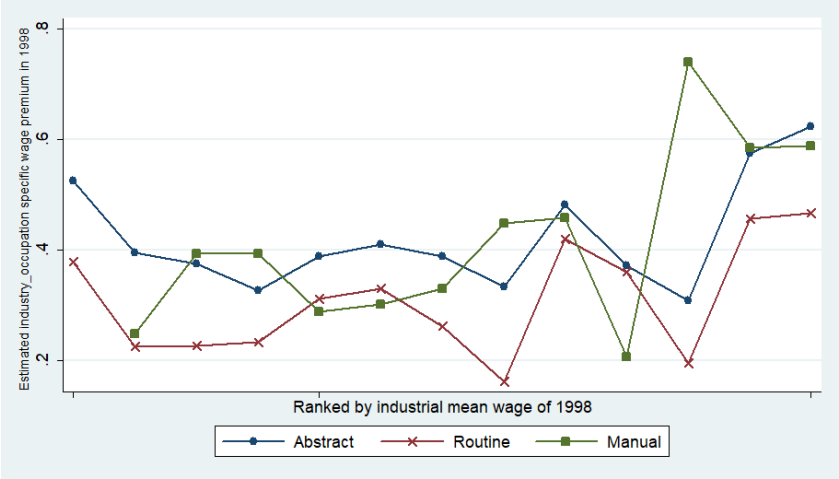


Figure 18 The estimated industry-occupation specific wage premium in 1998

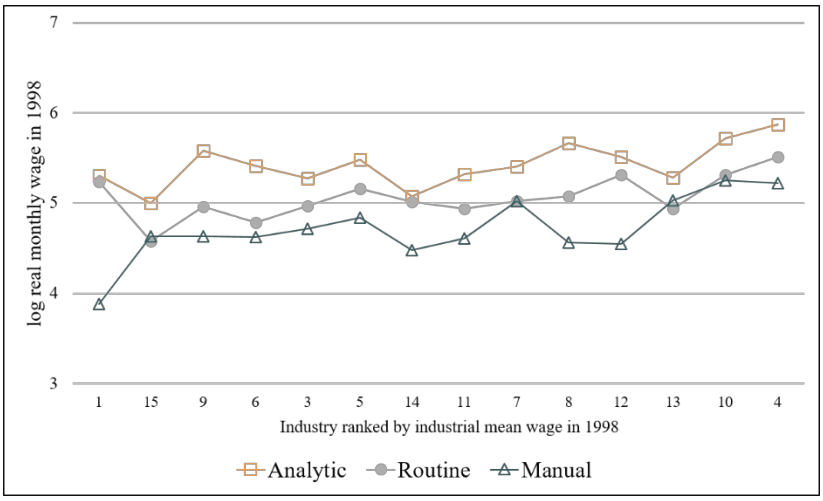


Figure 19 Mean wage of industry-occupation group

4.6 Conclusion

In history, there always have been debate whether technology substitute labor or complementary labor. Considering the portion of ICT capital and its power to drive

economic growth, its impact on economy enormous and extensive. In the pioneering research of Autor, Levy, and Murnane (2003), they found the price decline of ICT has caused polarization. This study explores this impact of ICT capital on the labor market and reveals the polarization triggered by it. As the price of rental ICT capital decline, firms have motivation to increase the input of ICT capital adjusting the input of routine task intensive labor. Considering the extent of adjustment would be dependent on the industry size and characteristics and workers with the same demographic conditions get different wages, this study introduces the industry specific wage premium. And it uses the theoretical frameworks explaining decline of ICT capital price and change in labor input ratio that the industry with higher initial wage premium has more incentive to reduce the routine incentive employment.

Statistics of wage and employment shows that labor demand in low wage has increased over the period between 1998 and 2012. The empirical analysis result confirms two facts. First, as price of ICT decreases industry with higher initial wage premium would reduce more routine intensive labor input in overall economy. But when analyzed in detail, industries consistently have increased the demand in analytic occupation workers. When the initial industry wage premium increases firms reduce more routine workers than manual workers. Second both ICT and non-ICT capital have substituted all kinds of workers in analytic, routine, and manual occupations, except only one case of analytic occupations which are complementary with ICT capital. This results directly confirms the role of ICT in the labor market.

Due to the availability of data, the period of analysis remains as shortcoming of this study. There is also problem of representativeness of data due to limitation of panel data. For example, actual employment shares of ‘Administrative, executive and managerial workers’ is higher than ‘Skilled agricultural, forestry and fishery workers’ according to the ‘Survey on Labor Conditions by Employment Type’ released by Ministry of Employment and Labor, but KLIPS shows the reversed. To overcome this drawback, KLIPS offers the longitudinal weights and all estimations are analyzed with this weights. Finally, within industry and between industry analysis are left for further study as theoretical framework predicts the polarization would be more intensive in higher wage industry.

Chapter 5. Polarized labor demand due to routine task- biased technological change

5.1 Introduction

The development of Information & Communication Technology (ICT) as main growth of recent technology development, has enabled the smarter and more connected society and promised the new opportunities of development (Luo & Bu, 2016; Schreyer, 2000; Vu, 2011). But this promise might not be for all. There have been fears that human would be replaced by computers since its appearance. Fear against AI, advance in automation and robotics and consequential job destroying are prevalent all over the world. Many studies have dealt with what new technology will do to jobs, but no one could make agreement on the numbers or give a clear diagnosis, ranging from optimistic to devastating (Erin Winick, 2018). Some researchers (Acemoglu & Restrepo, 2017; Boston Consulting Group, 2015; Bowles, 2014; Frey & Osborne, 2013) study how many jobs are to be at risk of robotics or computerization. In spite of those pervasive fear, computers or machines do not directly replace an occupation. Instead, the introduction and progress of technology make some tasks of an occupation more favorable to be substituted. Reduction in the cost and promotion in the speed of developing technologies boost replacement of tasks codified (Autor, Katz, & Kearney, 2006) - including not only computers but machine learning, developments in smart factory with internet of things, artificial intelligence and mobile robotics. After all controversial literature, there seem to be a common idea of the existence

and the necessity for policy attempts to mitigate the consequent effects of ICT on the labor market (Garcia-Murillo et al., 2018).

New jobs can be created and outdated jobs can be faded over time. However, the core tasks which is the essence of an occupation would exist, still performed by human or replaced by machine. Taking that into the consideration, it is important to take task-based or skill-based approach toward the forthcoming the labor market instead of occupation-based approach. With the task-based approach, an occupation can be regarded as complex of manual, routine and analytic tasks. In a word, development of ICT would affect the labor demand for routine or codifiable task-intensive workers, not affecting directly the certain workers or occupations which are mainly, but not exclusively, performed by middle-skilled workers. This labor shift is explained by "Routine-biased technological change (RBTC)" hypothesis, explaining polarization of work, decreasing the demand for middle-skilled workers relative to high- and low-skilled workers (Autor, Levy, & Murnane, 2003; Cortes, 2016; Goos & Manning, 2007; Spitz-Oener, 2006). This is an alternative hypothesis for "Skill-biased technological change (SBTC)", which emphasizes the role of rising wage premiums in growing wage inequality associated with the development of ICT (Card & DiNardo, 2002; Katz & Murphy, 1992; Michaels et al., 2014). Because SBTC concentrates on concurrent rising in demand and wage for high-skilled group, it overlooks another rise in low-skilled group and fails to explain the polarizing (Acemoglu & Autor, 2011).

Recently RBTC is observed in many developed countries such as US, UK, Germany, Japan and so on. There are considerable researches on wage inequality caused by global

trade or outsourcing and SBTC with the development of ICT in Korea (Kang & Hong, 1999; Kwack, 2012; H. Lee & Sim, 2016; S. Lee, 2017). But little study has been done in the view of RBTC (N. Kim, 2015). This paper serves two purposes, first is to study the polarization in Korean employment structure, and the second is estimate how routine tasks are vulnerable to decrease of labor demand growth-RBTC between 1993 and 2015 in Korea.

The study is organized as follows. The next section 5.2 describes the data and the measure of routineness of occupation. In Section 5.3, before modeling, covers the general progress of job polarization in Korea and depicts the employment share change and the relationship between the measure of routineness of tasks and wage. The two-stage production model for analyzing the effect of RBTC is explained in the latter part. It presents the polarization of employment structure in Korea and the outcome of analysis. I would discuss conclusion in Section 5.4. An appendix reports the supplement of analysis.

5.2 Data

5.2.1 Employment, wage, and industrial data

The main source of employment and wage is the ‘Survey Report on Wage Structure’ and ‘Survey on Labor Conditions by Employment Type’ released by Ministry of Employment and Labor from 1993 to 2015. For the demand of labor data, the total monthly working hour and the number of workers in each occupation of each industry are used. Total monthly working hour is the sum of normal working hours and overtime working hours. The analysis results are not affected by the measure of labor demand when using the

number of persons employed instead of the total monthly working hours. From 1993 to 2015, the classification code for occupation and industry has been changed. For industry, Korean Standard Industrial Classification (KSIC) was revised in 1998, 2000 and 2007 and for occupation, Korean Standard Occupational Classification (KSCO) was revised in 2000 and 2007. For analysis of data across classification system crosswalks are used at major (1 digit) level for industrial classification and sub-major (2 digits) or minor (3 digits) levels for occupational classification.

The sources of industry output, industry marginal cost, and the relative output prices are The Bank of Korea. For production, 'GDP by economic activities (not seasonally adjusted, current prices, annual)' is taken, as the production is defined as the value of goods or services produced in a year. For the measure of output, production is deflated by industry-year price indices using 'GDP Deflator by economic activity category (annual)'. To obtain a measure of industry marginal costs, the difference between production and net operating surplus is divided by output, taking 'Operating Surplus' factor from 'Gross value added and factor income by kind of economic activity (at current prices, annual)'.

5.2.2 Routineness of occupations

Autor, Levy, and Murnane (2003) first designed the measure of occupation task requirements form the Dictionary of Occupational Titles (DOT)- non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks. This model permits to measure the tasks performed in occupation and capture

the routineness of each occupation. On their following research, collapse ALM's original five task measures to three task aggregates for analytic, routine, and manual tasks[20]. Combining these three measures, a summary measure of routine task-intensity RTI by occupation is calculated as the difference between the log of Routine tasks and the sum of the log of Analytic and the log of Manual and standardized to have unit standard deviation and mean zero.

The literature seems to exist a general consensus about using RTI measures as the best way to capture the impact of technological progress or automation, especially explaining the job polarization, following several studies of Autor, Levy, and Murnane (David H Autor & Dorn, 2013; Goos et al., 2014; Gregory, Salomons, & Zierahn, 2016; Salomons, 2010). Also Michaels, Natraj and Van Reenen (2014) take task-based view and RTI to test whether ICT has polarized the labor market, and Graetz and Michaels (2017) use RTI as the index for more intensive industries in routine tasks.

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[20] Analytic task measure is the average of ′GED Math (non-routine analytic tasks)′, measuring general educational development, mathematics and ′Direction, Control, Planning (non-routine interactive tasks)′, measuring adaptability to accepting responsibility for the direction, control, or planning of an activity. Routine task measure is the average of ′Set Limits, Tolerances, or Standards (routine cognitive tasks)′, measuring adaptability to situations requiring the precise attainment of set limits, tolerances, or standards and ′Finger Dexterity (routine manual tasks)′, measuring ability to move fingers, and manipulate small objects with fingers, rapidly or accurately. Manual task is ′Eye Hand Foot Coordination (non-routine manual tasks)′, measuring ability to move the hand and foot coordinately with each other in accordance with visual stimuli.

Table 12 RTI measures of 10 major occupational groups

KSCO 5 code	RTI_ Analytic	RTI_ Routine	RTI_ Manual	RTI	n-RTI
Administrative, executive and managerial workers	1.88	0.70	-0.74	-0.43	-1.18
Professionals	1.53	1.21	-0.16	-0.16	-0.93
Technicians and semi-professionals	1.42	1.20	-0.10	-0.12	-0.89
Clerical Workers	0.51	0.80	0.39	-0.10	-0.87
Equipment, machine operating and assembling workers	0.23	1.61	0.20	1.18	0.34
Skilled agricultural, forestry and fishery workers	0.67	1.26	-1.59	2.18	1.29
Craft and related trades workers	0.63	1.80	0.41	0.76	-0.06
Service workers	1.09	1.59	-1.71	2.21	1.31
Sales workers	0.65	1.67	-1.15	2.16	1.27
Elementary workers	0.29	1.17	0.36	0.52	-0.28

RTI is based on the U.S. Census Occupational Classification (COC). To apply the RTI to Korean occupational system KSCO, a crosswalk offered by Statistics Korea is used. First construct a crosswalk between KSOC and International Standard Occupational Code (ISCO) 08, then between ISCO 08 and US Standard Occupational Classification (SOC) 2010, SOC 2010 and SOC 2000, SOC 2000 and COC 2000 are used in order. Table 12 is the result of conversion for 10 major occupational groups. As higher RTI value means an

occupation is more routine intense, therefore more vulnerable to the introduction of technology. The crosswalks among KSCO from 1993 to 2015 are presented in [21].

5.3 Understanding and estimating the employment structure of Korea

5.3.1 Polarization of the employment share in the Korean labor market

Table 13 and Figure 20 show a snapshot of change in the employment structure between 1993 and 2015. In table 11, occupations are ranked by skill level, which is approximated by the occupational mean wage in 1993[22]. For the sake of intuitive understanding, low-skilled group means three lowest-paying occupation group, four middling occupations for middle-skilled group, and high-skilled group refers three highest-paying occupations from Table 13. Higher RTI means more routine-intensive occupation and thereby high-skilled groups have relatively low RTI compared to middle-and low-skilled groups. 'Craft and related trades workers' and 'Elementary workers' have relative higher RTI compared to occupations in the similar wage group, because those are manual-intensive ones apparently from Table 12.

[21] Crosswalks between two KSCO (04-05 or 05-05) may have one to one match or multiplicity to multiplicity. In the latter case, wage or number of employees are averaged by number of employees weights.

[22] Autor and Dorn (2013) regard wage percentile as skill percentile.

Table 13 Changes in the Share of Employment, 1993-2015

	Occupation ranked by mean monthly wage in 1993	Average employment share in 1993 (%)	Percent point change	Rate of change	RTI[23]
		(1)	(2)	(3)	(4)
High-paying	Administrative, executive and managerial workers	4.47	-2.72	-60.80	-1.18
	Professionals	10.39	2.60	25.05	-0.93
	Technicians and semi-professionals	5.15	8.31	161.40	-0.89
	Clerical Workers	25.23	1.65	6.52	-0.87
	Equipment, machine operating and assembling workers	28.24	-10.46	-37.03	0.34
	Skilled agricultural, forestry and fishery workers	0.17	0.06	33.29	1.29
	Craft and related trades workers	17.27	-9.77	-56.57	-0.06
	Service workers	1.85	3.47	187.06	1.31
Low-paying	Sales workers	1.76	4.45	253.09	1.27
	Elementary workers	5.47	2.42	44.13	-0.28

Notes: Occupational classification is based on Korean Standard Occupational Classification Rev.5. Column 4: measure rescaled to mean 0 and standard deviation 1, a higher value means an occupation is more routine intense. RTI index is based on the five original DOT task measures in Autor, Levy, and Murnane (2003) and is identical to the index used in Autor, Dorn, and Hanson (2013).

[23] Column 4 in Table 13 uses the normalized RTI in Table 12

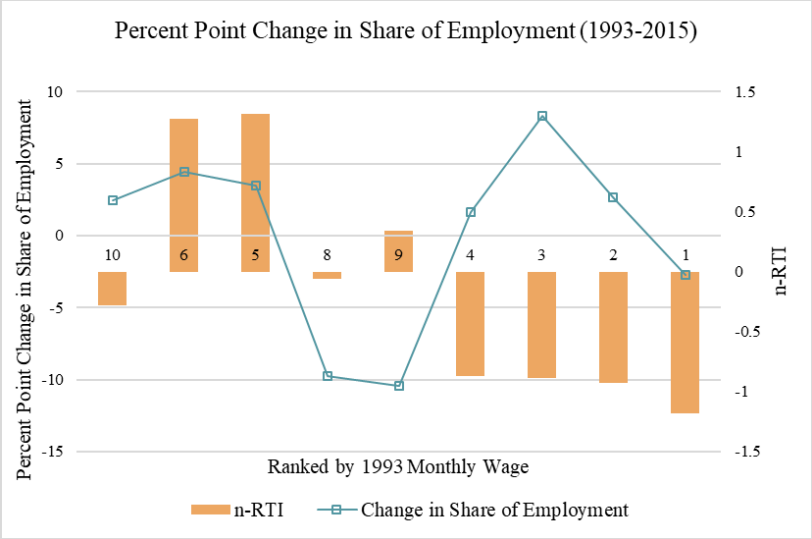

Figure 20 Percent point changes in the share of employment, 1993-2015

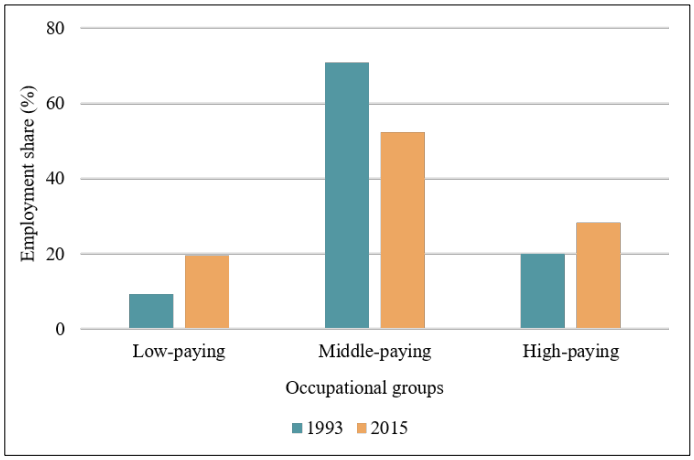

Figure 21 The share of employment of three occupational groups in 1993 and 2015

Figure 21 explains the demand growth change during about two decades for middle-paying group or middle-skilled group is relatively low compared to two ends of wage

groups and relatively high for low-skilled group. SBTC argues that the labor demand for high-skilled has risen as technology developed over time, but not in this case. This implies that the employment structure change in Korea cannot be explained by SBTC. In Figure 20, occupation group 'Skilled agricultural, forestry and fishery workers' is not included hence its share is only 0.17% in 1993 that it is too sensitive to change. Ignoring this minor group, the employment share changes have experienced the decline in middle skilled groups, showing U-shaped. From Figure 21, the employment share of the middle-skilled group has decreased in 28.5 percent point while the demand for the low- and high-skilled group has increased 10.3 and 8.2 percent point relatively. There has been significant decrease in 'Equipment, machine operating and assembling workers' and 'Craft and related trades workers' which covered about half of employment in 1993.

Higher paying occupations seem to have low but RTI is calculated by subtraction of sum of analytic and manual task, lower RTI does not guarantee the higher wage as shown in the case of 'Craft and related trades workers' or 'Elementary workers'. The correlations between components of RTI measure and monthly wage are tested for sub-major or minor occupational groups, 86 groups in 1993 and 87 groups in 2015. This test can reveal the relation between the characteristics of occupations and wage. According to the analysis, although the degree of routineness does not have significant relation to monthly wage, occupations more intense in analytic tasks have positive relation with higher monthly wages in 1993 and 2015. The negative relation between RTI for manual tasks and wage is also significant in 2015 (Table 14). The corresponding results are depicted in Figure 22.

The result of pairwise correlations of analytic, routine, and manual index confirms that each component has weak correlations (Table 15). The result of multicollinearity test of RTI components is in Table 16 which mean variance inflation factors (VIFs) is 1.05 for 1993 and 1.04 for 2015. Considering the employment polarization, the relationship between tasks and wage implies that the polarization in skill groups could also lead potential polarization in wage eventually.

Table 14 Relation between skill characteristic of occupation and wages

Variables	(1) log wage 1993	(2) log wage 2015
log RTI_ Analytic	0.226***	0.282***
	(0.0352)	(0.0452)
log RTI_Routine	0.0471	0.0486
	(0.0558)	(0.0741)
log RTI_Manual	-0.0174	-0.0881**
	(0.0258)	(0.0344)
Constant	13.25***	14.49***
	(0.0900)	(0.118)
Observations	86	87
R-squared	0.351	0.382
R2_adj	0.328	0.360

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15 Pairwise correlations of RTI components

	RTI_Analytic	RTI_Routine	RTI_Manual
RTI_Analytic	1		
RTI_Routine	-0.193	1	
RTI_Manual	-0.144	0.0089	1
Number of observations		87	

Number of observation is the number of occupational groups.

Table 16 Multicollinearity Test Results (VIFs)

Variable	log wage 1993		log wage 2015	
	VIF	1/VIF	VIF	1/VIF
RTI_Analytic	1.07	0.932	1.06	0.945
RTI_Routine	1.05	0.954	1.06	0.946
RTI_Manual	1.02	0.976	1.01	0.986
Mean VIF	1.05		1.04	

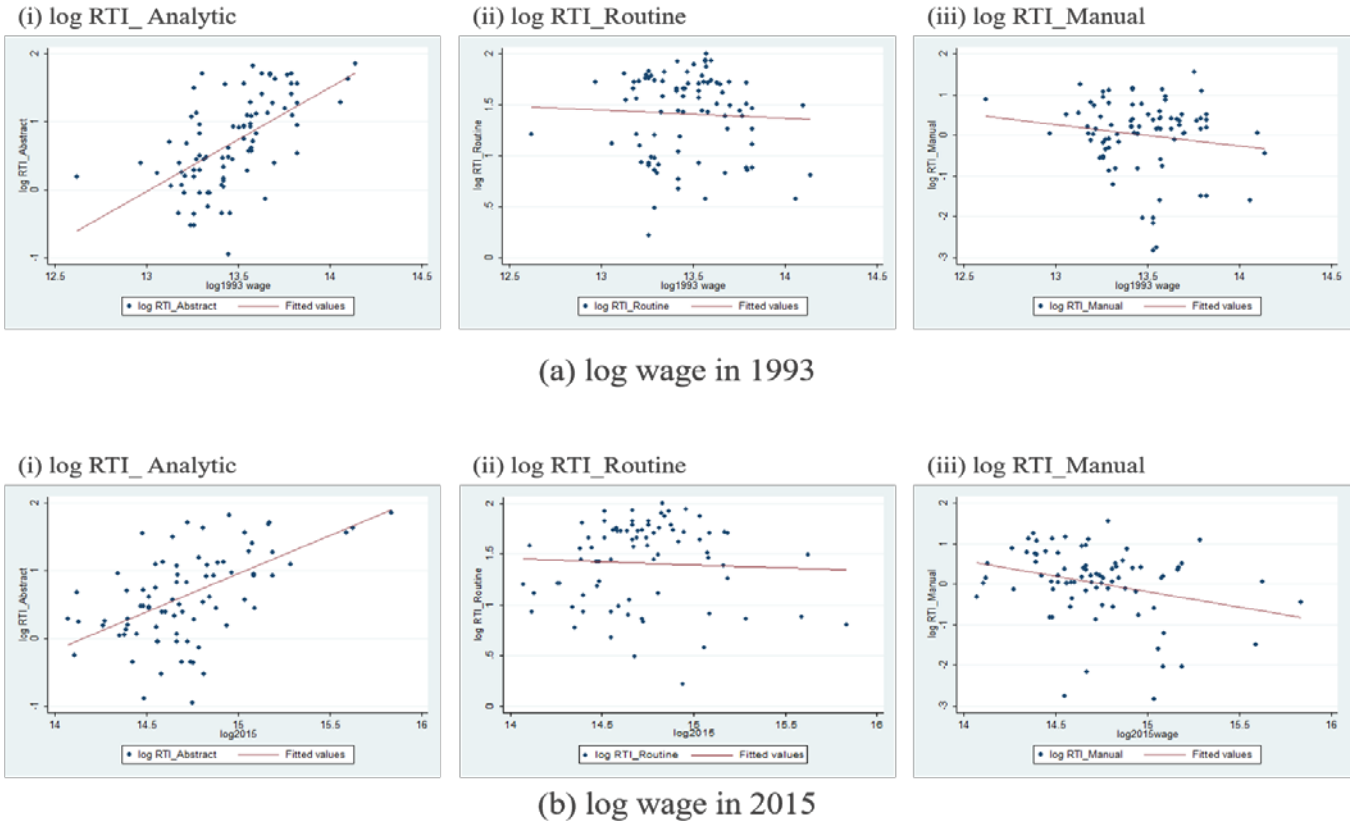

Figure 22 Relationship between three kinds of tasks and wages in 1993 and 2015

5.3.2 Estimating the job polarization: The structure of model

In this study, it modifies the model of Goos, Manning, and Salomons (2014). To explain the pervasive job polarization in 16 Western European countries, they estimated the effect of RBTC and offshoring on job polarization, reporting that RBTC plays much more important than offshoring[24]. Offshoring cannot explain the whole industry level of polarization while suitable for some routine tasks in production but poorly suited to service occupations (Autor & Dorn, 2013). So here it is tested whether technological change has impact on job polarization in Korea.

Goos, Manning, and Salomons (2014) set up two stage production model to understand job polarization. First, the production of goods, modeling output of industry is produced from combining certain common building blocks- a set of tasks. The production function of industry i using tasks $(T_{i1}, \dots, T_{ij}, \dots, T_{iJ})$ as inputs is assumed as CES production function:

$$Y_i(T_{i1}, \dots, T_{ij}, \dots, T_{iJ}) = \left[\sum_{j=1}^{J}\left[\beta_{ij}T_{ij}\right]^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \qquad \text{Eq. (32)}$$

where $\eta > 0$ is the elasticity of substitution between tasks in goods production and β_{ij} is the intensity of the use of task j in industry i. The following is the cost function for production where c_j^T is the unit cost of task j and $c_i^I(c_1^T, \dots, c_i^T, \dots, c_J^T)$ industry marginal

[24] Firpo, Fortin, and Lemieux (2011) also argued technological change and offshorability have different impact on wage polarization.

cost :

$$C_i^I(c_1^T, \dots, c_i^T, \dots, c_J^T | Y_i) = Y_i c_i^I(c_1^T, \dots, c_i^T, \dots, c_J^T) \text{ for } j = 1, \dots, J \quad \cdots\cdots \text{Eq. (33)}$$

The demand for task j conditional on industry output Y_i is as following where $t_{ij}(c_1^T, \dots, c_i^T, \dots, c_J^T)$ is the demand for task j to produce unit good of industry i:

$$T_{ij}(c_1^T, \dots, c_i^T, \dots, c_J^T | Y_i) = Y_i t_{ij}(c_1^T, \dots, c_i^T, \dots, c_J^T) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (34)}$$

Second, the production of tasks. It is assumed that output of task j is produced using technology that combine labor of occupation j and other inputs. These other inputs could be considered like computer to capture recent technological change and the cost of these other inputs changes over time according to the routineness of a task. Following Goos, Manning, and Salomons (2014), total production function of task j of industry i is given by Cobb-Douglas production function. As tasks are common building block, production function is also common across industries[25]:

[25] The task production function also can be assumed to be CES function as in the Eq. (32). Then the production will be given as

$$T_{ij}(N_{ij}, K_{ij}) = [\kappa N_{ij}^{\frac{\rho-1}{\rho}} + (1-\kappa) K_{ij}^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \text{ with } 0 < \kappa < 1, \rho > 0$$

where ρ is the elasticity of substitution between N_{ij} and K_{ij}, and assuming $\rho \to 0$ gives Eq. (32).

$$T_{ij}(N_{ij}, K_{ij}) = N_{ij}^{\kappa} K_{ij}^{1-\kappa} \text{ with } 0 < \kappa < 1 \cdots\cdots \text{Eq. (35)}$$

where N_{ij} is domestic labor of occupation *j* and K_{ij} is the other input.

The cost function for producing T_{ij} is given by with w_j and r_j the prices of N_{ij} and K_{ij} respectively which are common across industries.

$$\mathrm{C_{ij}}^{\mathrm{T}}(\mathrm{w_j}, \mathrm{r_j}|\mathrm{T_{ij}}) = \mathrm{T_{ij}}\mathrm{c_j}^{\mathrm{T}}(\mathrm{w_j}, \mathrm{r_j}) \cdots\cdots \text{Eq. (36)}$$

The demand for occupation j conditional on task output T_{ij} is given as:

$$N_{ij}(w_j, r_j|T_{ij}) = T_{ij} n_j(w_j, r_j) \cdots\cdots \text{Eq. (37)}$$

where $n_j(w_j, r_j)$ is the demand for occupation *j* to produce one unit of task *j*.

In this model, RBTC is assumed to affect the costs of employing an effective unit of the other input which means, the routineness R_j has linear relationship in

$$\frac{\partial \log r_{jt}}{\partial t} = \gamma_R R_j \cdots\cdots \text{Eq. (38)}$$

Substituting Eq. (34) into Eq. (37), taking logs and using Eq. (38) gives an expression for the log demand of occupation *j* in industry *i* conditional on industry output and marginal costs. Time subscripts are added below:

$$\log N_{ijt} = -[(1-\kappa)+\kappa\eta]\log w_{jt} + [1-\eta][1-\kappa]\gamma_R R_j \times time + \eta \log c_{it}^{I} + \log Y_{it} + (\eta-1)\log \beta_{ij} + \varepsilon_{ijt} \quad \cdots\cdots \text{Eq. (39)}$$

As routineness of tasks increases the labor demand is to decrease over time. Given that the coefficient γ_R is expected to be negative and if $\eta < 1$, then $[1-\eta][1-\kappa]\gamma_R$ is also negative.

5.3.3 The result of estimation

Eq. (39) predicts job polarization within each industry, using the estimation of coefficient $[1-\eta][1-\kappa]\gamma_R$ as RTI measure interacted with a linear time trend regression with occupation-year and industry-year fixed effects. This is because this article sets the labor demand data as panel, with 126 occupation-industry groups (14 major industrial groups and 9 major occupational groups). In addition to linear regression for time trend with fixed effects, the methodology for analysis is adjusted to take into consideration of time serial correlation. The heteroscedasticity and first order autocorrelation are tested and the test results are available in Table A 1, all have heteroscedasticity and first order autocorrelation at 1percent significant level. The estimation results of Eq. (39) are reported in Table 17.

Column 1 is the estimation of coefficient of $[1-\eta][1-\kappa]\gamma_R$, modeling occupational wages by a set of occupation-time dummies and industry output and industrial marginal costs by industry-year dummies. is the elasticity of substitution and is larger than 0 and smaller than 1 from Eq. (35), meaning that $[1-\eta][1-\kappa]\gamma_R$ has positive so γ_R would

have negative value, if labor demand growth is decreased. As expected, the coefficient of RTI has negative value (-0.0352) and statistically significant at the 1 percent level. Column 4 is the same as column 1 but excluding the occupation “Skilled agricultural, forestry and fishery workers” group. The coefficient values are overestimated when including this occupational group. Table 17 is the results of using log of total monthly working hour for labor demand, $\log N_{ijt}$. When the number of persons employed is used for $\log N_{ijt}$, the result is similar and also significant at 1% level– RTI coefficient -0.0365 (Table A 2).

Table 17 The result of estimation, 1993~2015: log total monthly working hour

Variables	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.0352***	-0.0337***	-0.0310***	-0.0278***	-0.0309***	-0.0281***
	(0.00352)	(0.00433)	(0.00423)	(0.00331)	(0.00427)	(0.00407)
log monthly wage		-0.598***	-0.742***		-0.764***	-1.015***
		(0.0888)	(0.137)		(0.0840)	(0.123)
log industry output		0.633***	0.643***		0.711***	0.700***
		(0.0520)	(0.0572)		(0.0461)	(0.0497)
log industry marginal cost		0.579***	0.646***		0.701***	0.720***
		(0.107)	(0.117)		(0.101)	(0.108)
Constant	11.49***	1.863	3.298	11.26***	1.769	5.371**
	(0.250)	(1.450)	(2.383)	(0.258)	(1.353)	(2.118)
Observations	2,770	2,770	2,770	2,500	2,500	2,500
Number of ij	126	126	126	112	112	112

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Set panel data for 126 occupation-industry groups, AR1 & heteroscedasticity considered. Columns 1 & 4 contain industry-year, occupation-year fixed effects. Columns 3&6 contain year fixed effects. Columns 4 - 6 contain results except "Skilled agricultural, forestry and fishery workers"

From the Table 17, it could be interpreted that an occupation with one standard deviation more routinized (higher RTI), the labor demand for it grows 2.78 percent points less fast each year (column 4). In column 2 and 5, the coefficients of log industry marginal cost, η are positive and significant as predicted. But the coefficients of log industry output are less than unit which assumed to be constant returns to scale in goods production. This might be because two decades are not enough time for industrial output to be reflected by employment[26]. The coefficient of log monthly wage estimates $-[(1-\kappa)+\kappa\eta]$ in Eq. (39), the rise in wage would reduce the labor demand. During the period from 1993 to 2015, there were two shocks brought by Korean crisis in 1997 and global crisis in 2007-2008 which had considerable impact on the labor market[27]. Columns 3 and 6 additionally include year fixed effects. The magnitudes of coefficient are comparable with models 2 and 4.

In the previous part, each component of RTI measure has different impact on wage respectively. Table 17 shows the similar relationship between three tasks of an occupation and the labor demand. Replacing R_j to three components of RTI in Eq. (39), the coefficient of each component explain the relation between the characteristic of occupation task and

---

[26] The result of Goos, Manning, and Salomons (2014) shows the same, explaining as: *'This is perhaps not surprising given that short-run movements in output are often not reflected in employment'.* As they use linear regression, they constrain the coefficient of industrial output to be 1. This constraint is not allowed for panel analysis so the constrained coefficient is omitted in this paper, but the result of output and marginal cost show comparable, confirming the result of this study.

[27] *"Layoffs were extensive, leading to 7.4 percent unemployment in August 1998"*(Hart-Landsberg & Burkett, 2001)

the labor demand change over time. The results report that labor demand changes for occupations demanding analytic and manual tasks have grown from 1993 to 2015, which could be suitable for explaining the increase of high and low-skilled occupations. We should not impetuously declare that analytic tasks are only for high-skilled and manual ones are exclusively for low-skilled occupations. But putting together the results, high paying occupations are more specialized in analytic tasks that analytic tasks are mainly performed by high-skilled group. From the results of Table 18, the labor demand growth for low-skilled grows faster than others. The discussion on polarization in wage is beyond scope of this estimation, but putting together the results from Table 14 and Table 18, the possibility for wage polarization can be also referred based on overall results.

Table 18 Relation between three tasks and labor demand

	(1)	(2)
Variables	log monthly total working hour	log number of persons employed
RTI_ Analytic	0.0228***	0.0225***
	(0.00769)	(0.00773)
RTI_ Routine	-0.00218	-0.00350
	(0.00550)	(0.00551)
RTI_ Manual	0.0548***	0.0553***
	(0.00522)	(0.00512)
log monthly wage	-0.441***	-0.304**
	(0.138)	(0.138)
log industry output	0.615***	0.621***
	(0.0481)	(0.0472)

log industry marginal cost	0.542***	0.536***
	(0.109)	(0.110)
Constant	0.272	-7.113***
	(2.149)	(2.145)
Observations	2,770	2,770
Number of ij	126	126

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.4 Conclusion

This study states the change of employment structure in Korea from 1993 to 2015. Utilizing the index for measuring how an occupation is routine intensive, we find the relationship between routineness of an occupation and employment share change or wage. Our study of employment structure confirms the polarization of the labor market, revealing the employment share increase in high- and low-skilled groups at expense of the decrease in middle-skilled groups. The simultaneous rise in some low-paying occupations and decline in high-paying occupations reveals the limitation of skill biased technological change (SBTC) for elucidating changes in the Korean labor market. To figure out more persuasive way for explaining the phenomenon, the framework accounting for how routine-biased technological change has affected the employment structure is applied to Korean case. The empirical analysis shows the evidence regarding polarization that labor demand for high-skilled (mainly performing analytic tasks) and low-skilled (mainly performing manual tasks) are in rise, on the other hand, for middle-skilled is in decline. By

decomposing into three characteristic components of occupation – analytic, routine, and manual tasks–, occupations with more intense in analytic tasks give chance for both higher wage and employment, while more manual specific occupations give higher opportunity for employment. With empirical and statistical analysis results, not only polarization in employment structure but in wage is also expected to arise with development of technology, enabling the routine and codifiable tasks substituted

RBTC progress assumes that the development of technology like computers or automation machines has substituted workers in routine intense tasks. And this study witnesses the disappearing of demand for routine tasks in Korea. It provides noteworthy implication for the next generation and industrial policy makers in both public and private sectors. Complementing the analytic, creative, problem-solving tasks will be demanded and make high-paying occupations while repeatable tasks and manipulating simply with fingers will make a worker dropout. And this employment demand polarization in tasks would lead wage polarization eventually, causing more complicated socioeconomic problems.

RBTC is assumed to be approximated by a steady process that the empirical estimation adopted linear trend analysis. However, the technology advance and its impact on the labor market might not be steady, once it would be more rapid or it would not take place at all. So this result is only the average effect of technological change over the period from 1993 to 2015. Technology is not the only factor to affect the labor market, hence other sources of shocks to the labor market also should be considered. By separating the time period of

analysis, this article restrictively considers the structural changes in Korea brought by the Korean crisis.

Chapter 6. The afterwards of hollowing-out routine workers

6.1 Introduction

6.1.1 Polarization of employment

The studies on polarization of the labor market are attracting public attention in developed countries. There are several causes of polarization such as trade, globalization, offshoring, and superstar economy. Above all, economists have focused on technological innovation, especially on the development of information and communications technology, and understanding this polarization phenomenon with technological interactions has been posing a considerable challenge (Michaels et al., 2014). In this context, it is observed that the rise in wage inequality has been explicated by skill-biased technological change. However, routine-biased technological change (RBTC) is the hypothesis assumed to explain the polarization. Studies on RBTC have documented that, currently, inequality caused by technology innovation not only increases the wage and demand for highly skilled (in turn highly paid) workers but also increases the demand for low-paid workers at the expense of middle-skilled workers (Van Reenen, 2011b). The main idea of RBTC is that, with development of technology, the repeatable, simple, and easily codifiable tasks can be replaced by computer or robots (Autor, Levy, & Murnane, 2003). From the perspective of this nuanced hypothesis of technological change, it can be stated that technology drives skill and employment change by acting as a substitute for routine workplace tasks,

considerably affecting the structure of the labor market.

Although many studies demonstrate the polarization of the labor market caused by technological advancements (Autor et al., 2003; Fernández-Macías & Hurley, 2017; Fonseca et al., 2018; Goos et al., 2014; Ikenaga, 2013; Spitz-Oener, 2006), little attention has been paid to the movements of the eroded middle-skilled workers after the hollowing out of the workforce. Concerning the direction of their job shift, researchers assume that these workers move to lower income occupations (Acemoglu & Autor, 2011). Empirical evidence of the direction of shift from middle-skilled workers has been found by Cortes. Cortes (2016) reveals the occupational mobility pattern of routine workers in which those who possess high ability are more likely to switch to analytic jobs, while workers with low ability are more likely to switch to manual ones. Despite the concern, the probability of switching to analytic jobs increases more than that of switching to manual job. However, if the collapsed middle-skilled workers are more absorbed by low-paying- than high-paying occupations, the consequent increase in polarization would be inevitable.

6.1.2 The mismatching between skills and education at workplace in Korea

It has been reported that there is a mismatch between the job and educational level or the major of workers in Korea (Kim, 2005). Table 19 presents the responses of the participants of the second wave (Wave 2) of the Korean Labor and Income Panel Study (KLIPS);these results determine whether the workplace tasks of middle-skilled workers

match their educational attainment or skill level. The respondents who think that their workplace activities match their educational attainment and skills account for only 72.6~9.3%. One in five workers express dissatisfaction regarding their workplace activities because they mostly perceive that their roles or duties are much lower than their skills and educational level.

Table 19 Survey of educational attainment and skill match

(1) Suitability for educational attainment	Much Lower	Lower	Suitable	Higher	Much Higher
Less than high school	0.9%	18.9%	79.3%	0.9%	0.0%
High school graduates	1.5%	21.8%	75.1%	1.5%	0.1%
College graduates	0.9%	24.9%	72.6%	1.6%	0.0%
University graduates	2.7%	17.9%	77.9%	1.4%	0.2%
(2) Suitability for skill	Much Lower	Lower	Suitable	Higher	Much Higher
Less than high school	0.8%	17.1%	81.1%	1.0%	0.0%
High school graduates	1.6%	20.3%	76.1%	1.9%	0.1%
College graduates	1.5%	20.8%	75.2%	2.5%	0.0%
University graduates	2.6%	15.4%	80.2%	1.6%	0.2%

Number of respondents: (1) 43,399 (2) 43,383, from 1999 to 2017

With an increase in the supply of college and university graduates (Figure 23), the real labor income for both types of workers has increased in Korea, except during the two crises in 1997 and 2007 (Figure 24). However, at the same time, it shows that, as explained in

Chapter 1, the wage premium of education or returns to education would not be fully rewarded, and hence the wage gap stays stagnant at the 0.4 ln point level. Judging from the continuous increase in both supply and wage, there has been a noticeable demand effect for workers with a college qualification and more, although less significant than the U.S. (Park, 2014). These facts imply that although the educational attainments of individuals comprise a crucial factor for understanding the wage level, it cannot clearly differentiate the evolution of wage structure and needs another standard to relate the work activities with the wage level in Korea.

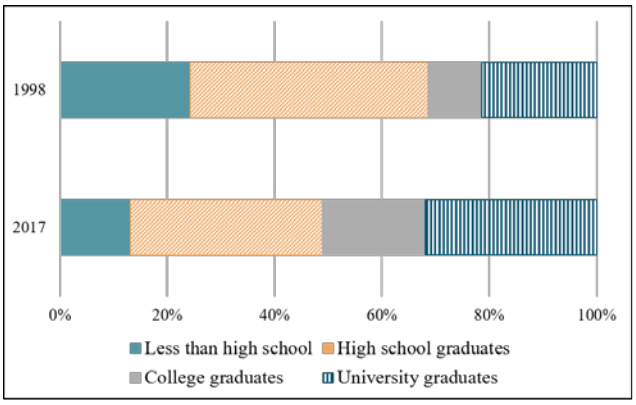

Figure 23 Increase in the labor supply of a college degree and more: 1998-2017

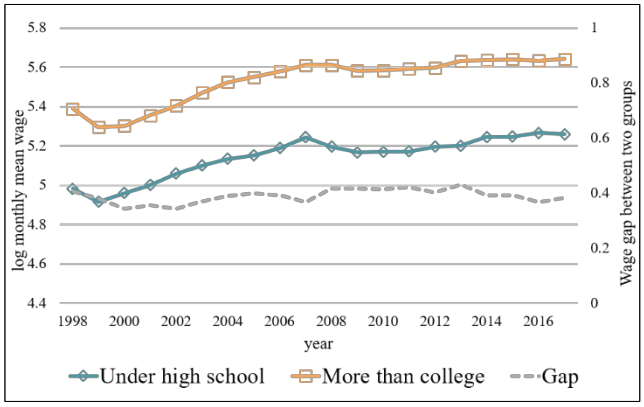

Figure 24 Wage gap between educational groups during two decades

Therefore, this study uses the task approach to relate the actual work activities with occupation and wage. This is not individual-based but occupation-base analysis to induce the task demand or price of tasks in the labor market. This approach is expected to give implications for the necessity of specific task education, unlike other conventional analysis tools such as years of schooling or the degree of education.

6.1.3 The limitation of previous studies

Based on Becker's human capital model (Caire & Becker, 1964), researchers have assumed that relatively high skilled workers earn higher income. Generally, the wage equation estimates the regression of individual wage on variables of individual's human capital affecting the wage. Schooling, years of experience, on-the-job training on the level, race, and gender have been used as typical wage determinants. Here, these factors would be denoted as human capital wage equation. This has been distinctively described as the

wage structure of the labor market differentiated by returns to education or college premium. However, human capital refers to general skills that are not occupational or workplace-specific. In this view, knowledge attained through “learning-by-doing” and enhanced skills on the spot would be overlooked, which cannot be simply reflected by the years of experience. Additionally, the main cause of polarization is advancements in technology; it has substituted parts of routine tasks within occupations, changing the set of tasks and, in turn, the skill demand.

Mincer wage equation is most widely and typically used to estimate the correlation between wage and human capital. Schooling may not serve as a proper proxy for individual skills when investigating the effect of technology-driven skill-demand change on wage in the labor market. As the effect of technology works on a specific task level, the worker’s characteristics human capital would not cover the demand side of human capital which can be understood as required skill sets at workplace, relevant with tasks of occupations. Hence, a conceptual framework is required to bridge the gap between the workplace task requirement and worker’s skill set (Autor & Handel, 2013). This study introduces task-based wage equation that relates wage with a worker’s skill set, which includes the information that she/he actually performs at work.

In the Korean labor market, unlike the U.S., the wage gap between high school graduate workers and those with a college or higher degree was found to be stable during 1998 and 2017. Hence, when education level is used as a proxy of skills, skill premium becomes unnoticeable in that the discussion on skill-biased technological change fails to attract

attention after a certain period. However, changing the stereotype of skills would spawn a new era of argument and increase the debate on the polarization in Korea.

6.1.4 The purpose and findings of this study

This article first confirms the collapse of the middle-paying and routine occupations using KLIPS data. The use of both the average wage of occupations and the task intensity of occupations helps the study to detect the polarization of the employment share. Subsequently, it discusses the direction in which the hollowed-out routine workers or middle-skilled workers moved after the collapse. By utilizing the strength of the panel data, this study explores the job shift and the consequent wage change at an individual level. Second, this serves as a distinct approach in the process of explicating. For estimating the wages of the ousted middle-skilled workers, the study uses a set of task intensities for the wage equation instead of the general human capital wage equation to verify the effect of skill-demand change on wage. This approach tests whether task-specific human capital can be introduced as a variable for explaining the wage differential.

The findings of this study are as follows. First, in the view of the occupational mean wage, during the period 998 to 2017, there was an increase in the labor demand for low- and high-paying occupations and a decline in that of the middle-paying occupations. Except from 2013 to 2015, more workers from the middle-income group moved to the low-income than the high-income group. Second, in the view of the occupational characteristics, it is confirmed that workers moved from routine occupations mainly to manual than analytic

occupations.

In empirical analysis, instead of using schooling and experience years for human capital, the study utilizes the character of skills required at the workplace. The results show that the wage of an occupation is significantly related to the extent to which an occupation is analytic, routine, or manual. Additionally, when workers switched over to a more manual occupation, they had to endure a decline in the wages. The use of task intensities appropriately explains the changes in employment and wage structures in the past two decades; additionally, the significant decline in the demand for routine-manual jobs and an increase in that of analytic jobs sheds light on the importance of a task intensity-oriented analysis.

6.2 Data

6.2.1 Task intensity of occupations

It follows the measurement of task intensity introduced in Chapter 3. Twenty variables from the occupational information network (ONET) database are used to measure the intensity of analytic, routine-cognitive, routine-manual, and manual tasks of occupations. The major occupational group numberings used in this article are represented in Table 16. The values of Table 16 denote the means of the major occupational group, while the values of 151 sub-occupational groups are standardized to have a zero mean and a unit standard deviation. The characteristics of occupations are determined by the scores of four task intensities. For example, for the [6] Sales workers occupational group, the routine-manual

score is the highest among the four task intensities, and it is denoted as a routine-manual occupation.

Table 20 Task intensity measures using ONET database

	Occupational Group	Characteristic	Task intensity			
			Analytic	Routine Cognitive	Routine Manual	Manual
[1]	Administrative, executive and managerial workers	Analytic	1.11	-0.38	-1.04	-0.86
[2]	Professionals	Analytic	0.79	0.09	-0.69	-0.72
[3]	Technicians and semi-professionals	Analytic	0.4	0.17	-0.44	-0.48
[4]	Clerical Workers	Routine Cognitive	-0.63	0.87	-0.02	-0.33
[5]	Service workers	Routine Cognitive	-0.33	0.25	-0.07	0.04
[6]	Sales workers	Routine Manual	-0.53	-0.5	-0.48	-0.93
[7]	Skilled agricultural, forestry and fishery workers	Manual	-0.92	-0.64	0.19	1.39
[8]	Equipment, machine operating and	Manual	-0.33	-0.1	0.44	0.87

	assembling workers					
[9]	Craft and related trades workers	Routine Manual	-0.61	-0.34	1.45	1.08
[10]	Elementary workers	Manual	-0.65	-0.25	0.55	0.64

The ONET values within each category (analytic, routine cognitive, routine manual, manual) are normalized to have a zero mean and a unit standard deviation

6.2.2 Employment and wage: KLIPS

KLIPS is a longitudinal study on a sample of 5,000 urban households and their members. It is conducted annually for collecting data pertaining to economic activities, labor movement, wage, education, and job training, among others. The Wave 1 of the study was conducted in 1998, and the related information is available from Wave 1 to Wave 20. This individual longitudinal data enabled us to trace the job shift in the middle-income group and the corresponding wage change. The original data contains 254,955 observations for 24,156 individuals.

Here, we used education, occupational, and industrial classifications and the wage data of wage and salary workers. This is because the labor income inequality is the main contributor in household income and the dependency of these households on wage and salary is relatively high in Korea (OECD, 2012). Hence, this article analyzes only wage and salary workers and excludes the self-employed and unpaid family workers. KLIPS presents information on job type (paid/unpaid worker) and employment type (paid-worker,

self-employed worker, and unpaid family worker). To reduce data loss, paid-worker in a particular employment type must be analyzed because it has less missing value. The job status refers to regular- and non-regular employment, self-employed worker/employer, and unpaid family worker. Non-regular workers are classified as temporary and dayworkers in KLIPS, and they are not classified in this article. After removing all missing values of the employment type, education, wage, occupational and industrial classification, 93,121 observations are obtained for 13,744 individuals.

As KLIPS offers occupational classification by the Korean Standard Classification of Occupations (KSCO) 05. According to KSCO 05, the major occupational groups are declared. Ten major groups are classified into three high-/middle-/low- paying occupational group by the mean monthly wage of 1998.

Table 21 Summary statistics of data

Total observation: 93121 (n=13744)	High-Paying Occupational Group				Middle-Paying Occupational Group				Low-Paying Occupational Group			
	1998-2003	2004-2010	2011-2017	1998-2017	1998-2003	2004-2010	2011-2017	1998-2017	1998-2003	2004-2010	2011-2017	1998-2017
No. of observation	5285	7959	10015	23259	12765	16540	19201	48506	4729	7035	9592	21356
Share of employment	0.23	0.25	0.26	0.25	0.56	0.52	0.49	0.52	0.21	0.22	0.25	0.23
No. of individuals	1906	2482	2655	4466	4275	4775	4748	8223	2005	2528	2709	4746
Mean real wage (million won)	230.2	286.5	296.0	277.8	173.9	223.9	248.7	220.6	115.5	133.1	143.8	134.0
Share of educational group												
Under high school	0.02	0.01	0.01	0.02	0.23	0.16	0.11	0.16	0.54	0.45	0.38	0.44
High school graduate	0.23	0.18	0.15	0.18	0.52	0.46	0.44	0.47	0.36	0.41	0.44	0.41
College graduate	0.19	0.21	0.23	0.22	0.11	0.18	0.20	0.17	0.06	0.09	0.11	0.09
University graduate or more	0.55	0.59	0.61	0.59	0.13	0.20	0.25	0.20	0.04	0.05	0.08	0.06

Real wage consumer price index=100, in 2015. The high school classification does not include schooling and high school dropouts. High school graduate includes college/university students or dropouts.

6.3 Empirical analysis of wage and task intensity

6.3.1 Explaining the wage in relation to task intensity

To examine the changes in wages as result of occupational shift, the simple adjusted wage equation is set following Ross (2017) and Autor and Handel (2013), which is motivated by the Roy model of the allocation of workers to tasks. It means that workers are assumed to make optimizing "self-selection" of their markets, wherein they can earn the highest return on their skills. The Mincer wage equation estimates the returns to a year of education, which yields an approximate market interest rate. In Autor and Handel (2013), the model uses a similar concept of return to tasks but adopts a different approach. In this model, workers i are assumed to be endowed with skills; they maximize their income with their skill endowment $\Phi_i = \{\phi_{i1}, \phi_{i2}, \dots, \phi_{iK}\}$. In the Mincer wage equation, the marginal productivity of education is the same across occupations, whereas the productivity of tasks is allowed to differ among occupations in this model. Let worker i in occupation j produce an output using K tasks, then the production equation will be:

$$Y_{ij} = \exp[a_j + \sum_K \lambda_{jk}\phi_{ik} + \mu_i] \quad \cdots\cdots \text{Eq. (40)}$$

where $\lambda_{jk} \geq 0, \forall j, k$ and μ_i is a worker-specific error term. Then, the wage of worker i paid in marginal product will be given as follows:

$$w_i = a_j + \sum_K \lambda_{jk}\phi_{ik} + \mu_i \quad \cdots\cdots \text{Eq. (41)}$$

This wage equation is in line with literature (Firpo et al., 2011), where ϕ_{ik} denotes the

skill components embodied in worker i, and λ_{jk} denotes the return to each skill component. In this model, task returns are occupation-specific:: $\partial w / \partial \phi_k|_{J=j} = \lambda_{jk}$.

An ordinary least squares (OLS) regression of log wages on task inputs of individual worker i with occupation j at time t can be written as:

$$w_{ijt} = \alpha + \beta_{A_j} A_j + \beta_{RC_j} RC_j + \beta_{RM_j} RM_j + \beta_{M_j} M_j + \gamma x_{it} + e_{ijt} \quad \cdots\cdots\cdots\cdots \text{Eq. (42)}$$

where A_j, RC_j, RM_j and M_j denote the task intensity of non-routine analytic, routine-cognitive, routine-manual, and non-routine manual occupations j, respectively which are consistent over individuals and time. Task intensity within an occupation is assumed to be "time equivalent" in this case; however, the return to tasks denoted by β coefficient can vary over time, though it is presented as time invariant for the simplicity of analysis. γx_{it} explains individual-specific demographical explanatory variables like years of schooling or years of experience.

The aim of this estimation is to interpret the relationship between tasks and wages. Considering return to tasks, in addition to returns to education, might be important because investment in human capital is durable, while it is not fixed in tasks. It means that this model allows variation in an individual worker's task intensity. Similar to Roy's model, a worker can change own job by self-selection in response to a change in the labor market. It means that workers can modify their task inputs according to the comparative advantage and reallocate these inputs when the market price of tasks changes. Hence, task intensity

should be considered to overcome the shortcoming of the existing human capital variables and to reflect the changes in task demand caused by technological changes. Returns to tasks also allow consideration of task-specific human capital accumulated through learning-by-doing at workplace.

However, an interpretation of returns to task is very challenging. Occupations are defined as complex tasks or a bundle of various tasks. A worker should utilize several tasks jointly within an occupation to achieve an outcome. In other words, bundles of tasks are indivisible and strongly correlated with each other. Hence, regression of log wages on worker's tasks would not generally recover the average returns to those tasks; however, they would only confirm the overall slack and conceptual relationship. The result of the regression Equation (5) is presented in Table 22.

Table 22 Regression of log monthly real wage on task intensity and human capital

	(1)	(2)	(3)
TI_Analytic	0.0382***		0.0242***
	(0.003)		(0.003)
TI_Routine cognitive	0.0300***		0.0119***
	(0.002)		(0.002)
TI_Routine manual	0.0267***		0.0158***
	(0.004)		(0.004)

	(1)	(2)	(3)
TI_Manlual	-0.00634		0.00416
	(0.004)		(0.003)
High school graduate		-0.0332	-0.0327
		(0.036)	(0.036)
College graduate		0.0652	0.0672
		(0.038)	(0.038)
University graduate or more		0.339***	0.340***
		(0.038)	(0.038)
Experience		0.0244***	0.0244***
		(0.001)	(0.001)
Non-regular		-0.326***	-0.321***
		(0.004)	(0.004)
Constant	4.863***	4.975***	4.972***
	(0.006)	(0.030)	(0.030)
N	93098	93098	93098
R^2	0.152	0.229	0.230

Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001

For education, “No schooling and less than high school” is the omitted category. “High school graduates” includes students college/university attending or dropouts. All estimations include the year fixed effect

The coefficients of task intensities in columns 1 and 3 show the comparable tendency

of the relationship between wage and task intensities. When the task intensity of an analytic task rises by one unit, wage increases the most among the analytic, routine-cognitive, and routine-manual tasks of an occupation. The manual task intensity does not turn out not to be significant. The educational attainment shows significance for university graduates or more, when compared to workers with less than high school education. As Table 22 depicts the result of the fixed effect, gender is not included for the variable. The effects of the years of experience and job status (regular/non-regular jobs) have almost the same effect, irrespective of whether the task intensity is considered, showing a wide disparity by job status. The model 3 shows that the wage growth for a routine-manual task is higher than that of a routine-cognitive task, which is consistent with the w age evolution depicted in Appendix Figure A 4.

6.3.2 Relationship between task intensity and human capital

The task intensity of occupations is regressed on the variables used in Equation (5). Table 23 is the result of the pooled OLS from 1998 to 2017, which is derived using demographic information at an individual level. This analysis investigates the extent to which workers' demographic conditions or human capital in the form of educational attainment and experience can explain the tasks performed by them at workplace. The occupation dummy reflects the technical requirements of the occupation itself in order to take the intrinsic properties of occupations into consideration. The signs of coefficients for education level coincide with the result of the affiliation network of tasks. Two types of

tasks—analytic and routine-cognitive—are positively related to the educational level; the higher the educational attainment, the higher is the value of the estimation coefficient, this relationship reverses in routine cognitive. The evolution of occupational mean wage by task occupational groups is shown in Appendix Table A 4. The same proportional tendency is negatively correlated for routine-manual and manual tasks with educational attainment. This result should present the R square values of each model with or without occupation-specific properties. Models 1, 3, and 5 of using human capital and demographic variables explain 7~ 25% of task intensity prediction within occupations. Introducing occupation-specific variables increases explanatory power to 34-66% in models 2,4, and 6. Additionally, the import of occupation dummy mediates the effect of education on all types of tasks while maintain the significance of results. Table 23 infers that although human capital continues to influence tasks within occupations, occupations serve as the dominant measurable predictor of task intensity, having structuring power in determining task contents (Autor & Handel, 2013; Autor & Dorn, 2013).

Table 23 Pooled OLS of task intensity on educational attainment, experience, gender, age, and occupation

Intensity of task	Analytic		Routine cognitive		Routine manual		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High school dropout	0.349***	0.260***	0.196***	0.0409***	-0.139***	-0.0981***	-0.167***	-0.148***
	(0.00057)	(0.00044)	(0.00059)	(0.00053)	(0.00057)	(0.00043)	(0.00057)	(0.00041)
High school graduates	0.640***	0.396***	0.512***	0.127***	-0.534***	-0.301***	-0.523***	-0.198***
	(0.00057)	(0.00045)	(0.00060)	(0.00053)	(0.00057)	(0.00044)	(0.00058)	(0.00041)
Attending or dropout college/ university	0.723***	0.373***	0.480***	0.0829***	-0.774***	-0.333***	-0.748***	-0.202***
	(0.00061)	(0.00048)	(0.00064)	(0.00057)	(0.00061)	(0.00044)	(0.00061)	(0.00044)
College graduates	0.814***	0.386***	0.639***	0.175***	-0.876***	-0.324***	-0.862***	-0.180***
	(0.00059)	(0.00046)	(0.00061)	(0.00055)	(0.00058)	(0.00045)	(0.00059)	(0.00042)
University graduates	1.052***	0.407***	0.605***	0.111***	-1.296***	-0.398***	-1.370***	-0.332***
	(0.00058)	(0.00046)	(0.00060)	(0.00055)	(0.00057)	(0.00045)	(0.00058)	(0.00042)
Experience	-0.00363***	-0.00145***	0.00274***	0.000167***	0.00373***	0.00210***	0.00380***	0.00253***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Female	-0.0191***	-0.160***	-0.00316***	-0.128***	-0.255***	0.00529***	-0.566***	-0.224***
	(0.00011)	(0.00009)	(0.00011)	(0.00010)	(0.00011)	(0.00009)	(0.00011)	(0.00008)

Intensity of task	Analytic		Routine cognitive		Routine manual		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Occupations		O		O		O		O
Constant	-0.882***	0.760***	-0.375***	-0.449***	0.911***	-0.726***	0.988***	-0.911***
	(0.00061)	(0.00074)	(0.00064)	(0.00084)	(0.00061)	(0.00057)	(0.00062)	(0.00054)
N	93098	93098	93098	93098	93098	93098	93098	93098
R2	0.07521	0. 44816	0.04548	0. 25183	0.19483	0. 52723	0.25316	0.62637
F	1782895.3	10173808	1044535.2	4216650.7	5304848.9	13970609	7431334.1	21001669

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All estimations include ages of individuals.

6.4 Hollow-out of the middle-skilled workers

6.4.1 Change in employment share by mean wage

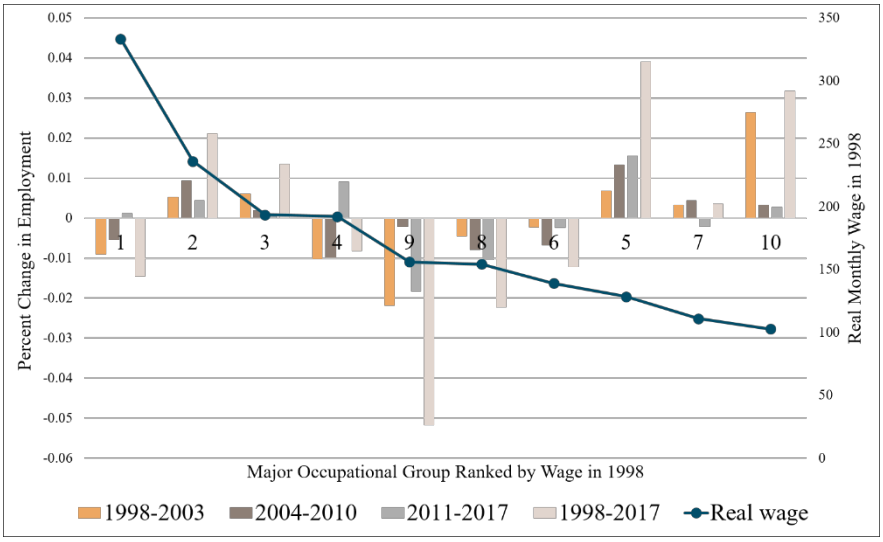

Figure 25 Percentage change in employment by occupational group from 1998 to 2017

Figure 25 depicts the change of employment share from 1998 to 2017. The period is divided into three, 1998-2003, 2004-2010, and 2011-2017. The x-axis is ranked by the mean wage of 1998 and the value is marked on the right vertical axis in Korean million Won. The left vertical axis shows the employment share change. Clearly the share of middle-paying groups has been declined over the period while the shares of the high- and low-paying groups have increased[28]. The numbers of occupational group follow that of

[28] For occupational group [1] 'Administrative, executive and managerial workers', when KSCO was revised, there was large reform in group [1], merging major level with sub-group level code. Hence

Table 20.

The change for the share of middle income workers decreased most in 1993-2003 and the degree of change decreased after that period. But increase in the share of high income groups are relatively stable (Figure 26).

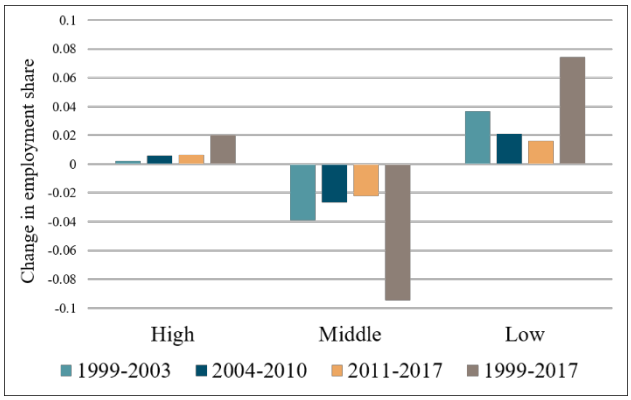

Figure 26 Changes in employment share of occupational group by monthly wage

At an individual level, the job shifts of middle-paying group were traced. The movements of each year are drawn in Figure 27. The sum of the frequency of movement to low and high groups was set to 1 for each year. The year depicts the period in which the movement occurs. Except three years, from 2012~2014, those who were in middle-paying jobs showed a tendency to shift more to the low-paying group rather than high-paying

there was a lack of clear criteria, the responds were of doubtful accuracy (Kang, 2010).

occupations. Those who moved to high-paying groups were mostly in group [4] “Clerical Workers,” and they entered group [3] “Technicians and semi-professionals.” The details of movement are in Appendix Figure A 5.

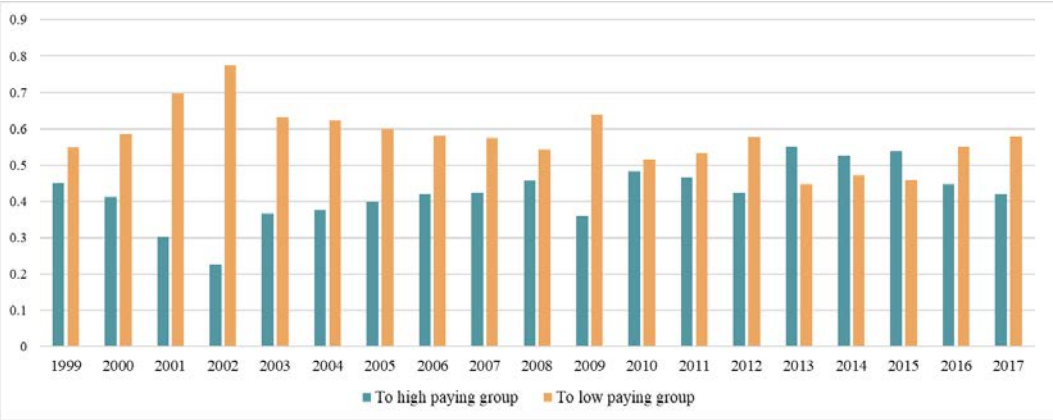

Figure 27 Job shift in the middle-paying group

6.4.2 Employment share changes by means of task intensity

6.4.2.1 Changes in employment share by task occupational groups

In previous section, the occupations are grouped by the occupational mean wage. To investigate whether the required tasks in occupations are polarized, and the corresponding wage polarization takes place. Occupations are classified into non-routine analytic, routine-cognitive, routine-manual, and manual task-intensive groups. Unlike most previous studies that have three groups, this study has four groups as routine-cognitive and routine-manual groups are classified as two categories instead of one routine group. This allows us to consider the effect of technology on task requirements at workplace. Once there is a

routine-biased technological change, the demand for routine tasks would reduce and those for analytic and manual tasks would increase. Twenty variables from the ONET database are used according to KSCO 05.

Figure 28 explains the evolution of the employment share in each task-intensive occupational group. The share of each group in 1998 is set to reference zero. For the manual occupational group, the share is always higher than that of 1998, though the degree of change decreases after the early 2000s. For analytic and routine-cognitive occupational groups, the share increases steadily after 2000, while the share of routine-manual only shows a monotonic decrease after 1998. Breaking down the routine occupations into cognitive and manual levels, instead of analyzing the routine task-intensive workers in one group, gives more precise results on the task demand polarization in the Korean labor market. Concerning the high-/middle-/low-paying groups, routine manual occupational groups are all middle-paying groups, consistent with the tendency of a decline in labor demand.

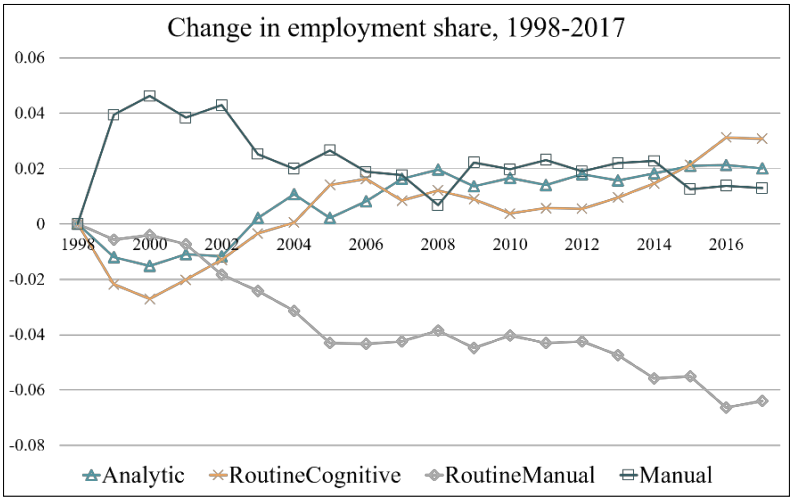

Figure 28 Changes in employment share of occupational group by task

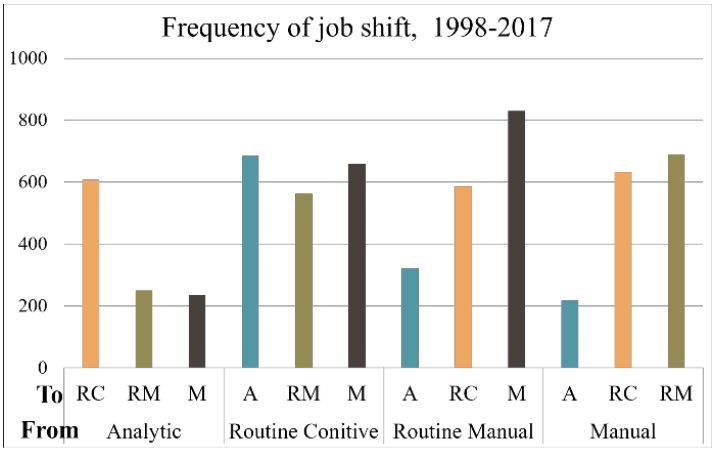

Figure 29 Frequency of job shift, 1998-2017

All types of job shift that happened in the past two decades are depicted in Figure 29. Figure 29 depicts the frequency of the job shift in absolute counts. Job shifts between task specific occupation groups are more active than expected. Workers from analytic

occupations moved mostly to routine-cognitive occupations. Routine-cognitive workers moved to analytic, routine-manual, and manual quite evenly. Shifts of manual workers are limited to routine occupations; they rarely moved to analytic occupations. Routine-manual workers mostly moved to manual occupations. Figure 30 resents the aggregate movement of routine workers. During the period, they always moved to manual occupations with a higher probability rather than the analytic group.

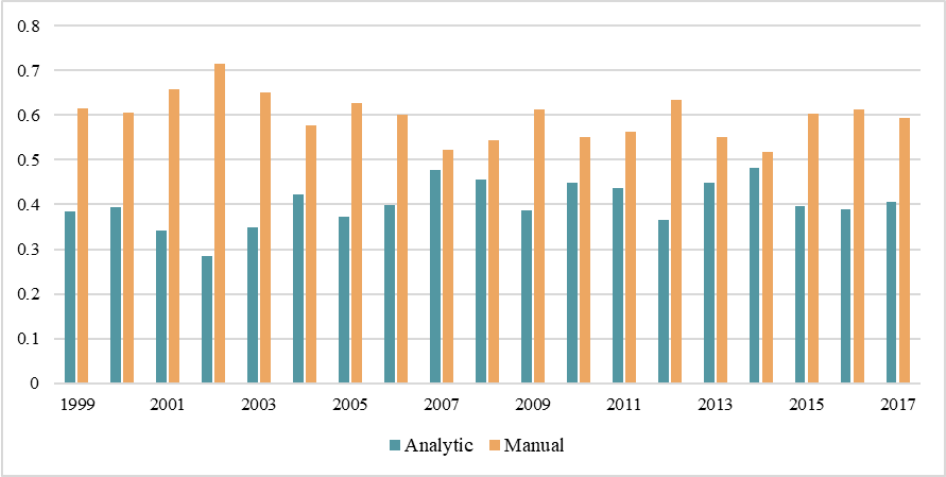

Figure 30 Job shift from routine cognitive and manual groups

6.4.2.2 Changes in wage after the job shift

As shown in Figure 27 and Figure 30, since the majority of middle-paying occupation workers moved to low-paying occupations or most of the routine workers moved to manual occupations, they were expected to face the wage cut after the job shift. When routine workers moved to manual jobs, they faced wage cuts, on an average (Table 24). However,

the movement within routine occupations, from routine-manual to routine-cognitive or vice versa, raised the wages in both cases when compared to the workers who stayed in their routine occupations. Additionally, without reversals, there was an increase in the monthly wage of workers who shifted from two types of routine to analytic occupations.

Table 24 Changes in log monthly wage accompanied by job shift

	Initial occupation: Routine cognitive				Initial occupation: Routine manual			
year	RC	M	RM	A	RM	M	RC	A
1999	0.013	0.120	0.122	0.130	0.020	-0.014	-0.058	0.042
2000	0.052	-0.212	0.285	0.172	0.055	-0.001	0.060	0.196
2001	0.071	-0.101	0.080	0.036	0.054	0.150	0.142	0.498
2002	0.102	-0.009	0.138	0.255	0.084	-0.026	0.257	0.325
2003	0.111	-0.371	0.077	0.248	0.067	-0.058	0.060	0.160
2004	0.080	-0.070	0.007	0.248	0.087	0.081	0.250	-0.002
2005	0.069	0.113	0.193	0.059	0.072	-0.176	-0.019	0.235
2006	0.051	0.106	0.044	0.092	0.052	-0.038	0.066	0.149
2007	0.049	-0.061	0.137	0.192	0.042	-0.136	0.161	0.259
2008	0.027	-0.002	0.203	0.046	0.032	-0.090	0.101	0.135
2009	0.033	-0.131	0.089	0.119	-0.005	-0.082	0.290	0.325
2010	0.021	-0.058	0.163	0.184	0.060	-0.177	0.005	0.265
2011	0.031	0.002	0.298	0.034	0.027	-0.047	-0.151	0.168
2012	0.037	-0.042	0.036	0.464	0.033	-0.117	-0.072	0.365
2013	0.042	0.056	0.089	0.132	0.029	-0.023	0.133	-0.043
2014	0.029	0.092	0.056	0.017	0.045	-0.006	0.100	0.089
2015	0.048	-0.111	0.145	0.108	0.045	0.005	0.055	0.229

	Initial occupation: Routine cognitive				Initial occupation: Routine manual			
year	RC	M	RM	A	RM	M	RC	A
2016	0.034	0.027	0.241	0.325	0.028	-0.060	-0.023	0.436
2017	0.035	-0.225	0.230	0.408	0.022	-0.108	-0.130	0.116
Average	0.046	-0.039	0.137	0.169	0.043	-0.052	0.063	0.178

A: Analytic, RC: Routine cognitive, RM: Routine manual, M: Manual occupations

The Table 25 presents the result of regression of the wage growth of individual workers who hold the same occupations on dummies of individual occupations in each year. Among the total observations from 1998 to 2017, the observations without any changes in an occupational group account for 78.5%. The routine-manual occupation is chosen to be the omitted category to compare. On an average, there have been a rise and decline in the mean wage of all occupational groups; workers who stay in manual occupations earn 9.57% less and expect their real wages to grow by 1.9% less than those who stay in routine-manual operations. It means that workers who are forced to move (or willingly) to manual from routine occupations have to give up the expected wage growth.

Table 25 Regression of log monthly wage for workers with no job shift

	log monthly wage	Change in log monthly wage
Analytic	0.0183	0.00822
	(0.01037)	(0.005)
Routine cognitive	0.0241**	0.00340

	(0.00882)	(0.004)
Manual	-0.0957***	-0.0199***
	(0.00809)	(0.004)
Constant	5.263***	0.0472***
	(0.00604)	(0.003)
N	73081	73081

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regression on dummy of occupational groups. Analytic is a dummy equal to 1 for the analytic occupational groups and 0 for others. The same assumption is applied to the routine-cognitive and manual-occupations. Workers staying in the routine-manual occupations are omitted for comparison. Regression includes the year fixed effect.

6.4.3 After job shifts of routine task-intensive workers

When a worker moves from her/his occupation, the corresponding wage change is estimated on the change in the degree of the analytic, routine, and manual tasks. As KLIPS is an unbalanced panel data, instead of using first differential methodology, the study analyzes the wage difference when there is an actual occupational shift from routine-cognitive or routine-manual to analytic or manual intensive occupation by detecting the change by the KSCO code. For those who change their occupations, 36.0% remain in their major industry group, and most of them (93.7% of the observations) maintain their education level.

Table 26 Regression of log wage on the change in degree of task intensity: All job shifts

	Change in log real monthly wage: All types of job shifts				
	(1)	(2)	(3)	(4)	(5)
Δ Analytic	0.0267***				0.0304***
	(0.00461)				(0.00526)
Δ Routine cognitive		0.0306***			0.0275***
		(0.00465)			(0.00471)
Δ Routine manual			-0.000660		0.0138*
			(0.00503)		(0.00728)
Δ Manual				-0.00205	0.00340
				(0.00513)	(0.00699)
Constant	0.0692***	0.0688***	0.0693***	0.0693***	0.0691***
	(0.00556)	(0.00555)	(0.00557)	(0.00557)	(0.00555)
N	10442	10442	10442	10442	10442
R^2	0.00321	0.00412	0.00000	0.00002	0.00731
F	33.67	43.21	0.0172	0.159	19.23

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26 is the result of estimation on whole job shift from 1999 to 2017. Certainly, certain workers never changed their jobs within the same period. This result includes all types of job shifts from one of the four groups to one of the remaining three groups. In this table, the increase in the intensity of analytic and routine-cognitive tasks has a positive relationship with log-real monthly wage growth. Irrespective of the inclusion of the effect

of the educational level, occupation, or industry, the results show a consistent relationship.

However, this mix in the direction of occupational changes might mitigate or offset the effects of each direction. Hence, in accordance with the purpose of this study, the occupational changes made from routine-cognitive or routine-manual are taken into account. First, Table 27 presents results of workers from routine to analytic and manual occupations when compared to those who stayed in routine occupations. The result confirms the statistical change in wages, as represented in Table 24. Workers with previous routine-cognitive or routine-manual occupations embraced the wage decline when they moved to manual occupations.

Table 27 Wage change of routine occupation workers after job shift

Direction of job shift	log wage change
To manual	-0.102***
	(0.009)
To analytic	0.0961***
	(0.011)
Constant	0.0585***
	(0.003)
N	36722

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Workers in routine occupations without job shift is the omitted category.

Table 28 shows the relationship between the change of task intensity and the change in wage. The individual wage change of workers who once in routine occupations is regressed on the job shift direction dummy with time fixed effect. In Appendix, the direction of job shifts in Table 28 is separated into analytic and manual. Table A 4 reports the results of the regression of workers from routine occupations to analytic occupations, and Table A 5 shows results of workers from routine to manual occupations. For those who actually made job shifts, the results show that the estimated sample population is much smaller than that of previous estimations. However, considering the sample size, it still suffers from low explanatory power.

Table 28 Regression of log wage on the change in the degree of task intensity: From routine to analytic and manual occupations

Chang in log real monthly wage: from routine to analytic and manual occupations					
	(1)	(2)	(3)	(4)	(5)
Δ Analytic	0.0550***				0.0570***
	(0.00998)				(0.0118)
Δ Routine cognitive		0.0364***			0.0259*
		(0.0102)			(0.0104)
Δ Routine manual			-0.0195		0.0114
			(0.0106)		(0.0153)
Δ Manual				-0.0123	0.00580
				(0.0108)	(0.0144)

Constant	0.0249*	0.0612***	0.0343**	0.0408***	0.0430**
	(0.0121)	(0.0130)	(0.0125)	(0.0118)	(0.0142)
N	2496	2496	2496	2496	2496
R^2	0.01205	0.00512	0.00134	0.00052	0.01508
F	30.42	12.84	3.352	1.291	9.537

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The main assumption of the framework of this analysis emerges from the Roy model. In the Roy model, the question was when there are two types of occupation, hunter and fisherman, would the best hunter choose to be a hunter and the best fisherman choose to be a fisherman while a job shift is allowed? Therefore, a worker is expected to allocate own skill or ability to an occupation that would earn the worker the highest return or reward. The observed job shift may not the result in optimizing earning; however, it would push workers against their willingness. Nevertheless, at the same time, all the workers who moved from their jobs did face the wage decline; this may be attributed to skill reallocation, and the estimation results are the complex of these two effects.

6.5 Conclusion

It is clear that there is polarization in wage and employment, but the movements of workers who would have shifted their jobs after the hollowing-out has been overlooked. This study covers the direction of job shift and the corresponding wage change of those who were once in middle-paying occupations.

This study has two distinct approaches. First, to measure the characteristics of the tasks

in the occupations, the ONET databased is used. While previous studies adopt the definition set by Acemoglu and Autor (2011), I analyze the effectiveness of tasks within an occupation and map the affiliated skill sets that are utilized together frequently. This polarized the skill map into manual and cognitive groups, validating the identification process. The second adjusted the wage equation for the task-specific human capital. There is a mismatch between the educational attainment and skills of individuals and the tasks one performs at the workplace. Therefore, the wage premium of higher education in Korea shows a pattern that is different from developed countries. Instead of the general human capital measured by schooling years, the task-specific human capital is considered, which can be accumulated through learning-by-doing.

The empirical analysis shows the collapse of the middle-paid workers, who move more to low-paying occupations rather than high-paying occupations. With this task-based view, the labor demand for routine-manual tasks is seen to have a decreasing monotonic tendency, and most routine-cognitive and routine-manual task-intensive workers go to manual-intensive occupations. Workers who move to manual occupations earn less than those who stick to routine occupations, but workers who move to other occupations, except the manual occupations, would witness a higher wage increase rate when compared to those who remain in routine occupations. The regression of wage on task intensity changes supports these results.

There is one implication of the characteristics of the database. Respondents of KLIPS report the income after tax. It means that the wage analysis result of this study reflects the

taxation for the redistribution of wealth. However, it also shows an increase in the low tail inequality and increased share of low-paying occupation; it implies that the income redistribution policy focusing on high-income earners has limitation in easing the wage distribution. In other words, selective supporting policy is important for those who are exposed to the risk of substitution and shift to lower-wage occupations.

The critical limitation of this study is that the taxonomy of ONET skills may not capture the real-time dynamics of skill categories as it is assumed to be invariant over time. The task-specific human capital is a key factor to be included when analyzing the relationship between wage and skills individual possess. Nevertheless, the valuable consideration of the task-specific human capital alone cannot cover the wage equation, as revealed by low R square values. Hence, it would be crucial to conduct an inclusive analysis with years of schooling, experience, and other demographic indicators.

Chapter 7. Conclusion

7.1 Summary

Many developed countries have experienced rising income inequality and the demise of middle-income workers. Technological advancement is cited as the major cause of this labor market disruption. Among the OECD countries, Korea is one of the countries with the highest inequality as measured by the Gini index of full-time workers, and it is even higher when non-regular or part-time workers are included in the calculation. Depending on the policies of each country, the patterns vary (Koske, Fournier, & Wanner, 2012). As AI, robotics, big data, and machine learning enhance productivity, technology continues to serve as the growth engine in the age of digital transformation (Manyika et al., 2017). It seems difficult to navigate between the incompatible interests of promoting technological progress while reducing income polarization in the labor market. This research aims to suggest methods to analyze the effects of technology on the labor market and confirm the polarization of demand in the Korean labor market in order to find solutions for this incongruent problem.

Income inequality has been explained as the income differential between skilled and unskilled labor. It is referred to as skill-biased technological change, and technology is assumed to favor highly skilled and highly educated labor. However, previous literature specific to the Korean labor market could not declare the existence of skill-biased technological change until the early 2000s. The reason studies failed to provide significant

results was related to the distinct characteristics of the Korea market. A relatively high proportion of tertiary and higher-educated workers made it difficult to ascertain the actual income dispersion of workers. Further, it is the concurrent increase of employment opportunities at both extremes of wage distribution that has been witnessed recently in developed countries rather than only the increased demand and wages for the highly skilled. Based on these observations, this research set forth with three main research questions. i) define the role of ICT in the industrial-level labor market using empirical evidence to indicate how ICT complements or substitutes workers depending on the tasks they perform, ii) if technology substitutes particular workers, what groups have been displaced most often by technological progress (the polarization of labor demands for middle-skilled labor is analyzed with data from 1993 to 2015), and iii) determine where workers who were displaced have gone in the last two decades. To answer these questions, this study introduces the RBTC hypothesis that explains how polarization functions at the expense of median workers. As explained, median workers mainly perform routine tasks that are repeatable, well-defined, and easily codifiable; in other words, tasks that can be readily substituted by existing technology, including computers or robotics that represent physical rather than human capital.

To illustrate the effects of technology on the labor market, we need a quantitative and comparable tool to diagnose the extent of technological impact. In this research, by introducing task-oriented analysis, the intensities of analytic, routine (cognitive and manual), and manual tasks are measured. Technology does not necessarily replace entire

occupations or job classes. It replaces certain tasks or parts of tasks. To clarify, consider the introduction of the dishwasher and the tasks still performed by the waitress or kitchen staff. According to the task intensity scores, the occupational groups are classified into analytic, routine, and manual occupations, and the task intensity of occupations are directly used for estimation.

The first question asks whether new technology is a “treat or threat” to workers. There has been ongoing debate about whether technology works as a complement or substitute for labor since the first industrial revolution. Chapter 4 tries to answer this question as it relates specifically to ICT in the modern labor market. Although historical wisdom has told us that technology has more of a capitalization effect than a destructive one, many still fear that this round of dynamic technological change might be different. Chapter 4 diagnoses this phenomenon. With the steady decline in ICT rental price, the introduction of ICT and non-ICT capital have displaced both routine and non-routine labor; however, demand remains steady for non-routine analytic workers who are creative, make solid decisions, form coherent strategies, and solve problems. Another important role of the first study is to find clear evidence of the impact of technology on the labor market.

Already convinced of the effects of technological progress on the labor market, the second study in Chapter 5 determines whether polarization has taken place in the Korean labor market; in other words, have routine-task biased technological changes occurred in Korea. The statistical and empirical results demonstrate that there has been RBTC for over 20 years, and the growth of demand for routine workers has diminished. Employment

proportions of high-paid analytic and low-paid manual workers have increased, with the wage rates of analytic workers rising disproportionately faster than other types of workers. In the labor market, polarization has been one negative result of technological advancement as new technology continues to replace routine-task intensive workers.

The final article discusses where mid-level workers have gone after being displaced by technology. As concluded in Chapters 4 and 5, many workers formerly in routine occupations were substituted, but their future career paths after displacement have rarely been examined. This article reveals the direction of job transition and the consequential impact on wages that may exacerbate polarization in the labor market.

Technological progress is inevitable and irreversible; therefore, the corresponding polarization should be taken for granted as one of the negative effects of economic development. However, this research warns that employment polarization could compound wage inequality. The increase in low-income groups is related to investments in human capital which depress skill development among individuals, thereby causing additional opportunity inequalities (Cingano, 2014). Apparently, the proportion of employment in non-routine manual and analytic-based occupations continues to increase. Figure 31 shows that manual occupations are mainly concentrated in the lower income levels while analytic positions are more prominent at the higher income levels. The figure shows which occupational groups benefitted the most during the previous one and two decades. This was calculated as the wage difference between 1998 and 2007 and between 1998 and 2017 for each wage decile. As explained in Chapter 1, wage inequality was strongly led by the

bottom tier, and Figure 31 suggests the same. Wage levels of the bottom 10 and 20 percent rarely increased, and they even decreased for the period. As a repercussion of technology advances, employment polarization occurred, and the transition of middle-skilled workers to lower-paying occupations could potentially intensify the wage inequality. The employment proportions calculated in the Survey on Work Conditions by Employment Type and the Economically Active Population Survey show more compelling changes in the share of routine workers compared to KLIPS. This implies that wage inequality might be more severe than originally anticipated. However, these changes might not be caused solely by technological advances. The openness of the economy, globalization, offshoring, superstar economies, the collapse of labor unions, structural or institutional changes, and other factors all affect labor markets; nevertheless, these create synergy and are reinforced by technology-driven displacement.

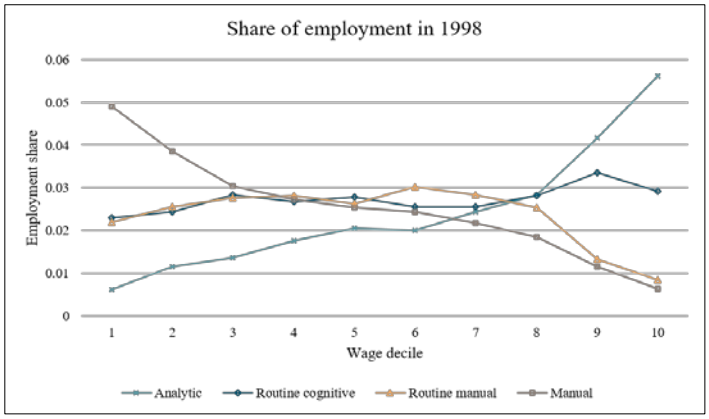

Figure 31 Majority occupational groups per wage decile

Policy implications derived from this research serve two important roles. First, the cautious and targeted policies of education and training for middle-skilled or middle-income workers would provide them with additional opportunities to upgrade their skills and qualify for better positions whenever changing jobs became necessary. The second is to control the supply dynamics of skilled labor. Technical feasibility is not the only factor that determines technological progress. A sufficient and continuous supply of properly educated and skilled labor remains a necessary component of development.

7.2 Implications

This research primarily discusses the effects of demand in the labor market after it was revealed that excess demand leads to changes as the result and response to technological change. At the same time, the causalities between labor market institutions and the economy should not be overlooked as the literature supports the contention that institutions have affected wage distribution (Freeman, 2009) The minimum wage serves as one clear example. Decisions made today will determine whether workers in future labor markets will either suffer from replacement or be able to create and strengthen timely skills as lifelong learners.

It is obvious that the work of the future will be very different than it is today. Education should prepare people for the changing requirements of the society in advance to avoid wasting resources by producing graduates with outdated skills. The education system should take two main actions: one relates to preparing the next generation while the other

would provide vocational training for workers who are already at risk of being displaced by automation. The government must express a willingness to reform education and proceed as soon as possible. Education for the next generation should be able to outpace the dynamic changes in technology and society. In addition to fundamental skills, the nurturing of “analytic cognitive” and “interactive social behavioral” human capital should be principle goals of education. Technology expands opportunities. It offers easier ways to create new types of jobs and improves access to education. Institutions should create environments where workers can focus on improving their skill sets rather than on degrees or additional years of formal education. Institutional support for workers would help them manage their human capital accumulation in the workplace. The role of technology in the labor market should not be limited to discussions of whether it is a substitute or complement to workers. It is already clear that technology will change everything.

Educational attainment alone cannot guarantee returns on education investments in Korea. There are severe disparities between education levels, the skills workers actually possess, and the tasks they are expected to perform for their jobs. An excess supply of highly educated workers lowered their value, and workers were not being rewarded for their skills and effort. The task-based approach offers a tool to analyze human capital accumulation at a finer, more detailed level and link it to the realistic skill sets required for work activities. Flexibility in the labor market would open new opportunities for workers with accumulated skills at one workplace to transition into new positions where they could display their true potential. Companies should not remain content as passive consumers in

the labor market, rather, they should train their workers to equip them with new skills because the workplace may very well be the best institution for education.

The technology revolution will change the classic form of employment and promote more flexible structures, including self-employment and on-demand third-party contract work. Workers should no longer naively expect employment stability like previous generations because the concept of “jobs for life” no longer exists. Likewise, the lifespans of acquired skills will be shortened by each new wave of technological advances. Workers will be freed from tedious and repetitive tasks, thanks to technology. Instead, they will be able to combine their skills to solve problems, improve communication, or help raise social awareness. The findings of this study clearly show that the possibility of substitution of routine workers with technology runs parallel with the rising demand for analytic and other advanced tasks, including creative thinking, problem solving, objectives and strategy development, in-depth analysis, as well as numerous soft skills.

7.3 Limitations and future study

There are several limitations of this research. First, as technology advances, the nature of an occupation changes. This suggests that the importance of required skill sets and the frequency in which they must be updated in order to continue to perform the responsibilities of the occupation also evolve. Reliance on DOT or ONET variables to measure task intensity cannot reflect these change as it is assumed that the essence of an occupation is

invariant over time. DOT and ONET indices successfully explain the relationship between task intensity and the changes of wages and employment. Also confirmed is that tasks that are effectively utilized within occupations show polarization with analytic and cognitive tasks on one end and manual tasks on the other. It is assumed that the intrinsic characteristics of occupations in Korea and the United States are similar to the findings of studies featuring other developed countries. The Korean Dictionary of Occupations offers general statements of duties, tasks performed, educational levels required, job intensity, and other factors with a 4-digit level of detail for 12,000 occupations. However, it states occupations in sentences rather than quantitative indices, thereby making the tasks of measurement and comparison between occupations impossible. This data could not be applied for this research.

As mentioned previously, technological change is not the only factor affecting the labor market. Macroeconomic disruptions such as the Korean crisis in 1997 or the global crisis in 2007 should be carefully analyzed as their impact on employment and wages was considerable. This study tried to account for them by dividing the period before and after the crises and comparing the results, but this might be insufficient. Also declared as a limitation of previous Korean studies is that the wage premiums for higher levels of education alone could not successfully explain the income inequality in Korea. There exists a large disparity between regular and non-regular employment in Korea that represents a more significant difference than wage premiums. The reduction of mid-level work and the subsequent job transitions could affect the changes in ratios between regular and non-

regular employment; however, they are not fully covered in this research. This remains as an interesting and important area for future study because recent innovations in digital technology have enabled on-demand job platforms that are dismantling many existing occupations while moving forward toward a job market featuring more task-based work. This would relate to the displacement of middle-income or middle-skilled workers and the consequential structural changes, thus implying that the structural changes of job status can also be the result of technological advances in the near future.

There are three factors that affect labor income inequality for individuals: the dispersion of hourly earnings of full-time workers, the dispersion of hours worked, and the unemployment rate (OECD, 2012). This research deals only with the first by analyzing the monthly wages of hourly and salaried workers including both full-time and part-time employees. The Korean labor market is undergoing a rapid transformation fueled by the implementation of new policies regarding working hours and the minimum wage. In 2018, the government enacted legislation that included a new 52-hour work week in order to seek better work-life balance by lowering the maximum number of weekly hours to 52, down from 68. Korea has also raised the minimum wage by 16.4 and 10.9 percent in 2018 and 2019, respectively. These policies were designed to boost consumption and growth, but they could also affect the standard of living of lower-paid workers, thus becoming a crucial factor in income inequality in terms of the dispersion of hours worked. This was not discussed in this study. It is also connected with the discussion of regular and non-regular employment that should be better defined to confirm the effects on labor market changes.

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Appendix 1 (Chapter 4)

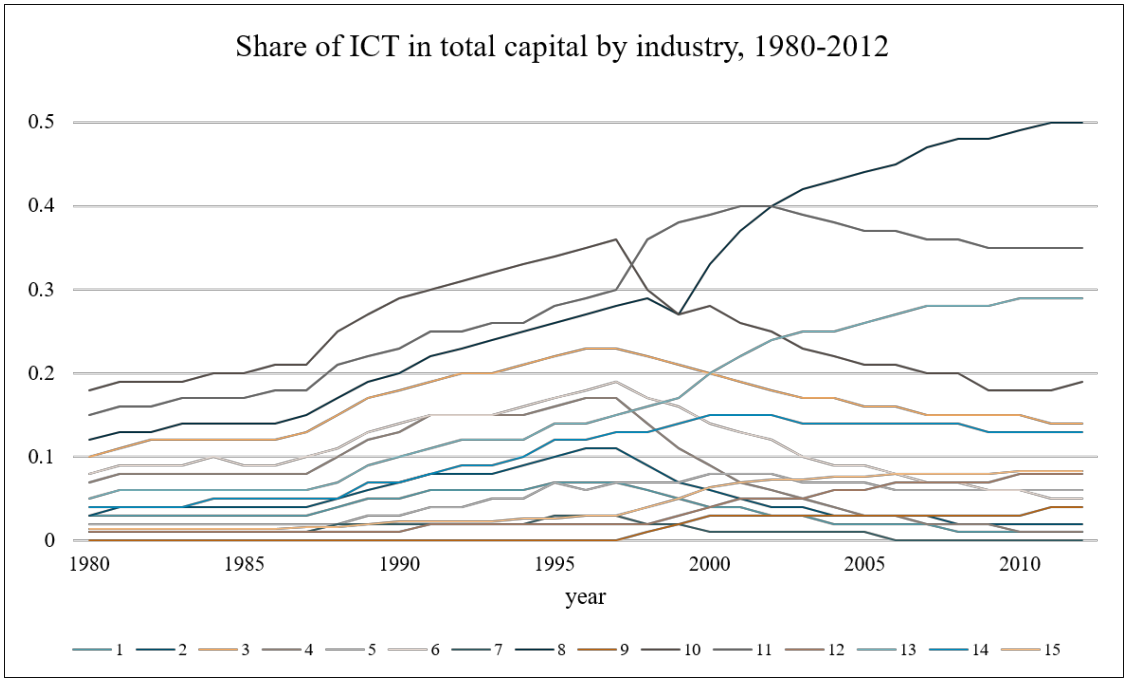
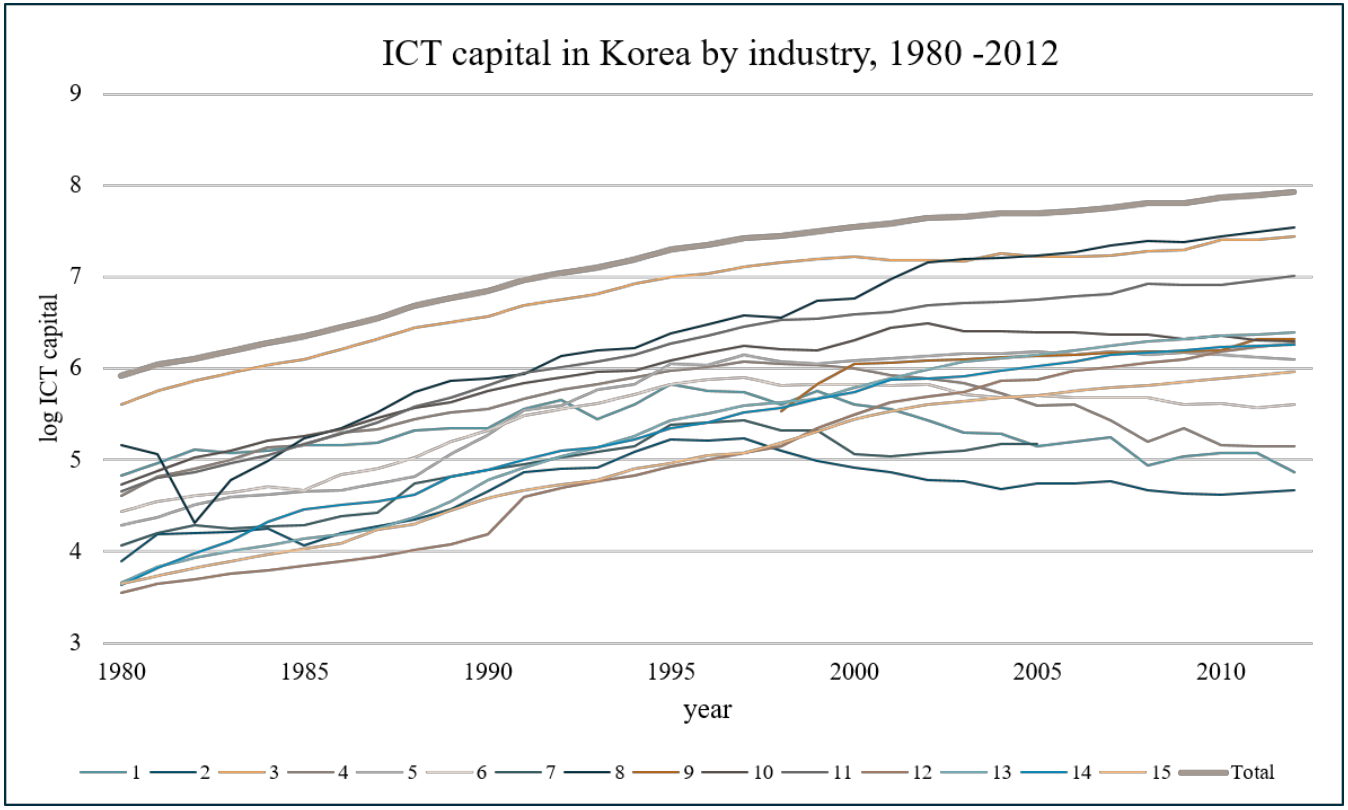


Figure A 1 Share of ICT capital in total capital, 1980-2012



Original data in million Korean won

Figure A 2 ICT capital of Korea by industry, 1980-2012

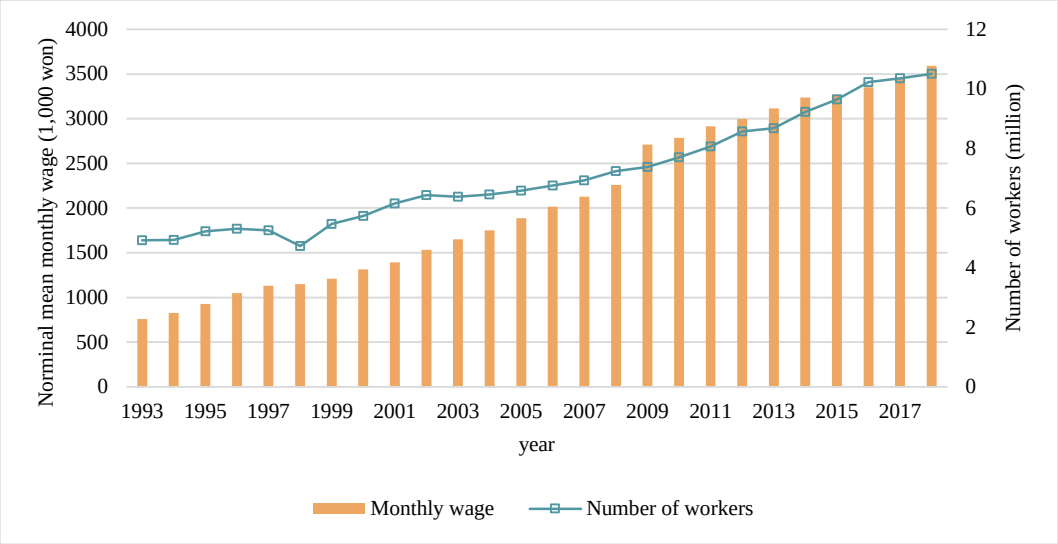


Figure A 3 Monthly wage and employment, 1993-2018

Appendix 2 (Chapter 5)

Table A 1 Heteroscedasticity and auto-correlation test for Table 17 & Table 18

	Heteroskedastic test: Likelihood-ratio test	Wooldridge test for autocorrelation in panel data
(1)	LR chi2(125)= 1963.43 Prob > chi2 = 0.0000	F(1,123) = 65.901 Prob > F = 0.0000
(2)	LR chi2(125)= 2507.89 Prob > chi2 = 0.0000	F(1,123) = 66.011 Prob > F = 0.0000
(3)	LR chi2(125)= 1870.11 Prob > chi2 = 0.0000	F(1,123) = 63.355 Prob > F = 0.0000
(4)	LR chi2(125)= 2453.99 Prob > chi2 = 0.0000	F(1,123) = 63.601 Prob > F = 0.0000
(5)	LR chi2(125)= 2434.65 Prob > chi2 = 0.0000	F(1,123) = 65.680 Prob > F = 0.0000
(6)	LR chi2(125)= 2396.31 Prob > chi2 = 0.0000	F(1,123) = 63.261 Prob > F = 0.0000

Notes: All have heteroscedasticity and first order autocorrelation at 1percent significant level.

Table A 2 The result of estimation, 1993~2015: log number of persons employed

Variables	(1)	(2)	(3)	(4)
RTI	-0.0365***	-0.0357***	-0.0289***	-0.0327***
	(0.00350)	(0.00423)	(0.00331)	(0.00418)
log monthly wage		-0.499***		-0.659***
		(0.0873)		(0.0825)
log industry output		0.645***		0.723***
		(0.0502)		(0.0446)
log industry marginal cost		0.573***		0.697***
		(0.107)		(0.101)
Constant	6.197***	-5.171***	5.966***	-5.329***
	(0.243)	(1.427)	(0.253)	(1.339)
Observations	2,770	2,770	2,500	2,500
Number of ij	126	126	112	112

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Set panel data for 126 occupation-industry groups, AR1 & heteroscedasticity considered. Columns 1 & 3 contain industry-year, occupation-year fixed effects. Columns 3&4 contain results except "Skilled agricultural, forestry and fishery workers". Column 2&4 include year fixed effect

Appendix 3 (Chapter 6)

Table A 3 Change in degree of task intensity according to job shift directions

From	To	Δ Analytic	Δ Routine cognitive	Δ Routine manual	Δ Manual
Analytic	Routine cognitive	-1.148	0.664	0.960	0.648
Analytic	Routine manual	-0.620	0.067	1.078	0.889
Analytic	Manual	-0.912	-0.401	1.116	1.448
Routine cognitive	Analytic	1.117	-0.567	-0.970	-0.650
Routine cognitive	Routine manual	0.568	-0.001	0.107	0.108
Routine cognitive	Manual	0.030	-0.709	0.277	0.501
Routine manual	Analytic	0.442	-0.093	-0.875	-0.676
Routine manual	Routine cognitive	-0.738	0.130	-0.079	0.027
Routine manual	Manual	-0.194	-0.533	-0.253	0.134
Manual	Analytic	0.999	0.574	-1.213	-1.549
Manual	Routine cognitive	-0.074	0.749	-0.341	-0.484
Manual	Routine manual	0.330	0.599	0.191	-0.169

Table A 4 Regression of log wage on the change in degree of task intensity: from routine to analytic occupations

	Chang in log real monthly wage: from routine to analytic occupations				
	(1)	(2)	(3)	(4)	(5)
Δ Analytic	-0.0225				0.00165
	(0.0183)				(0.0193)
Δ Routine cognitive		0.0451**			0.0325*
		(0.0151)			(0.0158)
Δ Routine manual			0.0845***		0.0542
			(0.0190)		(0.0309)
Δ Manual				0.0737***	0.0287
				(0.0201)	(0.0303)
Constant	0.192***	0.191***	0.251***	0.221***	0.254***
	(0.0250)	(0.0197)	(0.0258)	(0.0228)	(0.0281)
N	1006	1006	1006	1006	1006
R^2	0.00150	0.00879	0.01924	0.01329	0.02374
F	1.504	8.908	19.70	13.52	6.086

Standard errors in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A 5 Regression of log wage on the change in degree of task intensity: from routine to manual occupations

	Chang in log real monthly wage: from routine to manual occupations				
	(1)	(2)	(3)	(4)	(5)
Δ Analytic	0.0460***				0.0520***
	(0.0134)				(0.0156)
Δ Routine cognitive		0.0152			0.000479
		(0.0135)			(0.0149)
Δ Routine manual			-0.0123		-0.00212
			(0.0142)		(0.0184)
Δ Manual				0.0159	0.0309
				(0.0145)	(0.0167)
Constant	-0.0417**	-0.0367*	-0.0462**	-0.0507***	-0.0500**
	(0.0148)	(0.0169)	(0.0148)	(0.0154)	(0.0180)
N	1490	1490	1490	1490	1490
R2	0.00788	0.00085	0.00051	0.00081	0.01060
F	11.82	1.271	0.752	1.206	3.978

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

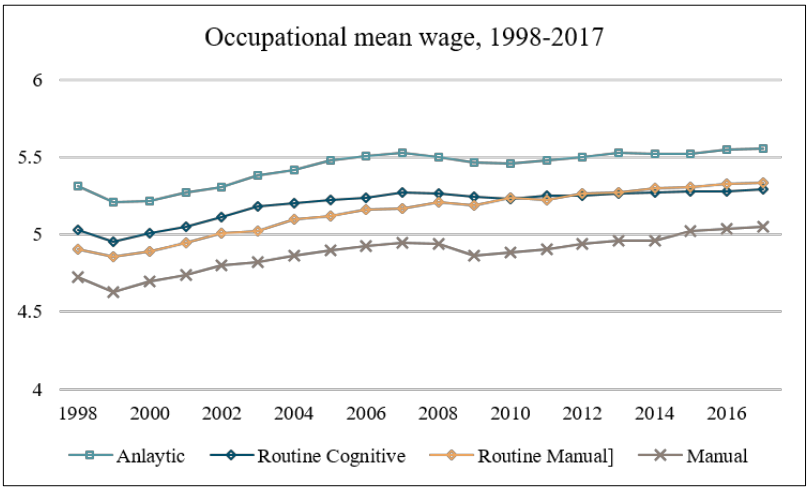


Figure A 4 Evolution of occupational mean wage by task intensity

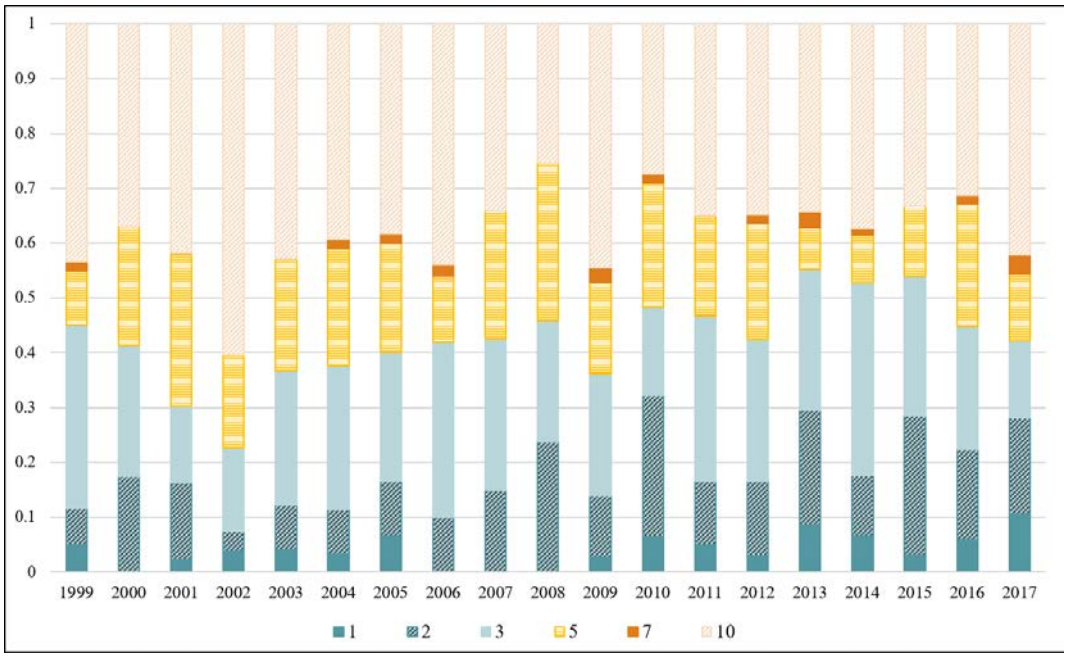


Figure A 5 Job shift from middle to high and low paying groups in detail

Abstract (Korean)

기술 진보는 경제 성장의 주요 성장 동력이지만, 중숙련 노동자에 대한 수요 감소와 함께 고숙련 및 저숙련 노동 수요를 증가시켜 고용 양극화를 주도해왔다. 장기적인 구조적 저성장, 투자 및 고용 부진, 고령화 등 한국 경제가 당면한 과제 해결을 위해 지속적인 기술 개발과 동시에 기술로 인한 충격과 변화의 속도를 통제하고 이에 적응하기 위한 대비책 마련을 간과해서는 안 되며, 정책 입안자들은 기술이 노동시장에 미치는 충격의 정도와 깊이를 이해하고 기술의 양면을 고려해야 한다.

노동시장 내 심화되는 불평등의 원인을 규명하기 위해 기술 진보가 숙련된 기술자를 선호하는 방향으로 일어나 발생한 저학력과 고학력 근로자 간 임금격차에 관한 숙련편향적 기술변화 연구가 시작되었다. 그러나 이 가설은 고숙련 및 저숙련 노동 수요가 함께 증가하고 중숙련 노동 수요만 감소하는 양극화 현상을 설명하지 못한다. 정형대체적 기술변화 가설은 반복적이며 잘 정의되고 쉽게 코드화 될 수 있는 직무들이 컴퓨터나 기계와 같은 기술로 쉽게 대체될 수 있다는 점에 주목한다. 한국의 경우, 기존 연구들은 2000년 중반까지 숙련편향적 기술변화에 의한 숙련프리미엄이 유효하게 나타난다는 증거를 찾지 못했으며, 학력프리미엄이 뚜렷하게 나타나지 않는 특성을 보인다. 양극화에 대한 많은 연구가 있지만, 기술의 정형적 직무 대체로 이를 확인한 국내 연구는 거의 존재하지 않는다.

직무 중심 분석은 한 직종 내에서 실제로 더 많이 사용되거나 더는 사용되지 않을 직무를 구분해 앞으로 근로자들이 어떤 기능을 더 강화해야 할지 파악할 수 있는 중요한 분석 도구이다. 본 연구는 직종이 여러 직무로 구성되어 있다고 가정하고, 비정형적 분석 업무, 비정형적 육체 업무, 정형적 인지 업무, 정형적 육체 업무로 각 직무를 분류하고 한국의 정형대체적 기술 변화를 분석하였다. 정형적 업무는 쉽게 프로그래밍할 수 있는 간단하고 구체적이며 반복 가능한 작업으로 기술 진보에 따라 대체 가능성이 증가한다. 직종의 업무 강도 측정을 위해 미국의 직업분류 사전과 ONET 직업정보 네트워크 데이터베이스를 사용해, 각 직종에서 공통으로 활용되는 직무들로 직무 네트워크를 구성해 직무 분류의 적합성을 확인하였다.

첫 번째 연구에서는 기술이 발전의 결과로 ICT 가격이 하락할 때 정형적, 비정형적 업무의 노동수요 변화가 어떻게 일어나는지 확인한다. 연구 결과 ICT 자본은 비정형적 분석 직종과 보완적 관계에 있지만, 정형적 및 비정형적 육체적 직종과는 대체 관계에 있음을 확인하였다. 두 번째 연구는 한국의 정형대체적 기술변화 현상을 분석한다. 지난 20여 년간 중간 소득 및 중숙련 노동자들의 수요 성장은 다른 직종에 비해 느리게 증가하고, 중간 소득층에 대한 노동 수요 감소와 더불어 나타나는 근로 소득의 변화는 추후 임금 양극화로 이어질 가능성이 있음을 시사한다. 마지막 연구는 한국노동패널 데이터를 사용해 중숙련 개별 노동자의 직종 이동 방향을 분석한다. 중간 소득 근로자는 주로 저임금, 비정형적 육체적 직종으로 이동해 그 결과 임금이 감소하는 반면, 원래의 직종을 유지한 근로자들은 임금이 지속적으로

상승하였다.

본 연구는 기술이 노동 시장에 미치는 영향을 확인하기 위하여 측정 가능한 방법론을 제안하고, 기술과 인간이 공존하는 사회에서 인간에게 요구되는 소양이 무엇인지 명확하게 가르쳐준다. 가까운 미래에 노동시장에서는 독창성, 대인 소통 및 상호 작용, 문제 해결, 정보 분석 등의 능력이 점차 더 많이 요구될 것이고, 이런 능력을 갖춘 인재를 키워내기 위한 교육과 투자를 위한 시의성 있는 새로운 방안 수립을 위해 본 연구의 결과가 활용될 수 있을 것이다.

주요어 : 정형대체적 기술변화, 노동 수요 양극화, 기술 주도 양극화, 직무 중심 분석

학 번 : 2016-30262