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Economics of Labor Markets for Non-regular Workers

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황 인 영

Abstract

Economics of Labor Markets for Non-regular Workers

Inyoung Hwang
Department of Economics
The Graduate School
Seoul National University

With non-regular workers continuing to emerge as a social issue since the 1990s, this study sought to systematically organize the economics flowing into the phenomenon of non-regular employment. We looked at what role non-regular workers play in workers, why firms use non-regular workers, and how non-regular workers are affected by the changing flow of labor demand along with technological development. The first chapter analyzes the pattern of wage dynamics of workers converted to regular jobs after non-regular workers and explained the mechanism by which empirical analysis results are derived from the perspective of job matching and employee learning. The second chapter notes the puzzling phenomenon of increasing income inequality despite the decrease in non-regular workers between 2004 and 2016. By systematically decomposing the relationship between the scale of non-regular workers and income inequality, we show the phenomenon is not puzzling. We suggest a model explaining the principle of job type employment of firms and explain that the above result is the firms' reaction to non-regular workers protection law acted in 2007. The third chapter analyzes the change in the Korean labor market by ICT technological development from the perspective of RBTC (Routine

Biased Technical Change), and analyzes the contribution of this change to wage inequality. Furthermore, it shows the impact of these changes on non-regular workers.

1. Wage Dynamics of Workers with Non-regular Job Experience: Wage Growth by Type of Job Transition

The first chapter is a study on wage dynamics of workers who have moved to regular workers through non-regular jobs. As the number of temporary jobs has increased over time, the labor markets in the world have seen increasingly more workers entering labor markets through temporary jobs and transiting to regular jobs later. Using a panel database (the Korean Labor and Income Panel Survey, KLIPS), we find evidence of partial convergence that the workers who held temporary jobs exhibit a higher wage growth than those who held regular jobs from the beginning of their work career. We also find that the higher wage growth tends to be associated with tenure for job stayers and with labor market experience for movers. Finally, we propose a theoretical framework to account for our findings. We argue that (i) for stayers, tenure reveals the learning process on the worker's ability and the matching component between a worker and an employer, and (ii) for movers, labor market experience reflects the reward of the search for a productive match

2. Does Inequality Rise with Non-regular Workforce?: Firm’s reaction to Non-regular Worker Protection Law

The second chapter analyzes how much non-regular jobs are contributing to income inequality and whether the contribution has changed with the recent decline in the proportion of non-regular jobs. Since 2004, South Korea's labor market has experienced a steady decrease in the rate of non-standard workers, but labor income inequality rather increased. Considering the unequalizing effect of non-standard jobs, 'the increasing inequality and decreasing non-standard rate' situation seems puzzling. As a result of applying Card (2001)’s decomposition method, we shows the contribution of nonstandard

jobs to income inequality rather increased although the proportion of non-regular workers decreased. That is the outcome of the skill-biased decreased of nonstandard jobs in skill distribution – the higher skill, the more decrease – which can lead to an increase in the between-income gap.

To explain this uneven reduction of non-regular workers, this paper suggests a theoretical model in which firms assign workers to regular and non-regular workers according to the complexity level of tasks at each skill group. The model explains that the skill-biased decrease in non-regular workers is the firms' reaction to the law on the protection of non-regular workers. The protection law increased the relative costs of non-regular workers. Given the increase in the relative cost of non-regular workers, firms replace non-regular workers with regular employees from complex tasks because non-regular jobs are less efficient in the complex tasks. This size of this substitution appears larger in the upper skill groups, leading to the skill biased drop in the ratio of non-regular workers. The data also confirmed the validity of this model and hypothesis.

3. Technology, Routinization and Wage Inequality in South Korea

The third chapter examines the influence of technological change in the labor market. As technology advances, the form of firms' labor demand changes, and this change in demand affects wage distribution. Due to the recent ICT technology, automation, and AI development, robots replace what humans used to do, and AI supplements doctors' diagnosis. The Routine-biased Technological Change (RBTC) explains that the pattern of the impact of technology on the labor market depends on the nature of the task each job has. The RBTC explains that for abstract tasks, the efficiency increases with the help of technology, and demand increases, while routine tasks are replaced by technology, resulting in reduced demand, and this pattern has emerged since the 1990s in the Western labor market.

We examines the Routine Biased Technological Change hypothesis in South

Korea. For 1993-2018, the routinization pattern – the decrease in the employment share of routine tasks – has appeared when the task-based approach is performed using KNOW data, the Korean version of O*NET. We confirm that the task scores – abstract, routine, and non-routine manual – have significant effects on wages, and in particular, the return and level of abstract task scores contribute to the wage inequality trend.

When analyzing the routinization trend by dividing it into non-regular and regular workers, it can be seen that the decline in the routine task for 2004-2009 in Korea was mainly absorbed by non-regular workers. This seems to have reduced overall routine tasks through non-regular workers while maintaining regular workers who are relatively key to their regular work. In addition, with the relatively large distribution of regular workers in abstract jobs, the increase in return due to rising demand for abstract tasks shows that the wage gap between regular and non-regular workers could widen further.

Keywords: Non-regular job; Wage dynamics; Job mobility; Job matching and Job search, Inequality, Firms' behavior, Technological change, Routinization

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Chapter 1. Wage Dynamics of Workers with Non-regular Job Experience[1]

I. Introduction

The proportion of non-regular workers has increased since the 1990s, and this phenomenon has been particularly noticeable among young workers. As a result, starting the first entry into the labor market as a non-regular worker is now what one-third of workers go through in Korea. Workers who have once entered the non-regular workforce often remain non-regular workers, but some of them move to regular workers. Little, however, is known about the meaning of workers' non-regular job experience at the early stage and the consequences of this transition in labor markets. What happens in this transition process? Why did the worker who would eventually become a regular employee come in as a non-regular worker? Once the worker becomes a regular worker, how does experience at non-regular job affect? We will answer these questions.

Although some people choose non-regular jobs for their convenience due to the temporary and short-term nature of non-regular employment, in many cases, entering the labor market as non-regular workers is likely to be the result of determination by firms given the workers' preference for regular jobs' high-paying and job security. There is a kind of "job queening" phenomenon in which workers are waiting to enter regular posts at non-regular jobs, which are relatively easy to enter. From a firm's point of view, regular employment is a factor that is hard to adjust in the short term, so they try to fill the regular posts as highly productive workers. However, frictions and misallocation are bound to occur in this allocation process because workers and firms have incomplete information

[1] JEL codes: J31 J62 D83

Keywords: temporary job experience; wage dynamics; job mobility; job matching and job search

about each other's capabilities and factors needed for production. In preparation for this incomplete information, a firm may intentionally hire non-regular workers as a screening or probationary course, or, if not unintentionally, convert non-regular workers to regular positions after assessing their performance during the period of non-regular employment.[2] Due to these characteristics of the non-regular job itself, workers and firms use non-regular job, and among the non-regular workers, some workers move to regular jobs. This study analyzes the meaning of the non-regular work process as an experience in the early stages of the labor market by focusing on the wage dynamics of workers who have gone through non-regular jobs and entered regular jobs.

Previous studies have focused on discussing the gap between regular and non-regular workers. As an early experience, they have mainly studied the probability of non-regular workers entering the next regular job. The impact on this probability of transition to regular employment also has significant meaning, but we think it only deals in part with the impact of the experience of non-regular workers. By analyzing the wages of those who went through non-regular jobs to regular jobs, the meaning of non-regular workers from a long-term perspective can be understood from their previous experience.

This study empirically shows the impact of non-regular workers' experience by comparing and analyzing the wage dynamics of workers who entered regular jobs through non-regular workers with those who entered regular jobs from the beginning. We present the model explain a mechanism arising from assigning two job types and converting non-

[2] Firms are using non-regular workers for various purposes. First of all, there are differences in contract types depending on the nature of the job. The use of non-regular workers, a short-term contract, is beneficial to companies 1) if the job ends in the short term due to the nature of the job, 2) if the company does not require special primary-special accounting, 3) if monitoring is not necessary because the scope of the work and performance evaluation are clear. Second, there are cases where non-regular workers are employed as a countermeasure against economic fluctuations. Because of the high cost of adjusting regular workers, non-regular workers, who are relatively easy to dismiss and hire, will be used to respond to the demand for sudden changes in the economy. Third, there are cases where non-regular workers are employed to determine whether a worker's ability or inclination is appropriate for the job. For the third reason, non-regular workers are explicitly used as a tool to address incomplete information about workers existing in the labor market, but in the first and second cases, information obtained through the non-regular work process is also used to make subsequent work decisions

regular workers into the regular workers, under incomplete information, to explain the results of empirical analysis systematically. Specifically, the transition of non-regular workers to regular workers may occur within firms that used to work as non-regular workers, but it can also occur through workplace movements. By distinguishing the path from non-regular to regular jobs, we will enhance a more accurate understanding of the process.

Wage dynamics over a career can reflect the accumulation of general human capital, the growth in firm-specific human capital within a given firm, and the changes of job match components. This study pays attention to match components between firms and workers. For workers who have previously held non-regular jobs and transit to regular jobs, the non-regular job experience potentially provides probationary stage and time to search for better-matched jobs. Also, employers can learn workers' productivity and screen workers during temporary contract periods. The change of the match component through these processes is shown through wage change in a regular job. "Experienced good" model of job matching (Nelson, 1970; Jovanovic, 1979b) has explained that match quality is not known ex-ante but is learned over time as the match is experienced and productivity-related information is revealed. Thus, wage change by the match quality within a given firm has been gradually reflected in tenure. For the realized match which is not as high as expected, workers try to search for another firm for a better-matched job and, if they succeed, they move to another firm. As the outcome for search, newly evaluated abilities obtained by mobility, movers gain wage growth, and it will be represented through labor market experience.

In an empirical analysis, we separate the wage growth path into tenure and labor market experience, and it will enable us to infer by which factors temporary work experience influences wage. Also, because the wage growth mechanism will be different depending on job mobility, we will distinguish whether a worker is promoted to regular jobs within a firm or by moving to another firm: stayers and movers. Using KLIPS data,

we find that the non-regular job experience has a negative effect on wage level, but higher wage growth of workers with non-regular job experience narrows the wage difference from initial regular workers; the higher wage growth is shown through tenure for firm-stayers and through labor market experience for movers.

Finally, to explain the empirical results, we provide the theoretical framework encompassing the matching model and employers' learning. The framework presents an explanation of the higher wage growth of workers with past non-regular job experience. For stayers, the results of the learning process on ability and matching component between workers and employers are revealed through tenure. For movers, the reward of the searching process for good matching is presented on the labor market experience.

In the following section, we introduce the non-regular workers in Korea and describe the data source and descriptive statistics for workers with prior temporary experience in the Korea labor market in section 3. Section 4 & 5 show empirical specifications for examining the impact of past non-regular experience on wage growth in regular jobs and the results. In Section 6, we introduce the theoretical background on mobility and wage growth. In Section 7, we provide a theoretical framework that integrates the job matching model and employer's learning to explain the empirical results of section 4. Lastly, the final section summarizes and concludes.

II. Non-regular workers in Korea

In Korea, paid employment comprise of two groups, regular and non-regular employment. Regular employment means full-time, permanent, and direct jobs, and non-regular employment refers to workers who are not included in regular workers. (Lee & Lee, 2007) The number of non-regular workers has increased since the 1990s, and now it accounts for about 30% of workers. The criteria for distinguishing non-regular workers are the type of employment, the duration of the contract, persistence of jobs, and working hours.

Specifically, non-regular workers are classified into distinct three groups: fixed-term workers (43%), short-time workers (31%), atypical workers (24%), including dispatched workers, temporary help agency workers, independent contracts, on-call/daily workers, and teleworkers/home-based workers. Because the non-regular worker is the concept that considers not only the duration of contract but also the type of employment, this classification does not correspond to "temporary workers" used in OECD, which is classified based on the temporality of work. Among non-regular workers, fixed term-workers dispatched workers, and on-call/daily workers are categorized as "temporary workers". According to the Supplementary Survey of Economically Active Population (SSEAP) in 2017, the ratio of temporary workers to paid employment is 21.9%, which is two-thirds of the number of non-regular workers.

The non-regular worker protection law acted in 2007 to restrict the duration of use of fixed-term workers by 2-year. Fixed-term workers should be converted into regular workers if they employ more than two years as fixed-term workers. The law also bans discrimination against non-regular workers (only for fixed-term, dispatched, short-time workers). When performing the same tasks as regular workers, the treatment of non-regular workers should not be differentiated from regular workers.

The characteristics of non-regular jobs are the short-working hour, lower wage, and lower insurance coverage rate. According to Supplement Labor Survey by Type of Labor of Economic Activity Population Survey (SSEAP) 2017, non-regular workers' working hours are around 80 percent of regular workers, and their average monthly wage is about 55 percent of regular workers. The national pension, health insurance, and employment insurance coverage rates are about 50% lower than regular employees. With the relatively poor employment conditions of non-regular workers, most workers prefer regular jobs to non-regular ones. Specifically, looking at the reasons for working as non-regular workers, only one-third of non-regular workers chose the posts because they were satisfied with their working conditions. The two-thirds chose as involuntary or as steps to

move to other jobs (SSEAPS 2017). That is, many non-regular workers try to move to a regular position with good employment conditions.

Looking at the reason for firms for using non-regular workers, according to Workplace Panel Survey (WPS) 2017, firms use non-regular workers for the flexibility of employment (51%), the characteristics of the task (20%), and the cost reduction (18%). In the question that asked firms with experience in converting non-regular workers to regular ones, firms answered the reason for conversion as follows. First of all, non-regular workers have been used as a preparatory step for the selection of regular workers (34%). Secondly, to cope with the government's policy (28%). Lastly, due to the nature of the task, the utilization of non-regular workers was judged to be inefficient (25%). Firms utilize the non-regular workers based on the characteristics of non-regular jobs, and firms use the period of non-regular work as the screening or probationary course by themselves and by the force of government' policy.

III. The experience of non-regular jobs

Previous research related to non-regular workers has mainly dealt with the difference between regular workers(Lee, & Kim,2009; Lee, 2009; Lee, 2011; Baek, & Ku,2010; Kim, & Kim; 2011) and the factors which affect the size of the non-regular workforce(Kim, & Ryoo,2001; Kim, 2003; Lee, 2005). The research on the effect of non-regular job experience analyzes the probability of workers' transferring to regular jobs, which can be seen as a somewhat short-run effect of temporary job experience (Amuedo-Dorantes, 2000; Nam, & Kim, 2000; Kim, & Kwon, 2008; Chung and Kwon, 2016). By studying the state dependency of non-regular workers, they show whether non-regular jobs play stepping stones for regular jobs or dead ends. Many studies report that non-regular

work does not help move to regular employment (Nam, & Kim, 2000; Kim, & Kwon, 2008; Chung, & Kwon, 2016).[3]

Studies on the long-term effect of the temporary work include Booth et al. (2000) and Amuedo et al. (2007); both examine how the temporary work experience affects the future wage of workers. Booth et al. (2000) analyze the influence of the number of previous temporary jobs on wages at regular jobs. Amuedo et al. (2007) show the effect of temporary work duration on subsequent wages depending on job mobility. According to the results of both studies, while temporary job experience has negative effects on the wage level, a certain type of temporary job[4] experience positively affects wage growth. Thus, these studies suggest that the wage difference between regular workers without temporary job experience and regular workers with temporary job experience can decrease owing to the higher wage growth of the latter group. Although these previous studies have shown how temporary work experience influences future wages, they did not explain what elements cause the effect. In this study, by focusing on the wage dynamics on regular workers after non-regular work, we explain the mechanism through which non-regular job experience affects the future wage of workers.

Working experience as a non-regular worker has several implications for a subsequent wage. First of all, from the human capital perspective, the difference in the quality and amount of human capital accumulation between two employment types will determine the impact of non-regular working experience on future wages. If employer recognizes the work experience at non-regular jobs as same as the work experience at regular jobs, then, given the same level of tenure and labor market experience, the wage profile between workers having worked at a regular job from the beginning(initial regular group) and workers having moved from a non-regular to a regular job(conversion group)

[3] According to Lee, & Yoon (2007), especially Korea and Spain show this trend. On the other hands, temporary jobs play a bridge for regular jobs in UK, Australia and the United States (Segal and Sullivan, 1995; Lenz, 1996; Booth et al., 2000; Storrie, 2002).

[4] For Booth et al. (2000), female regular workers with fixed-term contract show higher wage and for Amuedo et al. (2007), short-term fixed contract workers who do not move to another firm show higher wage growth.

do not show any difference. However, if firms regard the career at non-regular jobs as the lower level of skill accumulation, the non-regular job experience can have negative effects on the level and growth rate of wages. Secondly, even if there is no difference in actual productivity, the stigma effect and employers' discrimination against the experience at a non-regular job can also negatively affect wages. Thirdly, under the existence of incomplete information between firms and workers, employers use non-regular jobs as the screening device and probationary course, as well as workers use it as a job search process. Through a non-regular working period, workers' ability and job match components can be learned and evaluated. The newly updated information between employer and employee affects the afterward wage dynamics. The highly evaluated job match and workers' ability will be reflected in wages growth within the firm, and undervaluation can result in a decrease in wages within the firm or cause job movements.

IV. DATA and Descriptive evidence

This paper uses Korea data from Korea Labor and Income Panel Study (KLIPS) from 1 and 17 waves to show the wage dynamics of regular workers with non-regular job experience. KLIPS has surveyed households and individuals on job-related items since 1998 and provides long waves enough to demonstrate how workers' wages have changed. Since KLIPS has included job history data, it is observable for a worker to start a job and move to another post. Besides, this data contains not only job-related characteristics such as wages being paid, the number of jobs held, industry, and occupation but also individual characteristics such as age, sex, and marital status.

KLIPS has given three sorts of data on the classification of non-regular work contracts. The first of them is a voluntary declarative variable on whether an individual is a non-regular worker. Because this voluntary declarative variable has been surveyed since the initial wave, this variable is adequate for studying long-term wage dynamics. The

second one is a work status variable, which distinguishes fully-employed workers, temporary workers, and daily workers based on the contract period. If the contract spell of a worker is over only one year, the worker is classified into a fully-employed worker. Otherwise, a worker is classified into temporary and daily workers. Because, in practice, many of non-regular workers work over one year within a firm, the classification criteria of the work status variable do not adequately distinguish between regular workers and non-regular workers. The last of them is the variable of the type of non-regular contract surveyed since 2003. It fully reflects the concept of non-regular workers in SSEAP conducted by National Statistical Office and provides detailed classification criteria on non-regular workers. However, the missing of the initial four surveys causes incomplete job history data for a lot of samples, which makes analysis of wage dynamics difficult. Consequently, we choose the voluntary declarative variable as an indicator to distinguish non-regular workers form regular workers.[5]

The sample only includes males who report themselves as regular workers in the lastly observed survey.[6] The sample is consists of initial workers who enter the labor market as regular workers and conversion workers who start as non-regular workers and move to regular jobs. The conversion workers include stayers and movers. Stayers become regular workers within the firm and movers by shifting to other firms. The wage variable is the logarithm of hourly wages, computed as the ratio of monthly wage to a weekly hour of work[7]. Hourly wages are deflated using the consumer price index. The duration of non-regular jobs is computed using starting and end date variables[8] at each job and if a worker

[5] For robustness, we also analyzed the effects of non-regular work experience on wage growth for the sample who answered that they are non-regular workers in both the voluntary declarative variable and the variable of type of non-regular contract surveyed based on SSEAP. The result was consistent with those using the full sample.

[6] Considering the fact that many female workers choose non-regular jobs for time flexibility, we select male workers as samples. By avoiding the case choosing non-regular jobs for flexibility of time, we try to limit the discussion to workers with similar characteristics with regular position.

[7] The logarithm of average hourly wages is computed following equation,

$$\ln(\text{hourlywage}) = \ln\left(\frac{\text{monthly income}}{\text{weekly hours of work} * 4.3}\right)$$

[8] In case of missing values of end date, the end date is imputed using next job start date variable. For minimizing the imputing error, job duration variable is categorized by six months.

has more than one non-regular job, we sum the length of the non-regular job the worker has worked. We also create the past non-regular job number a worker has had. Stayers and movers are distinguished based on transition type dummy made using job sequence variable; if the job sequence changes when the worker becomes a regular one, the transition dummy is one and if the job sequence remains when the worker becomes a regular one, the transition dummy is zero. The regular job entry age is the age the workers report themselves as regular workers for the first. Of course, the initial regular workers' job entry age is the same as the labor market entry age.

For figuring out who works at a regular job from the start and who goes through non-regular jobs and become regular workers, Table1.1 summarizes the distribution of education and job characteristics by each group. The job characteristics are the information on the first jobs after entering the labor market. For comparison, this table also shows the information on the non-regular workers who enter the labor market and continues to maintain non-regular jobs. Of the sample reporting themselves as paid workers at the latest survey, 52.8% initially enter the labor market as regular workers(called initial regular workers), and 17.9% have non-regular work experience(called conversion workers); among the latter, 70% are transferred to regular jobs by changing firms(called mover) and 30% are promoted to regular jobs within a firm (called stayer). The rest, 29.3% are non-regular workers.

The distribution of education level in the conversion group is very similar to that of the initial regular group compared to non-regular workers. More than 40 percent of workers graduated from four-year universities.[9] What is noticeable about the transfer group compared to other groups is that college graduates account for a large portion of the group. This seems to be a sign that college graduates with job-oriented education and specific skills gain experience through non-regular jobs and move on to regular jobs.

[9] In detail, compared to initial regular workers, movers show the lower ratio for postsecondary education, each distribution of education level is not quite different between two groups. However, stayers have slightly lower percentage of postsecondary education than other groups.

Looking at the age of entry into the labor market, the average entry age for the conversion group is smaller than that of regular groups, and it is similar to non-regular workers. It may be due to the conversion workers' distribution of education with a large portion of two-year college graduates. Divided by academic background, while the entry age of conversion workers over a four-year college is similar to that of regular workers, the conversion group of two-year college graduates and high school graduates entered the labor market two or three years earlier. Since the classification of education level is based on final academic background, even a two-year college graduate may have entered the workplace as a student or it can be seen that they entered the labor market right after graduation.

In terms of occupations, the proportion of the so-called white color jobs such as professionals, associate-professionals, and office workers(office clerks) is large in the order of regular, conversion and non-regular groups. The ratio of craft and related trade workers and elementary occupations workers in each group are significant in the order of non-regular workers, conversion and regular workers. In the conversion workers, services and sales are a large part of the group compared to other groups. Even at the distribution of industry, the proportion of the service and sales industries in the conversion group is greater than that of other groups, as observed in occupations. It is consistent results with Kim and Kwon (2008), which shows the conversion rate of non-regular workers in service and sales jobs to regular workers is high.

The distribution of the firm size in the conversion group is similar to that in the non-regular group. In the conversion group, firms with more than 300 employees account for a relatively small portion and firms with less than ten employees are more than in regular groups. It indicates that many of the conversion groups worked as non-regular

Table1. 1. Education and Job Characteristics Distribution for Initial Regular, Conversion Workers

	Initial regular	Conversion	Conversion		Non-regular
			Stayer	Mover	
	52.8	17.9	30%	70%	29.3
Education Service(%)					
<High school	3.23	2.98	2.52	3.14	28.01
High school	27.5	28.1	33.96	26.21	44.41
2-year College Graduate	19.95	28.41	28.93	28.3	13.72
4-year College Graduate	40.38	32.81	25.79	35.01	11.67
Master or higher	8.95	7.69	8.81	7.34	2.19
Entry Age(mean)					
Total	27.01	24.53	25.28	24.27	25.54
High school	26.26	23.44	24.46	22.75	26.32
2-year College Graduate	25.95	23.74	24.37	22.82	25.06
4-year University Graduate	27.61	27.37	26.60	27.43	24.28
Master or higher	28.86	29.27	26.71	29.29	27.92
Occuapation(%)					
Manager	2.29	0.21	0.64	0	1.22
Professionals	22.33	10.08	13.46	8.54	4.95
Technicians and associate professionals	11.96	10.7	8.97	11.28	7.24
Office clerks	25.52	17.08	23.08	14.33	7.96
Service workers	4.89	12.14	6.41	14.94	7.31
Sales workers	3.24	10.29	11.54	9.76	6.09
Skilled agriculture workers	0.15	0.62	0	0.91	1.36
Craft and related trades workers	10.02	15.43	17.31	14.33	23.8
Equipment, machine operating and assembling workers	15.85	11.32	9.62	12.2	13.91
Elementary workers	2.09	12.14	8.97	13.72	25.95
Industry(%)					
Manufacturing	35.78	17.66	24.36	14.29	17.6
Electricity, Water supply	1.15	0.82	1.28	0.61	0.43
Construction	7.04	10.06	7.69	11.25	25.32
Wholesales and retail trade	9.08	15.61	14.74	16.11	10.75

Accommodation and Foodservice	2	9.65	3.85	12.46	6.85
Transportation	4.59	4.31	7.69	2.74	5.48
Information and Communication	4.04	4.11	4.49	3.95	1.44
Financial activities	3.19	1.85	3.21	1.22	1.8
Real estates	1	1.85	1.28	2.13	4.55
Business facility management and support service	11.28	8.62	7.05	9.42	7.79
Public administration	9.13	2.46	3.21	2.13	4.62
Education Service	5.19	9.45	7.69	10.33	3.32
Social and personal Service	1.85	2.67	3.21	2.13	1.15
Arts and Sports	1.25	5.34	2.56	6.69	3.61
Sewage, waste disposal and cleaning related service	2.89	4.52	6.41	3.65	3.32
Firm size(%)					
less 10	15.85	34.38	34.18	34.38	38.15
10-99	25.8	23.06	29.75	19.56	22.49
100-299	7.5	5.45	6.33	5.05	4.89
more 300	50.84	37.11	29.75	41.01	34.48

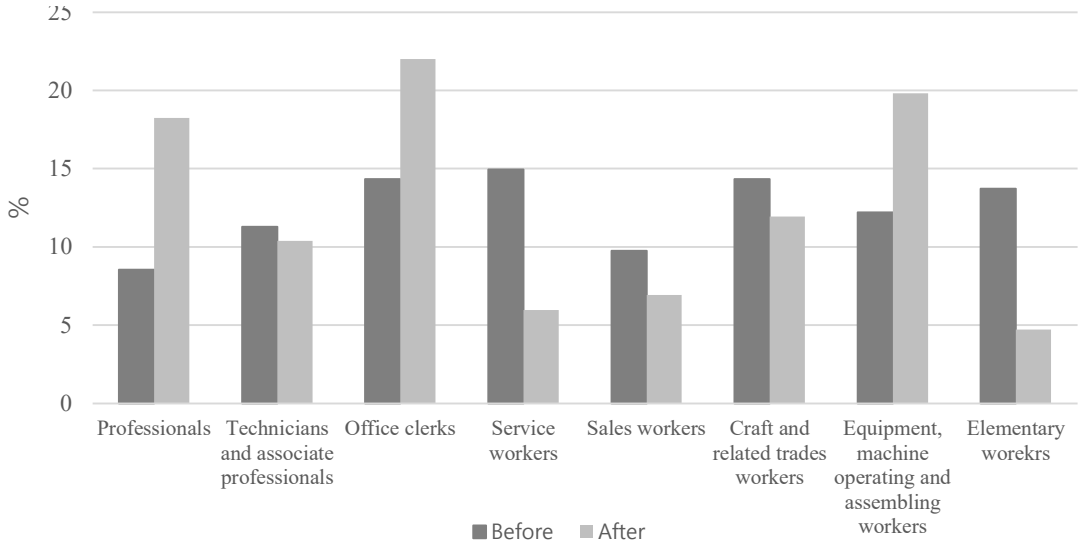
Note: The classification of education level is based on final academic background. The job -related information on the first job for initial regular and non-regular workers, on the latest non-regular jobs for conversion workers.
Source: Author's calculation, KLIPS(1-17 waves)

workers in a relatively small firm, but were internally converted to regular jobs or moved to large firms.

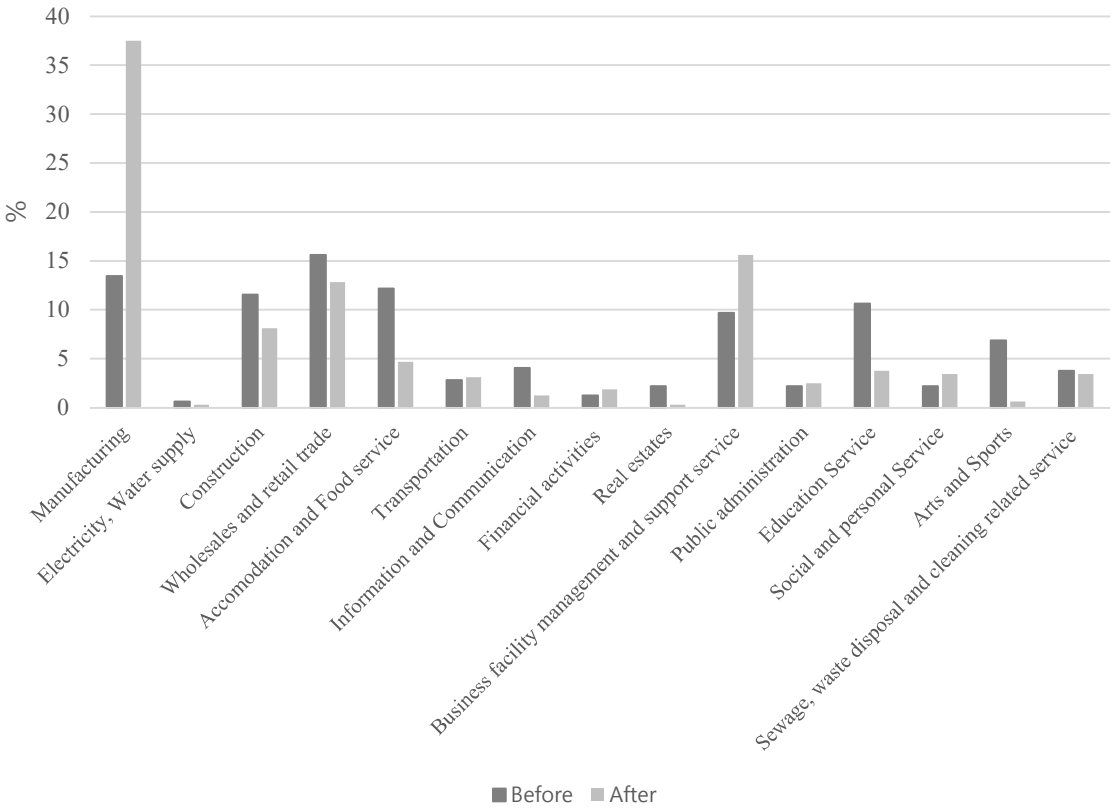
In detail, in the process of conversion group becoming a regular worker, in the case of stayers, there is no change in job characteristics. For movers' case, there is a change in job, industry, and firm size. Figure1.1 shows the job characteristics distribution of movers before and after conversion. In the case of occupations, it shows a trend of moving from craft and related trade job to assembly one, service and elementary labor to office work, and semi-professionals to professional. In the industry, moving from construction, sales, and service to manufacturing is the main trend and there is a tendency to stay in the wholesale and retail sales industry. For firm size, 45 % of mover works for the same level of firm size, 30% move to a larger firm and 23% move to a smaller firm. In many cases, it

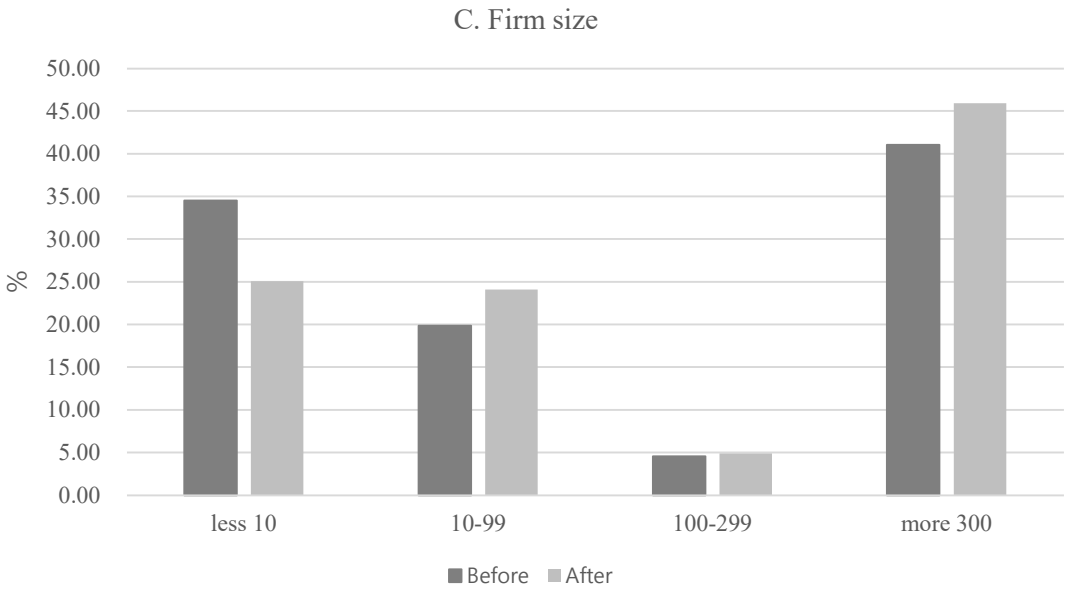
seems that as moving from firm to firm, movers upgrade their occupation, industry, and firm size.

Figure1. 1. Job Characteristic Distribution of Movers Before and After Conversion



B. Industry





*source: Author's calculation, KLIPS(1-17)

Table1.2 shows the information on the conversion group's experience in non-regular jobs and the labor market outcome since conversion to regular employment compared to the outcome of initial regular workers. The conversion group had an average of two years of non-regular work experience, with stayer about three years and mover about a year and a half (moving to regular jobs more quickly). The two groups had about 1.5 non-regular jobs. As seen in the duration of non-regular job experience, at the last non-regular jobs, the stayer worked for about three years, and the mover worked for about one year and four months. The total labor market experience at non-regular jobs is six years for the stayers and four years for movers. Based on these figures, the stayer appears to have stayed relatively long at his last non-regular job and mover seems to have worked relatively short and moved to a regular job.

The average log hourly wage for stayers at the time of non-regular workers is slightly higher than that of the movers, and the last period log hourly wage for stayers at the non-regular job is also higher than movers. It could be because the tenure for stayers was longer at the job, or because the stayer was highly evaluated at that job.

Upon reviewing the characteristics at the regular jobs, the initial group enters a regular job at about 27 years old, while the stayer enters at 31 years old and mover at 28 years old. The conversion groups' number of job movement (job sequence) is naturally higher than that of the initial group, of which mover has the highest number of jobs. On average, movers shift firms more than three times. They seem to have changed their jobs even after entering regular posts. In terms of tenure and experience at the regular jobs, because stayer has stayed in the job, they have a longer tenure than movers, and the labor market experience is not much different from each other.

The average log hourly wage at regular jobs is the highest for initial regular workers and is similar within the conversion group. The higher average wage for initial workers may be due to the initial regular workers' the highest tenure. Rather, considering movers' short tenure and the gap between their average wage and the first entry wage at regular jobs, movers may have a higher rate of wage growth. In terms of entry wages at regular jobs, while movers and initial regular workers have little difference, stayers receive relatively higher wages. It may be because the stayer had high tenure at the time of entering the regular jobs, and it could be because they were well-received by the firm as the reward of good screening.

Next, we will control other factors on wages and analyze how the experience of non-regular workers itself affects wage dynamics.

Table1. 2. Summary Statistics for Sample, 1998-2015: All and by Type of Regular Job Entry

	Initial Regular Worker		Conversion workers					
					Stayer		Mover	
			A. Work History Before Conversion to Regular Job					
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Duration of non-regular experience (six months as one unit)			4.24	3.79	6.09	4.24	3.61	3.41
Number of non-regular jobs			1.35	0.66	1.37	0.67	1.35	0.66
Tenure at the last non-regular job			1.82	2.39	2.99	3.08	1.43	1.96
Labor market experience at the last non-regular job			4.38	4.07	5.97	4.23	3.84	3.88
Average log(hourly wage) at non-regular jobs			2.44	0.53	2.61	0.47	2.35	0.53
Last period log(hourly wage) at non-regular jobs			2.54	0.57	2.69	0.52	2.43	0.58
	B. Labor Market Outcome After entering into Regular Jobs							
Regular job entry age	26.79	4.35	29.18	4.56	31.50	4.39	28.39	4.35
Job sequence at the latest jobs	2.36	1.79	4.04	2.14	3.40	2.18	4.26	2.08
Tenure at the latest observation	9.34	8.31	5.24	4.22	7.50	5.12	4.48	3.56
Labor market experience at the latest observation	13.63	8.36	12.83	4.67	13.36	4.63	12.66	4.68
Average log(hourly wage) at regular jobs	3.08	0.44	2.89	0.36	2.89	0.40	2.89	0.34
The first log(hourly wage) at the regular job	2.61	0.48	2.63	0.48	2.74	0.49	2.59	0.46

*Source: Author's calculation, KLIPS(1-17)

IV. Empirical model

We now analyze the effect of prior non-regular work experience on wage dynamics on a regular job. The specification of the wage equation adopting Mincer type can be written as

$$(1)\quad \ln W_{ift} = \alpha + \beta_1 \exp_{it} + \beta_2 \text{tenure}_{ift} + \beta_3 \text{temp}_i + \beta_4 \exp_{ift} * \text{temp}_i + \beta_5 \text{tenure}_{ift} * \text{temp} + \gamma X_{ift} + \eta_i + \lambda_{if(t)} + \epsilon_{ift}$$

where the subscripts refer to worker *i* in firm *f* at time *t*. $\ln W_{ift}$ is the log real hourly wage. $\exp_{ift}$ denotes labor market experience and tenure_{ift} is workers' tenure. We also include square terms of $\exp_{ift}$ and tenure_{ift}. The term $temp_i$ denotes the duration of non-regular work and $\exp_{ift} * \text{temp}_i$ and $\text{tenure}_{ift} * \text{temp}_i$ refer their interaction term with tenure and labor market experience, respectively. The vector of covariates(X) includes age, education, marital status, the sector and size of their employing organization, occupation, the dummy of existence of union in the firm, the number of non-regular job held before conversion to regular worker, the age when sample enters regular job, unemployment rate, year dummy. The error term contains a time-invariant individual-specific component, η_i, firm-specific matching component, $\lambda_{if(t)}$, and a white noise, ϵ_{ift}. We assume that the three components are independently distributed from each other.

The OLS estimation of (1) is consistent only if regressors, especially *temp,* are conditionally uncorrelated with the error term. In particular, the duration of non-regular work and the number of non-regular jobs have the possibility to be correlated with unobserved individual ability since there is a possibility that people with good abilities will be converted from non-regular to regular jobs early. For controlling unobserved

individual's innate ability, using the advantage of longitudinal data, we use fixed-effects models.

The fixed model takes the following equation:

$$(2)\quad \ln W_{ift} - \ln W_i = \beta_1(\exp_{it} - \exp_i) + \beta_2(\text{tenure}_{ift} - \text{tenure}_i) + \beta_4(\exp_{ift} * \text{temp}_i - \text{temp} * \text{temp}_i) + \beta_5(\text{tenure}_{ift} * \text{temp}_i - \text{tenure}_i * \text{temp}_i) + \gamma(X_{ift} - X_i) + (\lambda_{if(t)} - \lambda_{if}) + (\epsilon_{ift} - \epsilon_i)$$

β_4 and β_5 both captures the effects of non-regular working duration on wage growth. However, whether the impact of non-regular work period is revealed through tenure an labor market experience will vary depending on the actual mechanism by which non-regular work experience affects wages. If the factors within a firm are important, they will be revealed through the tenure, otherwise through the labor market experience.

V. Estimation Results

Table1.3 presents estimates of the causal effect of non-regular work experience on subsequent wage dynamics on regular jobs. The sample of this estimate is confined to the sample who have observed more than three subsequent periods after the transition to regular jobs for providing work history long enough to analyze the prior non-regular job experience's effect on wage dynamics. Also, the sample of the estimate is restricted to workers who enter the regular job before 40 years old.[10]

[10] There exist some workers who had worked as regular workers and after retirement got temporary jobs and then get back to regular jobs. This case is excluded in the analysis because this case has different economic meanings from young workers case.

Table1.2 displays the coefficient estimates from pooled OLS specification as well as from the fixed-effects model (Eq. (2)). The first column of Table1.2 shows that a man with six months of work experience at non-regular jobs faces 1.7% wage gain but 7.6% wage reduction as the number of non-regular jobs increases. For example, if a worker with six-month work history at a non-regular job worked for one year as a regular worker, it will have a wage reduction of about 6% compared to an initial regular worker. If the number of non-regular workers is controlled, the length of working periods at non-regular jobs themselves does not seem to have a negative impact on wages. The negative impact on wages held by non-regular workers themselves largely affects how many have gone through rather than the period.

In wage growth, non-regular job experience does not seem to have a significant effect on it through tenure and rather negatively affects it as labor market experience increases. However, OLS estimate results have the possibility to systematically underestimate the effect of non-regular work experience on wage dynamics. Thus, we focus our discussion on the complete specification between two models, the fixed-effect model. After we account for worker's unobserved heterogeneity in the fixed-effects specification, the return to experience for workers with six-month non-regular work history is higher 0.3% than for initial regular workers while the return to tenure is not significantly different between initial regular workers and workers with non-regular work history. Once non-regular workers become regular workers, they have confirmed that their experience does not harm wages, but rather has a positive impact on future wages. To more specifically identify why this positive effect occurs, we analyze the conversion group separately according to the type of job transition. (the conversion group is analyzed by dividing it into stayers and movers) As we notice in descriptive statistics, there is heterogeneity between stayers and movers. Regarding stayers and movers as one group would mask the precise estimate result of non-regular job effect on wage dynamics.

A separate analysis by type of entry into regular positions will provide more information on how the experience of non-regular workers works.

Table1. 3. The Effect of Non-regular Work Experience on Wage at Regular Jobs

	[1] Pooled OLS		[2] FE	
Independent Variables	coef	se	coef	se
temp duration	0.017**	0.007		
temp job number	-0.076***	0.007		
regular_entry_age	0.008***	0.001		
exp*temp duration	-0.003***	0.001	0.003***	0.001
exp2*temp duration	0.000***	0.000	-0.000*	0.000
tenure*temp duration	0.001	0.001	0.001	0.001
tenure2*temp duration	-0.000	0.000	-0.000**	0.000
exp	0.027***	0.002	0.065***	0.002
exp2	-0.001***	0.000	-0.001***	0.000
tenure	0.016***	0.001	0.004***	0.002
tenure2	0.000	0.000	0.000***	0.000
Individual characteristics	√		√	
job-related characteristics	√		√	
year dummy	√		√	
n	2749(493)		2749(493)	
N	19657		19657	

Note: n is the number of persons(conversion sample). N is the number of person-job-wave observations. *** p<0.01, ** p<0.05, * p<0.1. All regression include the age, education, marital status, the sector and size of their employing organization, occupation, the dummy of the existence of union in the firm, the number of the non-regular job held before conversion to the regular worker, the age when the sample enters regular job, unemployment rate, year dummy

In Table1. 4, we split workers with non-regular job history into stayers and movers and display the coefficient of non-regular work experience and their interaction term with tenure and labor market experience. Concentrating on the fixed-effect coefficient result as in Table1. 3, although we do not figure out the past non-regular work effect on wage level, but catch the effect on wage growth and the path of the wage growth

The second column of Table1. 4 shows that stayers have 0.3% higher wage growth than initial regular workers, and it is shown through tenure. According to the third column of Table1. 4, movers' wage growth is higher by 0.5% than initial regular workers as the labor market experience increases by one year. Although it is common for non-regular work experience to have a positive effect on wage growth, the path of wage growth is differently shown depending on the transition type. It seems reasonable for stayers that did not move at all to present the effect through tenure, which is an internal route, and for movers that moved the workplace to show the impact through experience in the labor market.

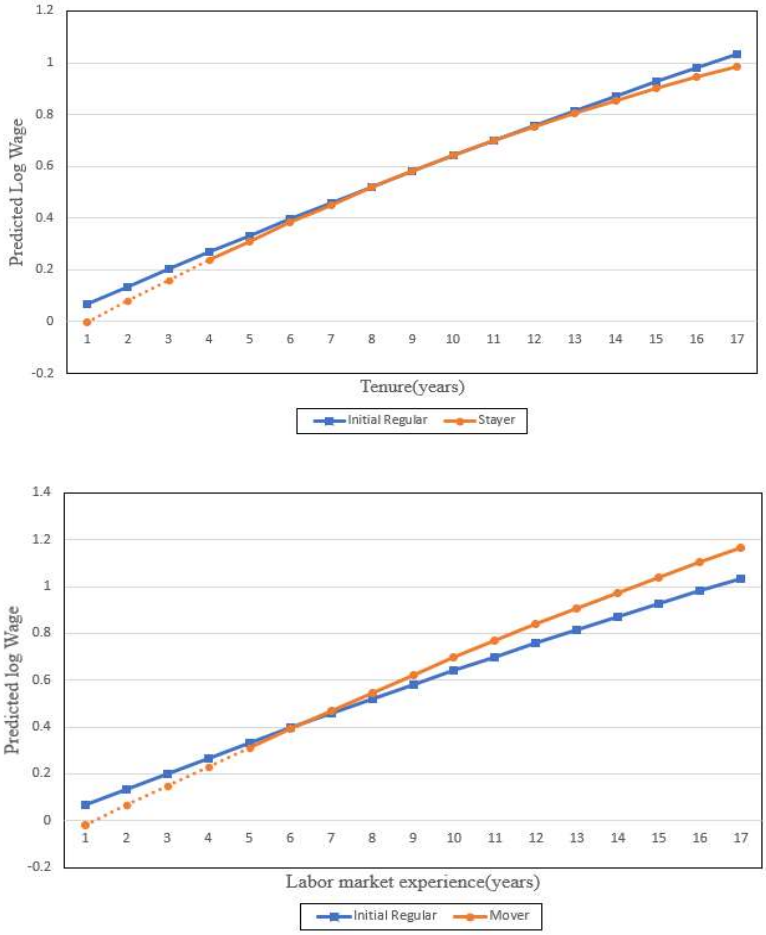
Table1. 4. The Effect of Non-regular Work Experience on Wage Growth by Conversion Types

	[1] Full Sample		[2] Stayer		[3] Mover	
Independent Variables	coef	se	coef	se	coef	se
exp*temp duration	0.003***	0.001	0.000	0.002	0.005***	0.002
exp2*temp duration	-0.000*	0.000	0.000	0.000	-0.000	0.000
tenure*temp duration	0.001	0.001	0.003**	0.002	-0.002	0.001
tenure2*temp duration	-0.000**	0.000	-0.000**	0.000	0.000	0.000
exp	0.065***	0.002	0.065***	0.002	0.065***	0.002
exp2	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
tenure	0.004***	0.002	0.004**	0.002	0.005***	0.002
tenure2	0.000***	0.000	0.000***	0.000	0.000***	0.000
Individual characteristics	√		√		√	
job-related characteristics	√		√		√	
year dummy	√		√		√	
n	2749(493)		2378(167)		2627(326)	
N	19657		17301		18857	

Note: n is the number of persons(conversion sample). N is the number of person-job-wave observations. *** p<0.01, ** p<0.05, * p<0.1. All regression include the age, education, marital status, the sector and size of their employing organization, occupation, the dummy of the existence of union in the firm, the

number of the non-regular job held before conversion to the regular worker, the age when the sample enters regular job, unemployment rate, year dummy

Figure1. 2. Predicted Wage Profile by Tenure and Labor Experience and Conversion Types



Note: Based on predictions from the estimate presented in Table4 for wage growth coefficient and from the estimate presented in Table A2 for wage gap for initial workers and conversion workers. For stayers, at 4 years(tenure), they start regular jobs. For mover, at 5 years(labor market experience), they enter the regular jobs.

Considering the negative effect of the number of non-regular jobs on wage level in pooled OLS (column [1]),[11] the higher growth rate of the stayers and the movers narrow the wage differential from initial permanent worker's wage. To describe the wage dynamics of workers with non-regular jobs experience, we compute the predicted log-

[11] The amount of the negative effect of the past non-regular job is corresponding to the estimate result of Booth et al(2002) using IV-GLS model.

wage profile from the column [2],[3] estimate of Table1.4. Assuming the entry wage gap is the value of the coefficient of $temp\ job\ number$ in OLS estimate by the conversion types(Table1.A2 column[1][2]), we draw the predicted wage profile. Figure1. 2 is the wage profile on regular jobs. The first row in Figure1. 2 is the predicted tenure wage profile for initial workers and stayers using the coefficient of $temp$ and $temp * tenure$ at the mean value of $temp$ variable(6) given the same labor market wage growth. The second raw in Figure1.2 is the predicted experience wage profile for initial works and movers using the coefficient of $temp$ and $temp * exp$ at the mean value of $temp$ variable(3.5) given the same tenure wage growth. On average, stayer becomes regular workers at four tenure and movers become at five labor market experience.

Stayers who had had about three years of non-regular work experience and were promoted to a regular job within a firm at four tenure catch up with the wage of initial regular workers by ten years tenure. Movers, who had worked as a non-regular worker for four years and switched to a regular position through turnover, receive similar wages with the initial regular workers from the beginning and exceed those of initial regular workers from eight-year labor market experience. Although the timing of wage convergence can vary depending on the wage gap coefficient, the wage gap taper off by the higher wage growth induced by non-regular work experience. In particular, the speed of catching up the wage gap is faster for movers than for stayers.

From the empirical analysis, we confirm that, even after entering the regular jobs, the experience of non-regular affects wage dynamics. It implies during the non-regular work period, the meaningful process occurs. Besides, the fact that the path of wage growth is represented differently by the type of transition to regular jobs leaves the question about what factors in the two groups change the path and cause of wage growth. In the next sections, a theoretical framework we propose will answer the question.

VI. Theoretical Background of Wage Dynamics and Mobility

A number of theoretical models have attempted to explain the wage dynamics and mobility. The models we focus on are the search model and the matching model. The matching model can be divided into two groups: "search good" model of job matching and "experienced good" model of job matching. Search good model (Burdett,1978; Jovanovic,1979a) assumes constant productivity within a particular job and it is observable ex-ante. Thus, job mobility is the process of searching for a good match. Due to job movement cost, the wage offers, which reflects matching quality, in the new job needs to be significantly higher than the current wage to induce an individual to switch the job. "Experienced good" model (Nelson, 1970; Jovanovic, 1979b) argues that productivity in a particular job is constant but there may initially be uncertainty over a worker's actual productivity within a particular job. Workers face the distribution of actual productivity arising from their ability within jobs available in the labor market. As job tenure increases, additional information related to the worker's actual productivity is revealed. If the realized match quality is higher than workers expected, the wage increase as tenure increases. However, if the realized match quality is lower than workers expected, workers move to another job. In the sense that the match component is not known ex-ante, the experienced good matching model seem to be more realistic.[12] Thus we encompass the logic of the experienced good matching model. Besides, considering that employers cannot have full information on workers' abilities in reality, we adopt the employers' learning model under incomplete information (Farber and Gibbons,1996; Altonji and Pirret, 2001). In terms that under incomplete information,

[12] Light, A., & McGarry, K. (1998) examine which model can explain the wage change of young workers among several models on the wage and mobility. As a result of the examination, they support "experienced good" matching model.

firms' recruitment outcomes are not complete, job mobility is the process to search employers who highly evaluate workers' expected ability.

Although each model suggests different predictions on wage dynamics, only one model could not consistently explain the wage dynamics and mobility observed in data. Thus, the synthesis of each model helps to understand the empirical results.

VII. Model

In each period, labor markets open. Workers i's innate ability is denoted θ_i, which follows the normal distribution with mean, μ_θ, and standard deviation, σ_θ. A worker i's effective ability, η_{ift}, is a function of the worker i's innate ability, matching component, λ_{if} with firm f, and worker's tenure, χ_{ift}, in a firm, f.at t.

(3) $$\eta_{ift} = (\theta_i + \lambda_{if})g(\chi_{ift}),$$

where $g(1) = 1, g' > 0, g'' < 0$[13] and $\lambda_{if} \sim N(\mu_\lambda, \sigma_\lambda^2)$

All firms are identical and the only input is labor. A firm consists of two different jobs, regular job(R), and non-regular job(NR). While regular job guarantee job security, non-regular workers are employed only one period and fired unless they are promoted to regular job workers. Workers produce output by the following production function at each job.

(4) $$y_{ift}^j = d_j + c_j(\eta_{ift} + \epsilon_{ift}), j = R, NR$$

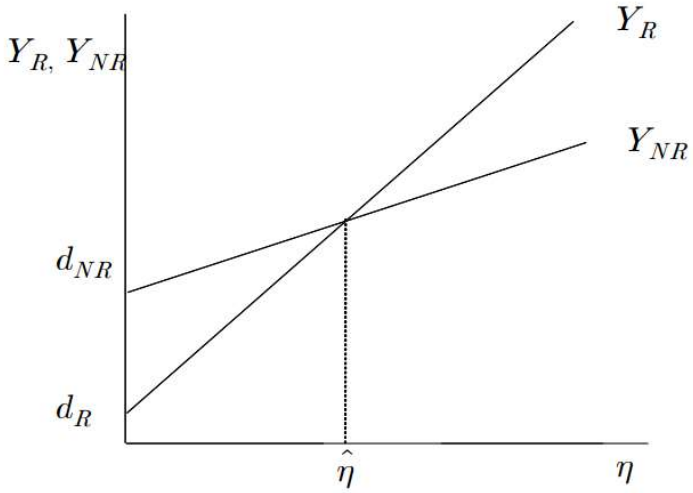
[13] Though we do not explicitly consider the effect of human capital accumulation, the term, $g(\chi_{ift})$, can reflect the accumulation of human capital. In the further study, in addition to the matching and learning, the human capital, if human capital accumulation can be considered, it would be more informative for the non-regular jobs' transition process.

where d_j and c_j are constants known to all labor market participants and ϵ_{ift} is a noise term drawn from a normal distribution with mean 0 and variance, σ_ϵ^2. We assume that $d_{NR} > d_R > 0$ *and* $c_R > c_{NR} > 0$. This type of production function specification (Gibbons and Waldman, 1999) implies that, in a non-regular job, once labor is inputted, a certain level of productivity is guaranteed but the growth rate of productivity of it reacts less sensitive to workers' effective abilities. This type of productivity technology can be shown in routine and standardized work. On the other hand, in regular jobs, inputting labor does not substantially increase productivity in a regular job but productivity substantially increases responding to workers' innate abilities. In high skilled and sophisticated works, this kind of technology could be observed. Considering the fact that non-regular jobs are concentrated on routine jobs and regular jobs show a high ratio on the high skilled jobs, this distinction of production technology between the regular job and the non-regular job seems to be appropriate.[14]

This production technology characterizes that the worker's productivity is not influenced by other worker's job assignments, which is also shown to those in Waldman (1984b), Gibbons and Katz (1992), and Bernhardt (1995). Thus, under this production technology, for the optimization of the firm's productivity, it is sufficient to assign all the workers to one of two jobs properly. There exists $\hat{\eta}$ such as $d_R + c_R\hat{\eta} = d_{NR} + c_{NR}\hat{\eta}$ as shown in Figure1. 3. Therefore, given full information on worker's innate ability, by the efficient assignment rule, the employer assigns worker i to a regular job(R) if $\eta_{ijt} > \hat{\eta}$ and to a non-regular(NR) if $\hat{\eta} \geq \eta_{ijt}$.

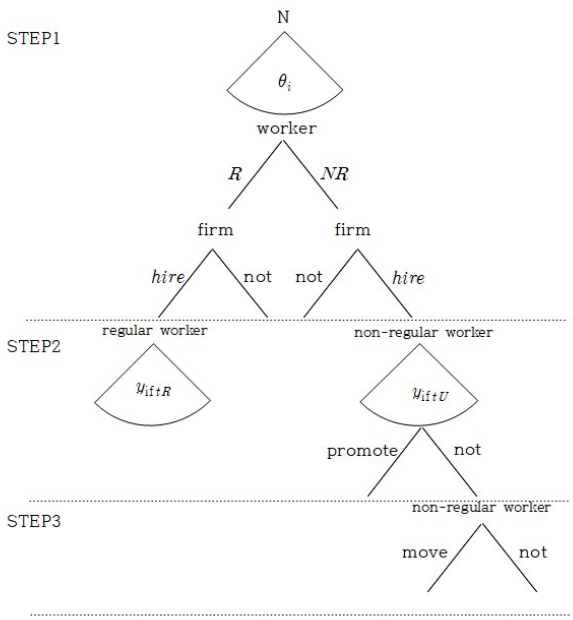
[14] Following SSEAP in 2017 by National Statistical Office, distribution of occupation of non-standard workers is simple labour(31.4%), service and sales workers(24.1%), management, professionals and tech. & associate prof(17.1%), clerks craft & related trade machine operator etc (16.5%) and farming, fishing(0.3%).

Figure1. 3. Production Technology of Regular and Non-regular jobs



A. Time line

Figure1. 4. Time Line



As shown in Figure1. 4, at the beginning of each period, each firm announces a recruiting plan and workers apply to each job. Then, each firm employs workers according to efficient allocation rule. Once workers are employed, matching components

are realized and workers product outputs. After observing the output, the employer updates the worker's effective ability and determines whether they promote each non-regular worker to a regular job. Remaining non-regular workers decide whether they try moving to a regular position.

B. Incomplete Information

Complete information case on workers' innate ability is written in appendix A.1. We now analyze the case of incomplete information on a worker's innate ability. Under incomplete information on workers' innate abilities, when workers enter the labor market, employers have uncertainty on workers' innate abilities. Employers know only the distribution of workers' innate ability, $\theta_i \sim N(\mu_\theta, \sigma_\theta^2)$. Once employers announce a recruiting plan, workers send signal on their innate ability, s_i

(5) $$s_i = \theta_i + e_{it},\ e_{it} \sim N(0, \sigma_e^2)$$

Signal tends to consist of elements that can be proved objectively; it can be thought of as an application form including worker's education level, job-related experience, and growth background and an interview through which employers can figure out the workers' characteristics. After observing the signal, employers update their belief on workers' innate abilities through Bayesian learning and calculate worker *i*'s expected innate ability,

(6) $$E(\theta_i | s_i) = \frac{\sigma_e^2 \mu_\theta + \sigma_\theta^2 (\theta_i + e_{it})}{\sigma_\theta^2 \sigma_e^2}$$

Then, employers assign workers based on the expected innate ability following the efficient assignment rule.[15]

[15] The detail derivation process is available in the appendix.

$$\begin{array}{ll} \textit{regular job} & \text{if } E(\theta_i|s_i) \geq \hat{\theta}^e \\ \textit{temporary job} & \text{if } \hat{\theta}^e > E(\theta_i|s_i) \end{array}$$

Completing assignment, each worker's matching component is revealed and workers produce output, y_{if1}^{R}, y_{if1}^{NR} at each job.

(7-1) $$y_{if1}^{R} = d_R + c_R((\theta_i + \lambda_{if})f(1) + \epsilon_{ift})$$

(7-2) $$y_{if1}^{NR} = d_{NR} + c_{NR}((\theta_i + \lambda_{if})f(1) + \epsilon_{ift})$$

To promote the non-regular workers to a regular job, employer, f, again updates the innate abilities of non-regular workers using each worker's output as another signal. Define $s_{yi} = \frac{y_{if1}^{NR} - d_{NR}}{c_{NR}} - \lambda_{if} = \theta_i + \epsilon_{ift}$ which denotes the signal extracted from the output produced by worker i. at period 1.

The updated expected worker i's innate ability is

(8) $$E(\theta_i\,|s,y) = E(\theta_i|s,s_y) = \frac{\sigma_e^2\sigma_\epsilon^2\mu_\theta + \sigma_\theta^2\sigma_\epsilon^2(\theta_i + e_{it}) + \sigma_\theta^2\sigma_e^2(\theta_i + \epsilon_{it})}{\sigma_\theta^2(\sigma_e^2 + \sigma_\epsilon^2) + \sigma_e^2\sigma_\epsilon^2}$$

Using $E(\theta_i|s,s_y)$, employers form the worker i's expected effective productivity. The promotion rule is also the same as in the complete information case. The promotion decision follows the efficient allocation rule.

Non-regular worker i is

$$\begin{array}{ll} \textit{promoted} & \text{if } E(\theta_i|s,s_y) + \lambda_{if} \geq \hat{\eta}^e \\ \textit{not promoted} & \text{if } \hat{\eta}^e > E(\theta_i|s,s_y) + \lambda_{if} \end{array}$$

Unlike the full information case, employers still do not know each worker's innate ability exactly. Under full information, remaining non-regular workers do not have the incentive to apply for regular jobs because their innate abilities are already revealed to other employers; there is no possibility for the worker to be employed in the regular job even if they try one more. In other words, the worker assignment process has no possibility of misallocation. However, in the incomplete information on the innate ability of workers, there is noise in the information of workers' innate abilities. The incomplete information brings about the case that a worker is assigned to a non-regular job but the workers should be assigned to regular jobs if the worker's innate ability is observable. The opposite case also can occur especially in the narrow range of θ_i centered on the $\hat{\theta}^{e}$. Thus, if a remaining non-regular worker's possibility to be assigned to a regular job at the next period is sufficiently large, the worker tries applying for the regular job. The probability of non-regular worker i's getting a regular job at the next period is in equation (9)

$$(9) \qquad prob(\mathrm{E}(\theta_i|s_i) \geq \hat{\theta}^{e}) = prob\left(\frac{\sigma_e^2\mu_\theta + \sigma_\theta^2(\theta_i + e_{it})}{\sigma_\theta^2\sigma_e^2} \geq \hat{\theta}^{e}\right)$$

$$= prob\left(e_{it} \geq \frac{(\sigma_\theta^2+\sigma_e^2)\hat{\theta}^{e} - \sigma_e^2\mu_\theta}{\sigma_\theta^2} - \theta_i\right)$$

$$= prob(e_{it} \geq A - \theta_i) = 1 - \Phi(A - \theta_i)$$

$$\left(\text{let } A \equiv \frac{(\sigma_\theta^2 + \sigma_e^2)\hat{\theta}^{e} - \sigma_e^2\mu_\theta}{\sigma_\theta^2}\right)$$

The probability of getting regular job increases as worker i's innate ability increase. The expected payoff of applying regular job is in equation (11)

$$(10) \qquad prob(e_{it} \geq A - \theta_i)W_R + prob(e_{it} < A - \theta_i)W_{NR} - k$$

where W_R is the expected wage in a regular job, W_{NR} is the expected wage in non-regular job and k is the application cost, which is non-negative. For simplicity, we assume application cost for non-regular jobs is zero.

Worker i

$$\textit{applies to regular job} \quad \textit{if} \ 1 - \Phi(A - \theta_i) \geq 1 - \frac{W_R - k}{W_R - W_{NR}}$$

$$\textit{not applies} \quad \textit{if} \ 1 - \frac{W_R - k}{W_R - W_{NR}} > 1 - \Phi(A - \theta_i).$$

Thus, a worker who owns a high innate ability and thinks him/her innate ability is underestimated in the first period applies for a regular job. Among the non-regular workers who apply to regular jobs, the successors are called mover. They will go through higher wage growth as a reward for searching good matched jobs. Therefore, the wage growth is shown through labor market experience; a mover moves to a new employer who estimates his innate ability higher than at the previous job and thus the wage increases gained by moving to new job could not be presented through tenure.

This incomplete information case shows why stayers and movers occur and why they present different paths of wage growth after the conversion to regular jobs. Like the full information case, for stayers, high matching component within a firm enables the worker to be promoted to a regular job even though his own productivity shown through the signal is not high enough to be employed as a regular worker. Then, higher wage growth as the result of promotion is shown through tenure. In the case of movers, unlike the full information case in which mover does not occur at all, the noise in the signal on the worker's innate ability causes non-perfect efficient assignment. Thus, some non-regular workers, who have relatively high innate ability and thus sufficient high probability of regular job assignment, try to move to regular jobs and get one more

chance to be reevaluated on their innate ability[16]. Those who succeed in turnover as a regular worker face higher wage growth through the total labor market experience.

VIII. Conclusion

With the increase in the number of non-regular jobs, many new entrants in the labor market have gone through non-regular jobs and later move to regular jobs. Using data from Korea Labor and Income Panel Study – which distinguish regular workers with past non-regular job experience into stayers and movers depending on the type of transition to regular jobs – we show that, while non-regular job experience has negative effects on wage level at regular jobs, regular workers with non-regular job experience have higher wage growth than initial regular workers. For stayers, higher wage growth is presented through tenure. For movers, it is observed through labor market experience. Thus, given the negative effects of non-regular job experience, the higher wage growth for stayers and movers reduces the wage differential from initial regular workers.

To explain our findings, we propose a theoretical framework encompassing "experienced good" matching model and employers' learning. Under incomplete information on job match and workers' ability, during the working period at non-regular jobs, the quality of both worker's ability and job matching has been learned and firms reevaluate the non-regular workers. After this process, the revealed high matching component within a firm enables the worker to be promoted to a regular job, stayers. The noise in the signal on the worker's innate ability causes non-perfect efficient assignment. Although non-regular workers did not enter regular jobs inside, if they have the ability enough to get a regular job elsewhere, they try to move to regular jobs and get one more

[16] This mode's prediction is consistent with the results of the data showing that movers have a relatively higher level of education than stayers.

chance to be reevaluated on their innate ability. The person who succeeds in this search process becomes the mover. The empirical results reflect this mechanism. We argue that, for stayers, the higher wage growth through tenure reveals the learning process on worker ability and matching component between a worker and an employer, and, for movers, the higher wage growth through labor market experience reflects the reward of searching for a productive match.

Given the workers' preference for regular jobs' high-paying and job security, there exists "job queuing" phenomenon in which workers are waiting to enter regular posts from relatively easy-to-enter non-regular jobs. With many non-regular workers facing this job queuing, this study implies that the non-regular jobs experience could provide a probationary stage and search time for workers and screening devices for employers.

Although this study views the past non-regular job experience mainly from the matching model, there exist possibilities that the higher wage growth of workers with non-regular workers is also contributed from other factors that are not considered in this study. The higher wage growth of stayers and movers could be explained by accumulated human capital during non-regular work, although there is less chance of on-the-job training for non-regular workers than for regular workers as reported in Supplementary Survey of Economically Active Population in 2017. Also, this study could not provide reasons for past non-regular job experience's negative effects on the wage level in regular jobs. There can be a variety of factors that cause this negative effect. The regular workers with non-regular job experience are likely to have lower unobserved individual productivity than initial regular workers. Also, it may be that the stigma on non-regular jobs was reflected in wages. From the human capital perspective, if the amount of human capital accumulated in non-regular jobs is relatively lower than that of regular jobs, the difference in the accumulated human capital may have been reflected in wages. Further

research is necessary on the reasons for the negative effect of past non-regular job experience. At last, because the ratio of non-regular workers who later move to regular jobs is not high, we need to interpret our results considering our sample's specificity.

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Appendix

A.1 The Full information

Under full information on workers' innate abilities, an employer can observe workers' innate abilities. However, before employment, employers and employees do not know how matching component will be realized. Thus. employers employ workers based on expected productivity and pay wages as same as the expected productivity.

(A1-1) $$E(y_{if1}^{R}) = d_R + c_R(\theta_i + \mu_f)f(1)$$

(A1-2) $$E(y_{if1}^{NR}) = d_{NR} + c_{NR}(\theta_i + \mu_f)f(1)$$

Let $\hat{\eta}^{e}$ denote expected effective level at which $E(y_{if1}^{R})$ is equal to $E(y_{if1}^{NR})$ and let $\hat{\theta}^{e}=\frac{\hat{\eta}^{e}}{f(1)} - \mu_{\lambda}$. Then, employers allocate workers to regular job if $\theta_i > \hat{\theta}^{e}$ and to non-regular job if $\hat{\theta}^{e} > \theta_i$. After employment, the matching component get realized and workers produce output.

(A2-1) $$y_{if1}^{R} = d_R + c_R((\theta_i + \lambda_{if})f(1) + \epsilon_{ift})$$

(A2-2) $$y_{if1}^{NR} = d_{NR} + c_{NR}((\theta_i + \lambda_{if})f(1) + \epsilon_{ift})$$

Then, employers observe the outputs and decide the promotion of non-regular workers to regular job based on efficient allocation rule. Because, once the matching component is realized and output is produced, employers know each factor of productivity, there is no uncertainty of information for promotion decision. Each non-regular worker is promoted to regular job if $(\theta_i + \lambda_{if})f(1) > \hat{\eta}$ and not promoted if $\hat{\eta} > (\theta_i + \lambda_{if})f(1)$. Remaining non-regular workers can try to apply for regular jobs in another

firm at next period. However, each firm already knows each worker's innate ability and expected productivity do not vary at next period. Thus, remaining non-regular workers are again employed as non-regular workers.

Among non-regular workers at the first period, only some workers who have sufficient high matching component and moderate innate ability can be promoted to regular job. Most of the non-regular workers remain in non-regular jobs and go through low wage growth than regular workers. Promoted workers face wage growth through tenure because of good matching component learned during non-regular work. Initial regular workers' wage grows as tenure increase. This result is accordance with the empirical result of stayer group. However, the full information case cannot explain the mover group. Thus, in next step, we ease the assumption on the completeness of information on workers' innate abilities.

Appendix 2.

A2. The Fixed Effect Model for Effect of Non-regular Work Experience on Wage

Table1. A1. The Fixed Effect Model for Effect of Non-regular Work Experience on Wage

	Pooled OLS			
	[1]		[2]	
	Stayer		Mover	
Independent Variables	**coef**	**se**	**coef**	**se**
temp duration	-0.004	0.007	-0.011	
temp job number	-0.089***	0.007	-0.107***	
regular_entry_age	0.011***	0.001	0.010***	
exp*temp duration	-0.001	0.001	0.001	0.001
exp2*temp duration	0.000	0.000	-0.000	0.000
tenure*temp duration	0.002	0.001	0.002	0.001
tenure2*temp duration	-0.000	0.000	-0.000	0.000
exp	0.036***	0.002	0.035***	0.002
exp2	-0.001***	0.000	-0.001***	0.000
tenure	0.008***	0.001	0.009***	0.002
tenure2	0.000***	0.000	0.000***	0.000
Individual characteristics	√		√	
job related characteristics	√		√	
year dummy	√		√	
n	2378(167)		2627(326)	
N	17301		18857	

Note: n is the number of persons(conversion sample). N is the number of person-job-wave observations. . All regression include the age, education, marital status, the sector and size of their employing organization, occupation, the dummy of existence of union in the firm, the number of non-regular job held before conversion to regular worker, the age when sample enters regular job, unemployment rate, year dummy *** p<0.01, ** p<0.05, * p<0.1

Chapter 2. Does Inequality Rise with Non-regular Workforce?:Firm's reaction to Non-regular Worker Protection Law[17]

I. Introduction

With the surge of the fraction of non-regular employments[18] in the late 90s, non-regular employment has been drawing attention as social problems due to the poor employment condition of non-regular workers compared to regular workers. Naturally, due to the presence of the income gap between regular and non-regular workers, the increase of nonstandard jobs has been considered one of the factors that expand income inequality. However, the ratio of non-regular workers peaked in 2004 and began to decline. The decline in non-regular workers, a disadvantaged group, is thought to ease income inequality, but contrary to expectation, income inequality has rather increased. Considering the unequalizing effect of nonstandard jobs, 'the increasing inequality and decreasing nonstandard job rate' situation seems puzzling.

Previous research(Kim and Kim; 2012, Jung et al; 2017 Kim;2014) on the relationship between inequality and non-standard jobs dealt with the non-regular jobs as one of many other factors that could affect inequality and focused on wage inequality. Although the impact of non-regular workers on wage inequality varies according to the timing and method, in general, the results regard non-standard jobs as one of the factors which enlarge the wage inequality. However, previous studies did not take into account

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[17] JEL codes: J23 J31 J46 D21
Keywords: non-regular jobs, income inequality, firms' behavior

[18] Non-regular jobs mean that jobs that are not included in regular jobs, which is directed-employed, permanent and full-time. In this paper, we use non-standard, non-regular as the term referring to non-regular jobs and use standard, regular, permanent as the term referring to non-regular jobs. The terms, 'job type' and 'employment type', refer to regular and non-regular jobs.

changes in the proportion of non-regular workers over time and did not take into account the impact of this pattern of change on the overall income distribution.

In addition, in order to consider the overall welfare of workers, it seems to be appropriate to deal with income inequality encompassing the change of both hourly wages and working hours. This is because, in general, non-regular workers are likely to choose the job involuntarily and are less likely to have the right to choose working hours. Usually, from a worker's point of view, a job is a commodity in which wages and time are tied together.[19] To our knowledge, there not exist a study analyzing the relation between income inequality and the rate of non-standard jobs and dealing with this puzzling situation in which the proportion of non-regular employment decreases and income inequality increases.

The goal of this paper is to give an explanation for this puzzling situation. Card(2001)'s decomposition method, which was used to measure the equalizing effect of the decrease in the proportion of unionism on wage distribution, we identify the effects of nonstandard jobs on labor income and confirm whether the decrease in the proportion of non-regular jobs indeed deepens the labor income inequality. At last, we propose the model for firms' decisions on job type, suggest the hypothesis to account for our findings, and confirm the hypothesis using data.

According to the results of decomposition estimate, despite the reduction of the rate of non-regular jobs, non-regular jobs have effects on the increase in labor income inequality. It is the outcome of the disproportionate decrease of nonstandard jobs in skill distribution − the higher skill, the more decrease. This skill-biased reduction in the rate of non-regular jobs could increase the income gap between job types to the extent that

[19] Of course, for time flexibility, there are workers who choose the non-regular jobs especially among female workers. However, in this study, we mainly focus on the non-regular jobs which is substitutable with regular jobs. Thus, we confine our sample to male paid-workers. The results for female also are provided for reference. The results for female do not deviate much from the results of men; there is a difference in size, but the trend is consistent.

they offset the equalization effect of the decrease itself in the fraction of nonstandard jobs.

By presenting a firm's employment model that adds task complexity to skill level, we suggests the hypothesis on the reason for this disproportionate decrease. Non-regular Worker Protection Law acted in 2007 induce the exogenous decrease(increase) in the relative cost of regular(non-regular) jobs. With the two types of employment having a comparative advantage over each task, the increase in the relative costs of non-regular workers has led to the transfer of more complex jobs to regular workers, and this phenomenon has been worse in higher skill groups. Thus, the reduction in the ratio of non-standard jobs is small in low-skill and is large in high-skill and the reduction is made from relatively more complex tasks. We confirm that data also support the hypothesis.

This paper is organized as follows. In section 2, we briefly explain Card(2001) decomposition method and show the data. Section 3 shows the results of non-standard job effects on labor earning inequality. Section 4 proposes the theoretical framework of firms' employment type allocation behavior and the hypothesis that give the explanation for the puzzling situation 'decrease in the rate of nonstandard jobs and an increase in the labor income inequality' and confirms the hypothesis using data. The final section presents concluding comments.

II. The effect of nonstandard jobs on labor income inequality

A. Method

To analyze the potential impact of non-regular workers on labor income inequality, it is assumed that workers can be classified into homogeneous groups of skills. $\mathrm{w}_i^n(c)$ is the log labor income that non-regular worker i in skill group c can earn and $\mathrm{w}_i^r(c)$ is the

log labor income of regular worker i in skill group c. Assume that an individual $i's$ income is:

$$\mathrm{w}_i^n(c) = \mathrm{w}^n(c) + \epsilon_\mathrm{i}^n$$

$$\mathrm{w}_i^r(c) = \mathrm{w}^r(c) + \epsilon_\mathrm{i}^s$$

$\mathrm{w}^n(c)$ and $\mathrm{w}^s(c)$ indicate the non-regular workers' mean income and regular workers' one in the skill group c.

Residual components, ϵ_i^n and ϵ_i^s meet the following conditions.

$$\mathrm{E}[\epsilon_\mathrm{i}^n] = \mathrm{E}[\epsilon_\mathrm{i}^u] = \mathrm{E}[\epsilon_\mathrm{i}^n | nonregular] = \mathrm{E}[\epsilon_\mathrm{i}^u | regular] = 0$$

These assumptions can be interpreted that workers in the same skilled group are considered to have the same productivity for potential employers.

The observed average income gap between non-regular and regular workers is as follows

$$\Delta_w(C) = \mathrm{w}^n(c) - \mathrm{w}^r(c)$$

Under the assumptions above, the observed average income gap is the expected wage loss when workers change their form of employment from regular to non-regular.

The type of employment affects the distribution of income within the level of skill as well as the average income level. The following equation is the variance of log income of the non-regular and regular employee for individuals in the skill group c

$$\mathrm{Var}[\epsilon_\mathrm{i}^n | c] = v^n(c)$$

$$\mathrm{Var}[\epsilon_\mathrm{i}^r | c] = v^r(c)$$

The variance gap between the two groups in the skill group c is as follows:

$$\Delta_v(C) = v^n(c) - v^r(c)$$

$\mathrm{n(c)}$ is the proportion of non-regular workers in the skill group c. Under the conditions mentioned above, the average log income for skill group c can be expressed as equation (1).

(1) $\mathrm{w(c)} = \mathrm{w}^r(c) + \mathrm{n(c)}\Delta_w(c)$

The second term in the right means the average loss income faced by workers in group c due to non-regular job type.

The equation (2) represents log income variance in skill group c

(2) $\mathrm{v(c)} = v^r(c) + \mathrm{n(c)}\Delta_v(c) + \mathrm{n(c)}\big(1 - \mathrm{n(c)}\big)\Delta_w(C)^2$

This equation shows the "within-job type" effect (the second term on the right) caused by the size of the variance of non-regular workers relative to that of regular workers within the skill group, and "between-job type" effect (the third term on the right) exerted by the average income gap between non-regular and regular workers.

Using equation (2), the total skill groups' variance can be written as

(3) $\mathrm{v} = \mathrm{Var}_c[\mathrm{w}(c)] + \mathrm{E}_c[\mathrm{v(c)}]$

$$= Var[\mathrm{w}^r(c) + \mathrm{n(c)}\Delta_w(c)] + E[v^s(c) + \mathrm{n(c)}\Delta_v(c) + \mathrm{n(c)}\big(1 - \mathrm{n(c)}\big)\Delta_w(c)^2]$$

$$= \mathrm{Var}[\mathrm{w}^s(c)] + Var[\mathrm{n(c)}\Delta_w(c)] + 2Cov[\mathrm{w}^r(c), \mathrm{n(c)}\Delta_w(c)]$$

$$+ E[v^s(c)] + E[\mathrm{n(c)}\Delta_v(C)] + E[\mathrm{n(c)}\big(1 - \mathrm{n(c)}\big)\Delta_w(c)^2]$$

If there is only regular employment in the labor market, the income dispersion is

$$\mathrm{v}^{\mathrm{r}} = Var[\mathrm{w}^r(c)] + E[v^r(c)]$$

Thus, the effect of non-regular workers on the total income distribution compared to the income distribution when there are only regular workers can be expressed as follows.

(4) $\mathrm{v} - \mathrm{v}^{\mathrm{r}} = Var[\,\mathrm{n(c)}\Delta_w(c)] + 2Cov[\mathrm{w}^r(c), \mathrm{n(c)}\Delta_w(c)] +$

$$E[\mathrm{n(c)}\Delta_v(c)] + E[\mathrm{n(c)}\big(1 - \mathrm{n(c)}\big)\Delta_w(c)^2]$$

The effect consists of the variance part and the mean part. The variance part is composed of the variance of the weighted wage gap and the covariance between the average income

of regular jobs and the weighted wage gap at each level of skill. If the income for regular jobs increases as skill increases and the wage gap also increases as skill increases, the effect becomes large. The proportion of non-regular jobs as a weight adjusts the degree of the effect. The mean part is the sum of the mean of the weighted variance gap and the mean of the weighted squared wage gap at each level of skill.

If there is no difference across skill groups, equation (4) can be represented as the equation (5). From the equation (5), we can simplify the key components that determine the size of the nonstandard jobs' effect on labor income inequality: the rate of nonstandard jobs, the variance gap and the labor income gap between nonstandard and standard jobs.

(5) $\mathrm{v} - \mathrm{v}^{\mathrm{r}} = n\Delta_v + \mathrm{n}(1\text{-}\mathrm{n})\,\Delta_w^2$

However, the equation (4) is defined under the assumption that there is no difference in average productivity for workers in the same skill group except for the difference due to employment type. If the non-regular and regular workers have different productivity and receive different incomes beyond the income difference based on the type of employment, then the above formula should be modified as follows.

$$\mathrm{w}_i^n(c) = \mathrm{w}^n(c) + \mathrm{a_i} + \epsilon_\mathrm{i}^n$$

$$\mathrm{w}_i^r(c) = \mathrm{w}^r(c) + \mathrm{a_i} + \epsilon_\mathrm{i}^r$$

$\mathrm{a_i}$ represent an individual's unobserved productivity and $\theta(\mathrm{c})$ is the difference in unobserved productivity between non-regular and regular workers.

$$\theta(\mathrm{c}) = \mathrm{E}[\mathrm{a_i}|nonregular, c] - E[\mathrm{a_i}|regular, c]$$

If there is an unobserved difference in productivity between two employment types, the mean income difference between non-regular and regular jobs in skill group c includes the true employment type income premium and the difference caused by unobservable heterogeneity:

$$\mathrm{E}[\mathrm{w}_i^n(c)|nonregular] - E[\mathrm{w}_i^s(c)|regular] = \Delta_w(c) + \theta(c)$$

Taking into account unobserved productivity, the effect on the distribution of income for temporary workers is as follows:

$$(6)\quad \mathrm{v} - \mathrm{v}^{\mathrm{r}} = Var[\,\mathrm{n(c)}\Delta_w(C)] + 2Cov[\mathrm{w}^r(c), \mathrm{n(c)}\Delta_w(C)] + E[\mathrm{n(c)}\Delta_v(C)] + E[\mathrm{n(c)}\big(1 - \mathrm{u(c)}\big)\{(\theta(c) + \Delta_w(C))^2 - \theta(c)^2]$$

The fourth term in equation (6) that reflects the average income gap between non-regular and regular workers within the same skill level is different from the equation (4).[20] According to a study that analyzed the wage gap between non-regular and regular workers (Lee and Kim; 2009, Kim; 2011), when individuals' unobserved heterogeneity is controlled, the wage gap between two groups is reduced. It means that the fourth term in equation (4), which shows the average income gap between non-regular and regular workers, can be smaller than the observed value. Then, the effect of non-regular workers on the overall income distribution would be reduced. That is, the actual computed value of equation (4) should be interpreted as an upper limit on the magnitude of the impact of non-regular workers on the overall income distribution.

B. Data and Trend

This paper uses Supplement Labor Survey by Type of Labor of Economic Activity Population Survey from August 2004 and 2016 surveys. This data contains monthly labor income, working hours and individual characteristics.[22] The period 2004 is the peak point of the rate of non-standard jobs in the data and the 2016 survey is the latest available data at the beginning of the study. Although there exist several inequality

[20] Of course, the distribution of unobserved productivity between non-regular and regular workers may not be the same, but this part is beyond this paper.
[22] Hourly wage data used in this paper is calculated using monthly labor income and weekly working hours.

measures, to consistently follow Card(2001) method, we mainly use variance as the main index for measuring inequality.

Table2.1 gives a descriptive overview of the changes in the rate of non-regular employment from 2004 to 2016. The sample used in this table is restricted to paid male workers who ages 16-65 and reported monthly income and working hours. The variable of non-regular workers is based on the definition by the Korea Tripartite Commission of labor, management, and government.[23]

The first low in Table2.1 shows, in 2016, the proportion of non-regular workers decreased by 30% for men. In terms of educational level, the decrease in the proportion of non-regular workers is the largest rate in higher education. By age and labor market experience, there was a significant drop in workers aged 25-45-years old and workers with15-30-years of labor market experience who are more likely to take up major jobs in firms. The biggest drop in occupations occurred in professional and related workers and office clerk. The decline mainly occurred in big firms(larger than 100 employment). Taken together, the decreasing trend is mainly driven by the sharp decline in high-educated, white-collar, professionals and large firm workers[24], who are located in relatively good employment conditions. The group with the lowest rate of decline is young and less-educated workers. These significant drops in the non-standard rates in these relatively good condition jobs and the slight drop in the non-standard rates in low skilled or low-quality jobs can have a negative effect on the overall distribution of labor income distribution by increasing the income gap between the two job types.

[23] Non-standard workers include distinct seven groups: fixed term- workers, part-time workers, dispatched workers, temporary help agency workers, independent contracts, on-call/daily workers, and tele-workers/home-based workers.

[24]The proportion of non-regular workers decreased by 20% for women (In both genders, the decrease in the proportion of non-regular workers was mainly found in high-education, large-enterprise workers.)

Table2. 1. The Rate of Non-standard Jobs in 2004 and 2016

	Men		ratio
	2004	2016	2016/2004
all	29.99	20.82	0.69
By Education			
<High School	49.54	42.47	0.86
High School	31.98	27.44	0.86
Some College	24.51	18.63	0.76
College or More	22.27	13.11	0.59
By age			
16-24	40.3	44.02	1.09
25-34	28.89	18.62	0.64
35-44	26.55	15.53	0.58
45-54	31.42	21.24	0.68
55-64	40.42	29.23	0.72
By exp			
5	36.19	32.7	0.89
10	28.38	19.07	0.67
15	26.33	14.69	0.56
20	24.67	14.52	0.59
25	26.34	17.08	0.65
30	32.34	18.84	0.58
35	33.96	24.21	0.71
40	48.19	36.79	0.76
By occupation			
1. Managers	16.36	13.87	0.85
2. Professionals and related workers	24.96	13.91	0.56
3. office Clerks	17.27	9.18	0.53
4. Service and sale workers	27.87	24.7	0.89
5.Skilled agricultural, forestry and fishery workers	47.23	28.67	0.61
6. Craft and related trades workers	43.82	33.13	0.76
7.Equipment, machine operating and assembling workers	23.13	16.68	0.72
8.Elementary workers	58.66	50.63	0.86

By industry			
1. Agriculture, forestry and fishing	44.47	36.48	0.82
2. Mining and quarrying	23.74	16	0.67
3 Manufacturing	19.32	9.26	0.48
4. Electricity, gas, steam and air conditioning supply	13.37	9.58	0.72
5. Construction	63.12	46.83	0.74
6. Wholesale and retail trade	26.31	19.86	0.75
7. Transportation, storage, Information and communication	24.74	16.76	0.68
8. Financial, insurance activities, Real estate activities and Business facilities management and business support services; rental and leasing activities	39.43	31.48	0.80
9. Social and personal services	20.18	17.18	0.85
10 Public and foreign agencies	28.81	16.46	0.57
By firm size			
1~4	41.69	36.13	0.87
5~9	40.3	29.59	0.73
10~29	32.51	23.11	0.71
30~99	26.73	17.39	0.65
100~299	24.98	12.86	0.51
more than 300	15.25	8.24	0.54
No.obs	13,765	11,206	

Another point to note is that when classified by industry, the decrease in the rate of non-regular workers in manufacturing stands out. The non-standard rate in the manufacturing industry decreased by 50%. On the contrary, the percentage of non-regular workers in the service industry, which had a high proportion of non-regular workers, has not decreased much.[25]

[25] There is a clear difference in the size of change of the ratio of non-regular workers in the service industry and manufacturing industries. Therefore, we analyzed manufacturing and service industries separately. The results can be found in the appendix.

Table2. 2. Naïve Estimates of the Contribution of Non-standard Workers

Description		Men		
		Nonstandard	Standard	Total
2004	Mean Log Income	4.603	4.973	4.861
	Variance Log Income	0.351	0.228	0.294
	Non-standard Rate			0.302
	Non-standard Income Gap			-0.370
	Non-standard Variance Gap			0.124
	Within-Type Effect			0.037
	Between-Type Effect			0.029
	Total Effect			0.066
2016				
	Mean Log Income	5.149	5.692	5.579
	Variance Log Income	0.435	0.225	0.318
	Non-standard Rate			0.211
	Non-standard Income Gap			-0.544
	Non-standard Variance Gap			0.210
	Within-Type Effect			0.044
	Between-Type Effect			0.049
	Total Effect			0.093
Changes from 2004 to 2016				
	Change in Variance of Income			0.024
	Change in Total Effect of Non-standard jobs			0.027
	Share Attributable to Non-standard jobs.			1.133

**Note*. See text for formulas and Table1 for underlying data.

Table2.2 presents summary statistics on income by job types and the naïve calculation results for the effect of nonstandard jobs to rising labor income inequality. The summary statistics provide information on several key factors along with the size of the decrease in the proportion of non-regular workers. Firstly, the variance for non-standard workers is larger than that of standard workers in both periods. Thus, the decrease in the proportion of non-regular jobs is likely to reduce income inequality in that the group with big dispersion shrinks. Secondly, the income gap between the two

job types has been increased(-0.370 to -0.544). Last of all, the variance gap between the two employment types has also been enlarged(0.124 to 0.210). After all, the relative size of the factors will determine the direction and magnitude of non-regular jobs' effect on income inequality.

Assuming each component does not vary across skill groups, as in equation (5), the naïve estimate of nonstandard jobs' contribution to income inequality is 0.066(/0.294)in 2004 and 0.093(/0.318) in 2016. The change of the contribution from 2004 to 2016 is 0.027, which explains most of the change in labor income variance(0.024). In particular, the substantial increase in the between-type effect accounts for the largest portion. We can infer the rise in the earning gap is caused by the significant decrease of non-regular workers in relatively good employment conditions. The within effect has not changed relatively much during this period. The within-type effect is the outcome of the interaction between the rate of non-standard workers and the additional variance contributed by non-regular jobs. The unequalizaing effects of the increased variance gap and the equalizing effects of the decrease in the rate of nonstandard jobs offset each other, thus shrink the role of within-type effect.

C. Effects of Non-standard Jobs on Labor Income inequality

The naïve estimate results have limitations in that they do not allow the difference across skill groups. To consider the variation of the income gap and variance gap across skill groups, we set 5 equal-sized quintile skill groups based on the predicted hourly wage regressed on education level, labor market experience and its squared term in standard jobs.

Table2.3 shows the non-standard rates, the average income gap and the variance gap between non-standard and standard workers across each skill group for 2004 and

2016. The quintile share of non-standard indicates how many non-standard workers are distributed in each quintile and the sum of the share across quintile is 100.

Table2. 3. Distribution and the Effect of Non-standard Workers across Skill Quintile

Quintile	2004				2016			
	Percent non-standard	Quintile Share of Non-standard	Raw Non-standard Gaps:		Percent non-standard	Quintile Share of Non-standard	Raw Non-standard Gaps:	
			Income	Variance			Income	Variance
Men								
1	36.25	25.68	-0.25	0.18	30.82	32.60	-0.51	0.39
2	37.53	23.71	-0.30	0.14	19.66	19.90	-0.30	0.15
3	28.58	19.18	-0.28	0.08	21.98	19.75	-0.47	0.06
4	29.17	18.73	-0.37	0.13	18.83	16.75	-0.47	0.12
5	19.36	12.71	-0.27	0.21	11.13	11.00	-0.52	0.23

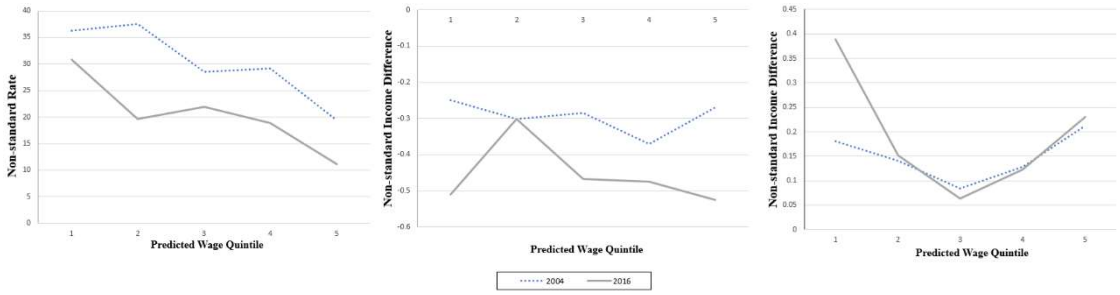
**Note*: Skill quintiles are based on the predicted wage in the standard jobs. The quintile share of non-standard represents the percentage of all non-standard workers in the skill quintile. The wage gap is difference in mean log wages between non-standard and standard workers in the skill quintile. The variance gap is the difference in variance of log wages between non-standard and standard workers in the skill quintile. See Table2. 1 for the sample definition.

As seen in Figure2.1, the proportion of non-regular workers has a negative relationship with the level of skill, which can be seen to have worsened in 2016 compared to 2004 (except for the 2nd quintile). From 2004 to 2016, although there is an overall drop in non-standard jobs' rates across skill groups, the rate of reduction in non-standard workers is the lowest in the lowest skill group and the highest at the top skill groups. Thus, the negative slope on skill-non-regular rate became steeper. This pattern of change reflects a significant decrease in the drop in the proportion of non-regular jobs in the high-educated, white-collar, large-firm worker seen in Table2. 1.[26]

[26] The large decline in the 2nd skill group shows a high rate of decline in the manufacturing industry The industry in which the 2nd skill group's workers belong most is manufacturing.

The average income gap increased monotonically in the upper-middle-quintiles. In terms of hourly wages, the monotonicity of the wage gap across skill quintiles is more evident as in Figure2. A4. It implies that, in the upper-middle quintiles, non-regular workers who receive relatively high earnings even within the skill group may have been converted to regular workers. This composition effect within the skill group can enlarge

Figure2. 1. Non-standard Rates, Wage Gaps, Variance Gaps by Skill Groups



the income gap between non-regular and regular workers within the same skill and lead the negative slope on skill-income difference. In the case of the 2nd skill groups, there is little change in the average income gap. In the 1st skill quintile, there is also an expansion in the earning difference, most of which is caused by the decrease in working hours of non-regular workers in the 1st skill group confirmed in Figure2. A4. Compared to the smallest drop in the ratio of non-regular workers in the 1st group, working hours seem to have been adjusted a lot. During the analysis period, in addition to changes in the extensive margin of non-regular workers, there seems to be an adjustment of intensive margins for non-regular workers, especially in the 1st quintile.

The variance gap follows the U-shape pattern across skill groups. However, during the periods, there was little change in the non-regular variance gap except for the 1st skill group. Only in the 1st skill group, the labor income variance gap rose, which implies that the lowest skill group drives the rise of the variance gap seen in Table2.2.

From these trends, it can be expected that the impact of non-regular jobs in income inequality will be strengthened due to the widening overall earning gap and the

growing variance gap in the 1st skill group on which non-regular workers are concentrated.

Table2.4 presents the result of the estimate of equation (4) and the change of non-standard effects on income distribution. Table2.4-1 shows the calculated value of each component in equation (4). According to the estimated results of equation (4), non-standard jobs account for 23%(0.7/0.294) of income variance in 2004 and the share increased by 28%(0.142/0.351) in 2016. The change of non-standard effects on income inequality explains about 80%(0.21/0.24) change of income variance for these periods.[27] Compared to the naïve estimate in equation (5), the calculated value of the nonstandard jobs' effect on inequality is slightly decreased, allowing for the difference across skill groups. That's because, by allowing heterogeneity in skill groups, the overall composition effect has been narrowed down to the composition effect within the skill level and because the influence of the increased variance gap in 1st skill group is reduced. However, the overall result of the estimate does not vary with the naïve estimate results. Despite the decrease in the rate of non-standard jobs, non-standard jobs contribute to the increased income variance.

Table2.4-1 in detail shows which factor caused this result. First of all, the enlarged income gap($E[\mathrm{n(c)}(1-\mathrm{n(c)})\Delta_w(c)^2]$) accounts for about 75% (0.016/0.02) of the effect. The increase in covariance between the earning of regular workers and earning gap between employment types($2Cov[\mathrm{w}^r(c), \mathrm{n(c)}\Delta_w(c)]$) explain about 25%(0.006/0.02) of the impact. Both facts can be understood as the result of the disproportionate decrease in non-standard workers within the skill group as well as between skill groups. Although the reduction in non-standard workers itself can reduce the earning inequality, the increased variance gap offset the equalizing effect of the decrease in the rate of non-regular workers($E[\mathrm{n(c)}\Delta_v(c)]$)

[27] In the case of female, the accounting share increased from 40 % in 2004 to 43% in 2016

Table2. 4. Estimates of the Contribution of Non-standard Jobs to Income Inequality,

Description	2004	2016	Change(16-04)
Male Workers			
Non-standard Rate	0.302	0.211	-0.091
Variance in Log Income	0.294	0.318	0.024
Effect of Non-standard Job Using Raw Wage Differentials (Equation 5)	0.070	0.090	0.021

Table2.4-1.Details on Estimates of the Contribution of Non-standard Jobs to Income Inequality

Male	Var[n(c)△w(c)]	2Cov[Ws(c), n(c)△w(c)]	E[r(c)△v(c)]	E[n(c)*(1-n(c)) *(△w(c))^2]	Total	Within	Between
2004	0.000	0.007	0.044	0.018	0.070	0.007	0.063
2016	0.001	0.013	0.043	0.034	0.090	0.014	0.076

Source: SSEAP(2004,2016)

D. . Counterfactual results

The earning gap and the variance gap between job types, and the change of the share of non-regular workers are the main factors comprising the nonstandard jobs' effect on income inequality. More specifically, to identify how much each element contributes to income inequality, we calculate the counterfactual results. Prior to the analysis, to check when this change occurred evidently, we calculate the effects over time in Table2.5. The puzzling situation of "decreasing non-regular workers and increasing inequality" and changes in the impact of non-standard jobs on income inequality were more pronounced in 2004-2009. To accurately explain the variation in factors, the rest focus on 2004-2009.

For counterfactual analysis, in each skill group, we fix the factor in 2009 one by one to the 2004 value and calculate the effect of nonstandard jobs on income inequality. For example, in Table2. 6, in the case of "no decline", the rate of nonstandard jobs in 2004 is assigned to the counterpart in 2009. In the case of "proportion decline", we average the decreasing rate across skill groups for 2004-2009 and assign the average value.

Table2. 5. The Effect of Non-standard jobs on Income Inequality for 2004,2009,2016

	△Non-standard rate	△ Variance of Income	△Effect of Non-standard jobs
2004 to 2016	-0.091	0.024	0.021
2004 to 2009	-0.053	0.042	0.022
2009 to 2016	-0.038	-0.018	-0.002

Table2.5 shows that if there had been no decline in nonstandard jobs, income inequality would have been widened. That is, the decline of the size of nonstandard jobs itself can reduce income inequality[29]. Indeed, however, the proportion of non-regular workers occurred unevenly in skill distribution and was accompanied by a widening income gap. If the reduction had occurred equally in the skill distribution, the equalizing effect would have reduced by about 25%(0.022 to 0.017). Unless the income gap and variance gap had expanded, most of the impact of strengthening inequality induced by non-standard jobs would not have occurred.

Table2. 6. Counterfactual Estimate of the Contribution of Non-standard Jobs to Income Inequality

	real	no decline	proportional decline	no wage gap change	no variance gap change
△nonstandard jobs effect 2009-2004	0.022	0.035	0.017	0.004	0.009
counterfactual effect - real effect		decline effect	non-proportional rate effect	wage gap change effect	variance gap change effect
		-0.013	0.005	0.018	0.013

[29] In the case of the manufacturing industry, the pattern of the ratio of non-regular workers was similar to that of the whole in the skill distribution, but the impact of non-regular workers on inequality was actually reduced by a significant decrease in the proportion of non-regular workers. The case implies that the reduction in the ratio of non-regular workers itself has the effect of alleviating inequality.

Three factors, however, do not move independently: a reduction in the imbalance in non-standard jobs and an increase in income gaps and variance gaps. Rather, the former results in the latter, and leads the puzzling state of "decreasing non-standard jobs and increasing income inequality."

If the analysis so far has been to figure out the situation, now it is necessary to discuss why this situation occurred. The starting point for the study is the decrease in the proportion of non-regular workers. We need to explore what factors lead to this disproportionate decrease in the rate of non-regular workers. Depending on what caused this decline in non-regular workers, the pattern and impact of the reduction will be different. The following sections propose hypotheses about the reasons for the rate reduction and describe the situation.

III. Hypothesis

Given the labor supply is enough and most workers prefer regular jobs to non-regular jobs, the change of decrease in the rate of nonstandard employment is the result of the reaction of firms. Thus, we focus on the demand side. We need to find a mechanism through which firms determine the share of each job type and which factor causes firms to change it. Of course, the change in percentage of job type can be endogenously derived by the firms' learning on the efficiency of each job type. However, because the learning behavior of firms is hard to be captured by data, in this study, we focus on the exogenous changes that can affect the firms' choice of job type. This section firstly proposes the mechanism of determining the employment type by firms based on task distribution at each skill group[31]and then suggests a hypothesis leading to both the disproportionate

[31] Task is the contents of the job and skill is the endowment of workers.

decrease of non-regular workers in skill distribution and the increase in income inequality at the same time.

Briefly, the story is as follows. Firms product the final output using a combination of a continuum of tasks at each skill labor market (low, middle, high). By assumption, regular jobs are more productive than non-regular jobs as task complexity increases. This comparative advantage in the task is enhanced as the skill level increase. For example, in the low skill labor market, no matter how high the complexity level of the task, the productivity of regular and non-regular jobs is not much different, while in the high skill labor market, the higher the task's complexity level, the greater the productivity of regular than non-regular jobs. However, even in the low skill labor market, there are top-level tasks that must be assigned to regular jobs. Under this assumption, in each labor market, the firms allocate two job types to each task considering each job type' comparative productivity at each task level and relative cost between two job types. In 2007, the action of Non-regular Work Protection Law(henceforth, NWPL) [32] exogenously increased the relative price of nonstandard workers compared to regular workers. Facing the change in the relative price of the non-regular job, the firm adjusted the allocation of job type. Because the marginal productivity of nonstandard jobs in high skill is not high enough to cover up the increase of the cost of the nonstandard job, more nonstandard jobs is replaced by regular job which are more productive at the task level. On the other hand, at low skill, the difference in productivity between regular and non-regular jobs is not as much as large. So, if there remains a little cost advantage at a task, the task is allocated to non-regular employment. That is, in the low skill labor market,

[32] The non-regular worker protection law acted in 2007 to restrict the duration of use of fixed-term workers by 2-year. Fixed-term workers should be converted into regular workers if they employ more than two years as fixed-term workers. The law also bans discrimination against non-regular workers (only for fixed-term, dispatched, short-time workers). When performing the same tasks as regular workers, the treatment of non-regular workers should not be differentiated from regular workers.

there is less decline in non-regular jobs. Besides, within the skill groups, the passed tasks to regular jobs are relatively complex than the remaining task on non-regular jobs. This skill-asymmetric decline of the share of non-standard jobs can be interpreted as strict skill and task sorting between job types.

A. Model

This section proposes the theoretical mechanism of firms' job type allocation to the task. This model is constructed based on the Ricardian model of the labor market (Acemoglu and Autor, 2011), Card (2001) skill group, add job type allocation (Basu et al., 2016)

The model assumes that there exist three different labor markets based on skill endowment (low, medium, high). Workers are divided into three skill groups, and within each skill group, all workers are homogeneous.

All firms are identical and firms are price-takers. In j labor market, $j \in \{L, M, H\}$, firms produce the final output following production technology.

$$F(y_j) = y_j^{\alpha}, \alpha \in (0,1)$$

The intermediate goods y_j is produced on completion of a continuum of task i, $i \in [0,1]$. i indicate the complexity level of the task; as the number increases, the complexity level increases.

$$y_j = \left(\int_0^1 y_j(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{1-\eta}}$$

There exist two job types-regular,R, and non-regular jobs,N. Within a labor market j, firms allocate two job types to each task i considering each job type's productivity, $E_{*j}(i)$, and wage, w_{*j} at the task complexity i.

$$y_j(i) = E_{Rj}(i)l_{Rj}(i) + E_{Nj}(i)l_{Nj}(i)$$

The critical assumption of the model is that the relative efficiency of job type is a function of task level and the degree is also different depending on labor markets(skill). As the complexity of the task increase, the relative productivity of regular jobs increases.

Let the relative productivity of regular workers to non-regular workers at task i in j labor market $a^j(i)$,

$$a^j(i) \equiv \frac{E_{Rj}(i)}{E_{Nj}(i)}$$

Assume that

i) $a'^j(i) > 0, a''^j(i) \geq 0$ [33], $a(0) = 1$

ii) $a^H(i) \geq a^M(i) \geq a^L(i) \quad for\ all\ i$

iii) $\lim_{i \to 1} a''\ (i) \geq \lim_{i \to 1} a''\ (i) \geq \lim_{i \to 1} a''\ (i)$

iv) $w_{Rj} > w_{Nj}\ for\ all\ j.$

The assumption (i) means that the more complex the task, the higher the relative productivity of regular workers. At the lowest task level, the productivity in both job types is the same. At the highest task level, however, the regular job is much

[33] Using the Korea version O*NET, we confirm that as task level increase, the wage premium of regular workers increases. We think that the empirical results can provide the justification for the assumption.

more productive to the extent that the task cannot be undertaken by non-regular jobs. The assumption (ii) implies that the level of relative productivity is always greater in the higher-skilled labor market than in the lower labor market at the same task level. The assumption (iii) means that as the task level becomes as close as to 1, the growth rate of relative productivity for regular jobs is steeply increasing in the lower-skilled labor market. In contrast, the growth rate in the higher-skilled labor market increases relatively gradually. These assumptions suggest that the productivity gap between regular and non-regular workers in the low skilled labor market is not significant, but at the highest level of internal tasks, regular workers are more efficient and assigned.

In this model, the wage of each labor market is exogenously given. We assume that there exists a wage gap between job types $w_R > w_N$ in (iv); the level of the wage of each job type reflects the productivity, hiring, firing cost and quasi-fixed cost of each job type. Because, in general, the firing cost and fringe of regular jobs are higher than that of non-regular jobs, this assumption is reasonable to some degree.

Cost function

$$C_j = \int_0^1 [w_{Rj}\, l_{Rj}(i) + w_{Nj} l_{Nj}(i)] di$$

l_R and l_{NR} indicate the number of workers employed in regular jobs and non-regular jobs. For simplicity, we assume that l is the same for all job types and labor markets.

The unit cost of task i,

$$C_j(i) = \frac{w_{Rj}}{E_{Rj}(i)} l_{Rj}(i) + \frac{w_{Nj}}{E_{Nj}(i)} (1 - l_{Rj}(i))$$

Firms choose optimal task complexity level $I^*$to minimize the unit cost of each task i

There exist I^* such that an employer is strictly indifferent between allocating a regular worker and allocating a non-regular worker to the task with complexity I^*

$$I^{j*} = \{\, i \in [0,1] |\, w_{Nj}(i)a^j(i) = w_{Rj}(i)\}$$

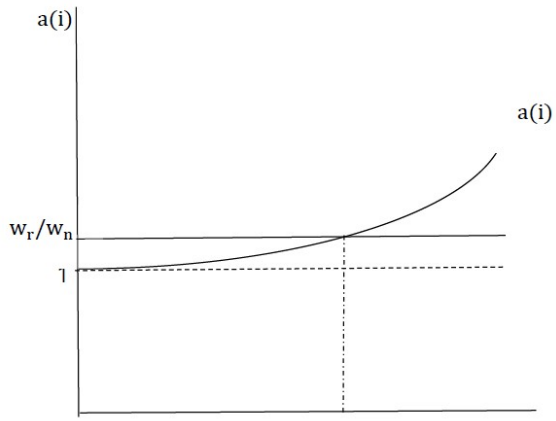


Figure2. 2. Efficient allocation

Under the wage and relative productivity assumptions, the proportion of non-regular job in each labor market is determined as

$$I^{L*} > I^{M*} > I^{H*}$$

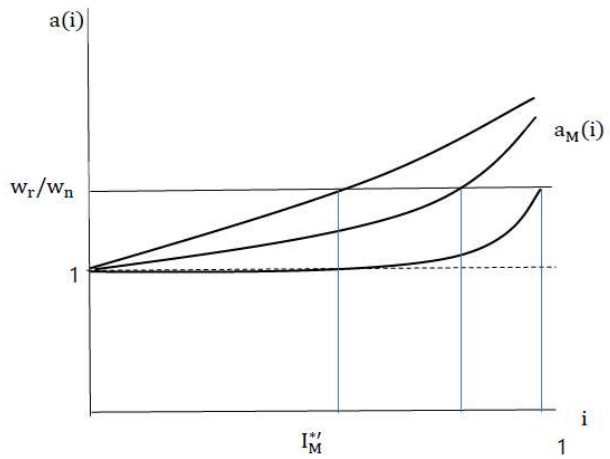
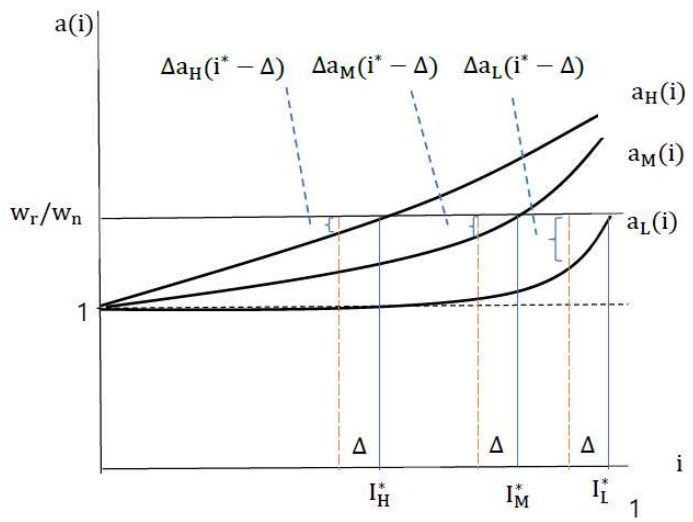


Figure2. 3. Efficient allocation by skill-labor markets



Given I* and relative wage in each labor market if more Δ units of the task are allocated to regular jobs, the decrease of regular jobs' relative marginal productivity, $\Delta a^j(I^* - \Delta)$, occurs.

Let $\Delta a^j(i-\Delta)$ *the size of relative marginal productivity loss of regular jobs when allocating more* Δ *tasks to regular jobs at task* i.

Given $I^{L*} > I^{M*} > I^{H*}$, the size of the loss in regular jobs' relative marginal productivity is in the order of

$$\Delta a^H(I_H^* - \Delta^i) < \Delta a^M(I_M^* - \Delta^i) < \Delta a^L(I_L^* - \Delta^i)$$

That implies that in the low skill market if a task at a slightly lower level than the current equilibrium, I^*-Δ^i, is allocated to a regular job, the productivity of regular workers has plummeted to the point where there is not much difference from non-regular workers (a large loss of productivity for regular workers). On the contrary, in the high skill market, the productivity of the regular job slowly decreases and there is still considerable difference with non-regular workers at a slightly lower level task(slight productivity loss in regular jobs).

If the relative regular wage decreases exogenously, the firm moves the allocation threshold I^* by comparing the relative regular wage and the relative productivity at i. Provided that the size of the decrease of relative regular wage is the same across labor markets, the firm move the boundary to the left side(the increase(decrease) in the share of regular(non-regular) jobs) until $\Delta w_R/w_{NR}$ become equal to the $\Delta a(I_H^* - \Delta^i)$.

$$\textit{There exist } \Delta_j^{i^*} \textit{ such that } \Delta\frac{w_{Rj}}{W_{Nj}} = \Delta a^j\left(I_j^* - \Delta_j^i\right)$$

$\Delta_j^{i^*}$ means the size of increase(decrease) in the share of regular(non-regular) jobs in the labor market j. If the size of wage decrease equal across all labor market, in the low skill labor market where a^L drop quickly with a little task downward movement,

there will be a slight decrease(increase) in the proportion of non-regular(regular) workers. In the high skill labor market where a^H falls slowly as the task level decrease, a significant decline in the proportion of non-regular jobs is necessary for covering up the reduction of relative wage, $\frac{w_{Rj}}{w_{Nj}}$.

The size of the increase in the share of regular jobs is determined as

$$\Delta_H^{i\,*} > \Delta_M^{i\,*} > \Delta_L^{i\,*}$$

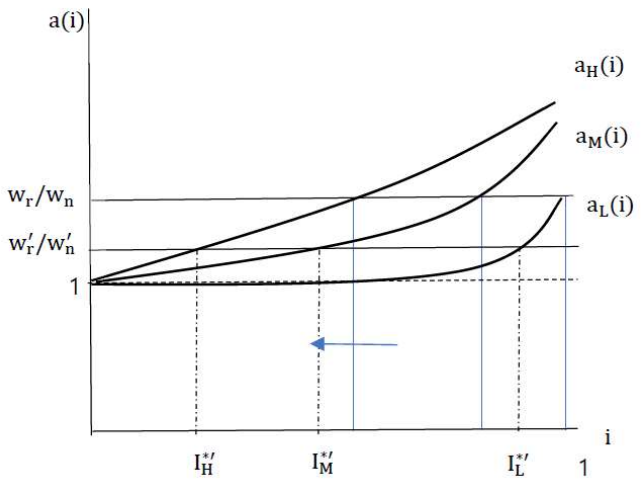


Figure2. 4. Exogenous increase in relative wage of regular jobs

Thus, when the relative cost of regular workers decreases, $I^{M*}$and I^{H*} decrease a lot relative to change of I^{L*} in Figure2.4

B. Non-regular Workers Protection Law in 2007

Non-regular Workers Protection law (henceforth, NWPL) was enforced in 2007. The Act limits the duration of fixed-term employment within 2-years and includes the equal treated right for non-regular workers with regular workers. The limitation in the length of employment induces the recurring hiring costs, and the equal treated

right increases the non-wage cost for non-regular workers. From the firm's stance, NWPL causes the relative cost for the employment of non-regular workers to increase. That is the decrease in the relative wage for regular works. In addition, considering that NWPL was enforced regardless of skill and task, all markets face the same size exogenous decrease in the relative cost of regular workers. Consequently, as seen in Figure2.4, NWPL leads to the disproportionate increase(decrease) in the share of regular(non-regular) jobs across skill groups. At each skill labor market, relatively more complex tasks are transferred to regular jobs. As a result, regular jobs become relatively more high-skill intensive groups. Non-regular jobs become concentrated on low skill and undertake less complex tasks.

C. Hypothesis Verification using Data

Using data, we check whether the NWPL has caused this phenomenon and whether the distribution of tasks has changed as predicted by the model.

Table2. 7. Estimates of the Contribution of Non-standard Jobs in Income Inequality by Age Groups

	△Non-standard rate	△ Variance of Income	△Effect of Non-standard jobs
Age < 55	-0.062	0.031	0.027
Age =>55	-0.035	0.045	-0.030

Firstly, to confirm NWPL indeed affect the increase in the inequality contribution of non-regular workers proved from the decomposition result, we use workers aged 55 and older, an exception groups to the Non-regular Workers Protection Act. We divided the sample into less than 54 and more than 55 years of age and conducted the decomposition. As a result, for 2004-2009 periods, the decrease in the proportion

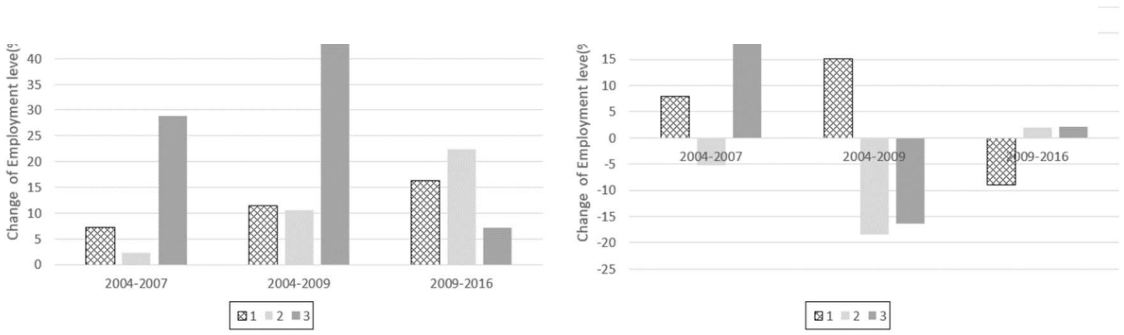
of non-regular workers under 54 increased income inequality, but that of non-regular workers over 55 did not increase income inequality. The results also support NWPL's impact on the decrease in the proportion of non-regular jobs that involves widening income inequality.

Figure2.5 shows the change of employment at each task group for 2004-2016. The task group is divided into three groups, following Kim (2015). As the number increase, the task's complexity increase. We can check the noticeable drop in the rate of non-regular jobs in high and medium task groups, especially for 2004-2009. Compared with the 2004-2007 changes, the decline in non-regular employment in the mid- and upper-level task occurred mainly in 2007-2009 when NWPL were enforced sequentially. To precisely examine whether the task change pattern is the reaction to NWPL, we use a difference-in-difference frame. The NWPL was applied except for firms with less than five employees and except for the non-type(atypical)[34] workers. Using the two exceptions, we identify the effect of NWPL on the share of non-standard jobs. To identify patterns of decline in the rate of non-regular workers at different levels of the task, we analyze the effect separately at different levels of task.[35] The model suggests the lower the degree of complexity of the task, the lower the decrease of the share of non-regular jobs.

[34] Non-regular workers are classified into distinct three groups: fixed-term workers, short-time workers , atypical workers. The atypical workers include dispatched workers, temporary help agency workers, independent contracts, on-call/daily workers, and teleworkers/home-based workers.

[35] In that the highly complex tasks (so called abstract task) are mostly assigned to high-educated workers, analysis based on task level can even capture the impact on the level of skill.

Figure2. 5. The Change of Non-standard Workers by Task Groups for 2004-2016



**Note*: The label 1,2,3 shows the degree of task complexity. The higher the number, more complex the task. The task group is divided based on Kim(2015) using KSCO occupation classification 1-digit. The data source is SSEAP on August.

We confine the sample to workers at firms more than five employees. Because NWMP did not influence atypical workers, if we subtract the time trend of employment growth rate in the fixed contract workers from the time trend of atypical contract workers, we can identify the NWPL effect as seen in Table2.8. The analysis covers the period from August 2004 to August 2008. Since NWMP was enforced from July 2007, it is classified as the "after" period from August 2007. We calculate the growth rate of non-regular employment by contract type by waves[36] and average the growth rate for before and after periods.

Table2. 8-1 shows the effect of NWPL on the growth rate of non-regular employment. The rate of decrease in the less complex task(1) is much lower than in the middle(2) and highly complex task(3). The results confirm that the NWPL indeed affected the reduction of the proportion of non-regular jobs, and the decline is concentrated in the top and middle task groups.

[36] SSEAPS provides data in March and August every year.

Table2. 8. The difference in difference Frame for the Non-regular Employment Growth Rate by Contract

			Before	After	After-Before
Treat	Fixed-term	emp=>5	Before trend	After trend+Effect	Time trend+Effect
Control	Atypical	emp=>5	Before trend	After trend	time Trend
			Treat-Control		Effect

**Note*: It includes the period from August 2004 to August 2008. As of August 2007, After and Before were divided.

Table 2.8-1. Result for Diff-in-Diff

			After - Before (Employment Growth Rate)		
(2004.8-2008.8)			1	2	3
Treat	Fixed term	emp=>5	0.034	-0.047	-0.107
Control	Atypical	emp=>5	-0.018	0.004	0.018
		effect	0.052	-0.051	-0.124

* *Note*: 1,2,3 show the degree of task complexity. The employment growth rate is calculated using the difference between log(non-regular employment level) during the periods.

IV. Conclusion and Discussion

Non-standard jobs have been considered one of the factors which increase income inequality. However, in South Korea for 2004-2016, the puzzling pattern has emerged that income inequality is growing even in the face of a drop in non-regular jobs.

When analyzing whether the nonstandard jobs contribute to the increase in income inequality using the Card (2001)'s decomposition analysis, the nonstandard jobs, in reality, contributed to the enlarged income inequality. Specifically, the results come from the disproportionate decrease of nonstandard jobs in skill distribution accompanied by the increase in the between-income gap.

By presenting a firm's employment model that adds task complexity to skill level, we suggests the hypothesis on the reason for this disproportionate decrease. Non-regular Worker Protection Law acted in 2007 induce the exogenous decrease(increase) in the relative cost of regular(non-regular) jobs. With the two types of employment having a comparative advantage over each task, the increase in the relative cost of non-regular

workers has led to the transfer of more complex jobs to regular workers, and this phenomenon has been worse in higher skill groups. Thus, the reduction in the ratio of non-standard jobs is small in low-skill and is large in high-skill and the reduction is made from relatively more complex tasks. We confirm that data also support the hypothesis.

The policy for protecting the non-regular workers and easing inequality can give unexpected results. Most of the workers, who moved to regular jobs from non-regular jobs for 2006-2009, had previously been receiving a similar level of wages as regular workers. Some of the remaining non-regular workers face worse conditions than before NWPL went into effect. Although the overall welfare should be analyzed through the general equilibrium model, on the surface, the welfare of workers remaining in non-regular jobs does not seem to have increased. In addition, given the reduced movement from non-regular workers to regular ones, the prospects for the welfare of non-regular workers maybe even worse. In determining policy, it is important to consider the firms' employment mechanism and to predict they will behave in response to polices. Policies that give incentives to firms to move according to the policies' goal should be designed. Limiting the period of use of non-regular workers seems to have limits in fundamentally increasing the welfare of non-regular workers. Clearly, on the one hand, efficiency may have increased as regular workers are assigned to tasks where regular jobs are more productive. In terms of protecting non-regular workers, however, NWPL appears to have failed to attract firms at all.

Furthermore, the widening income gap between regular and non-regular workers seen may be also related to factors other than the NWPL. Prior to the implementation of NWPL, even if a task was more suitable for regular workers, it was common to see allocating the task to non-regular workers due to the large benefits of non-regular workers' expenses. After the implementation of the law, most of these tasks were converted to regular workers. The passed tasks to regular jobs are relatively complex

than the remaining task on non-regular jobs. It may be said that the tasks have been more strictly distinguished between job types. The two groups' strict skill sorting and task separation exacerbate the income gap between standard and nonstandard workers as there is a wage premium for the high-skill group and complex task under the influence of SBTC and RBTC[37] influence. Advance in technology enhances the productivity of high-skill and complex task workers and increases the demand for the high skill and complex task. If SBTC or RBTC had progressed further during the period, the income gap between regular and non-regular would have increased further.[38]

The model has the limitation of not addressing the increased variance gap in 1st skill group among the key factors for the effect of non-regular jobs on income inequality. Although not covered by the same model, the increased variance gap in 1st skill group seems to be induced by the working hour adjustment by firms. As more non-regular workers of the lowest skill group experienced the working hour reduction, the variance of non-regular workers in the 1st skill group increased.[39] Because our model shows the choice for the rate of non-regular jobs, for dealing with the working hour, it is necessary to develop a model which deal with the firm's choice on extensive and intensive margin at the same time under the presence of two job type. Also, the theoretical framework

---

[37] The basic idea behind SBTC is that new technologies that foster productivity are "skill-biased", meaning that high-skilled workers are more able to use new technologies than low-skilled workers who, in fact, are at risk of being substituted by them.The RBTC hypothesis(Autor, Levy, & Murnane, 2003) predicts that ICT development and digitalization lead to a decline in jobs that are rich in the routine component and an increase in the number of jobs that are rich in the cognitive non-routine component(abstract, in this paper, complex task). The theory does not make clear predictions about employment in jobs that are mostly non-routine manual, as these are not directly affected by the digital revolution.

[38] Besides, the financial crisis in 2007 caused the negative demand shock and increased the uncertainty firm facing. Under the negative shock and increased uncertainty, a firm reduce the number of workers in the job type with the lower adjustment cost. Firms use a temporary job as a buffer worker because temporary workers have lower adjustment costs than regular workers. Thus, the crisis may have further amplified the size of the decline in temporary workers

[39] To better understand the change of labor income distribution, we decompose the variance of the labor income into three parts, variance of wage, hour and covariance between hourly wage and working hours and check which factors lead the change of the labor income distribution and through which factors non-regular jobs affect the labor income inequality. The details are given in the appendix.

proposed in the study does not deal with the wage-setting mechanism. If the wage-setting can be included in the framework, the model can explain the income inequality pattern in a richer way. In addition, it is necessary to reflect the technological change in the model. In the next step, the data work and theoretical back-up are needed to provide justification for the assumptions in the model.

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Appendix

A1. Non-standard Jobs and Labor Income Inequality: decomposition into wage and hour

1. Method

To better understand the change of labor income distribution, we decompose the variance of the labor income into three parts, the variance of wage, hour and covariance between hourly wage and working hours and check which factors lead the change of the labor income distribution and through which factors non-regular jobs affect the labor income inequality.

The variance of log labor income can be decomposed into three parts, the variance of wage, hour and covariance between wage and hours as seen in Equation (A1) and each component can be represented the weighted average of each type of jobs in Equation (A2).

$$\text{(A1)}\quad \mathrm{Var(lnWH)} = \mathrm{Var(lnW)} + \mathrm{Var(lnH)} + 2\mathrm{Cov(lnW, lnH)}$$

$$\begin{aligned}\text{(A2)}\quad &= \mathrm{pVar(lnW|1)} + (1-\mathrm{p})\mathrm{Var(lnW|0)} + \mathrm{p}(1-\mathrm{p})[\mathrm{E(lnW|1)} - \mathrm{E(lnW|2)}]^2 + \\ &\quad \mathrm{pVar(lnH|1)} + (1-\mathrm{p})\mathrm{Var(lnH|0)} + \mathrm{p}(1-\mathrm{p})[\mathrm{E(lnH|1)} - \mathrm{E(lnH|0)}]^2 + \\ &\quad 2\{\mathrm{p\ Cov(lnW, lnH|1)} + (1-p)\mathrm{Cov(lnW, lnH|0)} + \\ &\quad \mathrm{p}(1-\mathrm{p})[\mathrm{E(lnW|1)} - \mathrm{E(lnW|0)}][\mathrm{E(lnH|1)} - \mathrm{E(lnH|0)}]\}\end{aligned}$$

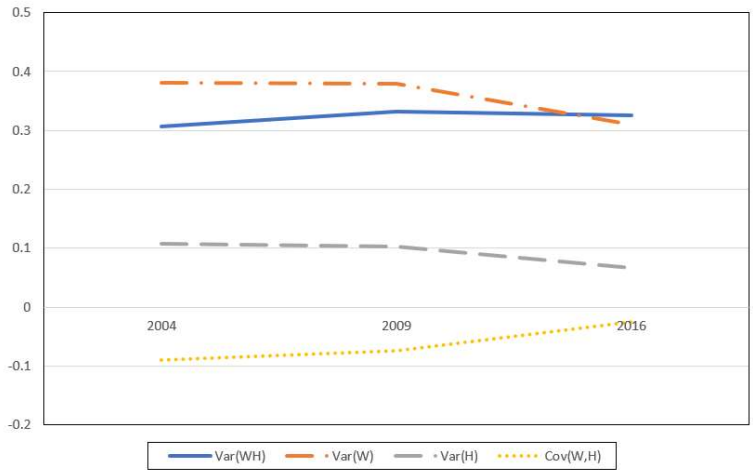
(p: the rate of nonstadard jobs, 1 = nonstadard jobs, 0 = standard jobs)

2. Trend

Figure2. A1 shows the trend of the variance of log labor income and its three components for total sample in 2004, 2009 and 2016 and Figure2.A2 presents the within value by each job type (each component's variance and their covariance) and between

value between two job types (each component's gap between two job type and the covariance between each component's gap). In Figure2. A1, income inequality does not change a lot but shows a little increasing trend. There is a downward trend in hourly wage and working hours and, on the other hand, covariance is increasing. It can be seen that the downward trend of both variances of wages and working hours and the upward trend in their covariance have offset by each other, resulting in a slight increase in income inequality.

Figure2. A1. Labor Incom e Variance Decomposition

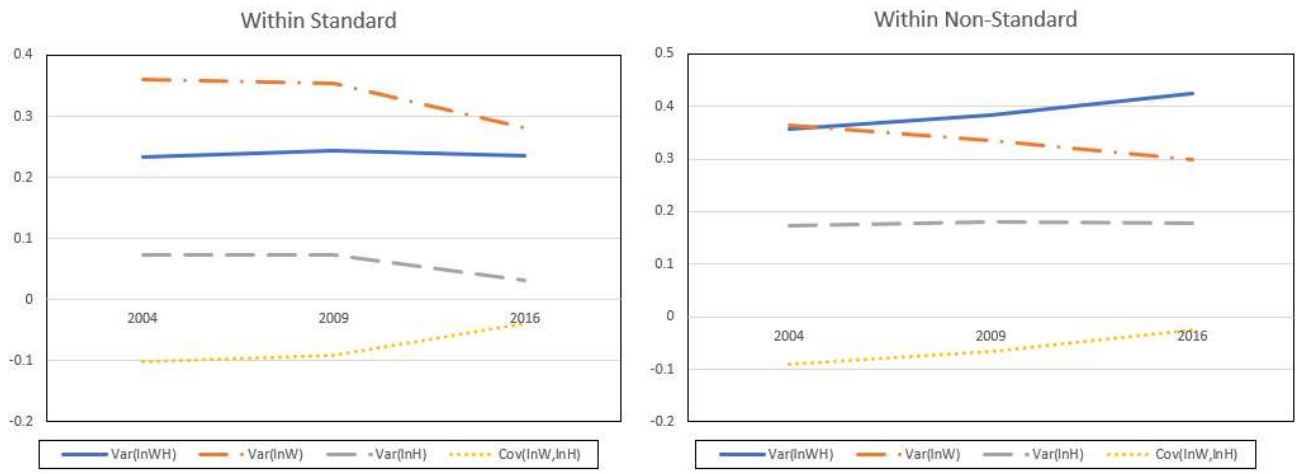


Note. Var(WH) is labor income variance, Var(W) is hourly wage variance, Var(H) is working hours variance, and Cov(W,H) is covariance between hourly wage and working hours.
Source: Authors' calculation, SSEAP 2004-2016

Upon looking at the within change in Figure2.A2, the income dispersion of regular workers is almost unchanged, and only the income dispersion of non-regular workers increases. The decreasing trend of the hourly wage variance and the increasing trend of the covariance can be seen in both standard and nonstandard jobs. However, while the variance of working hours also decreases in standard jobs, the variance of working hours have changed little in nonstandard jobs. This difference seems to have resulted in a difference between the two groups' tendency to increase variance.

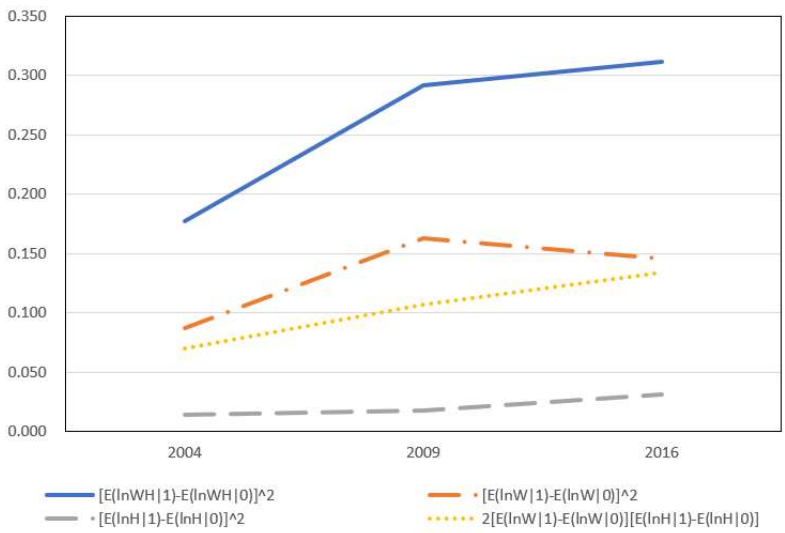
In the case of the between value in Figure2. A3, the hourly wage gap and the working hours gap simultaneously increased. To sum up, the increasing trend of covariance within each job type and the simultaneous increase of between gaps of wage and working hours lead to the rising trend in total labor income inequality.

Figure2. A2. Labor Income Variance Decomposition within Job Types



Note. Var(WH) is labor income variance, Var(W) is hourly wage variance, Var(H) is working hours variance, and Cov(W,H) is covariance between hourly wage and working hours.

Figure2. A3. Between Value of Labor Income Variance Decomposition



3. The estimate

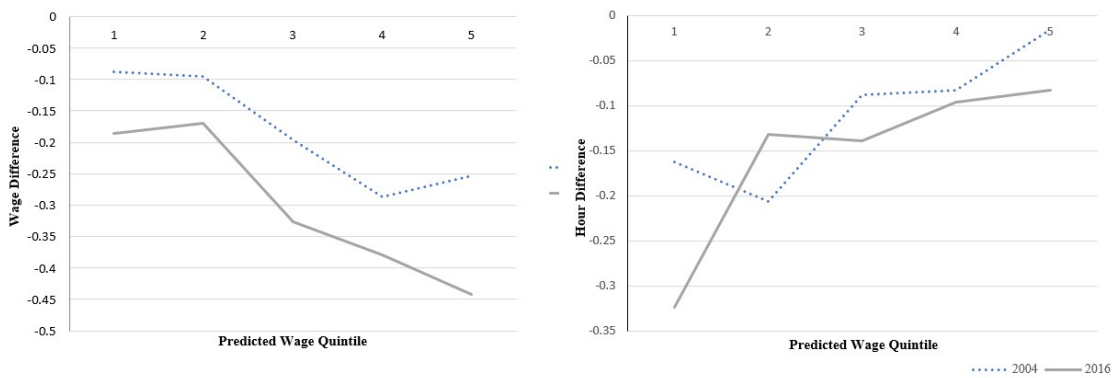
As was applied to labor income, Card(2001)'s decomposition method can be applied to each element of the labor income variance.

Table2. A1.Non-standard Gaps of Wage and Working Hours across Skill Groups

	2004		2016	
	Raw Non-standard Gaps:		Raw Non-standard Gaps:	
Quintile	Wage/Hour	Variance	Wage/Hour	Variance
Wage				
1	-0.09	0.10	-0.19	0.11
2	-0.10	0.08	-0.17	0.07
3	-0.20	0.04	-0.33	0.01
4	-0.29	0.08	-0.38	0.09
5	-0.25	0.09	-0.44	0.17
Working Hours				
1	-0.16	0.13	-0.32	0.23
2	-0.21	0.13	-0.13	0.10
3	-0.09	0.06	-0.14	0.07
4	-0.08	0.11	-0.10	0.11
5	-0.02	0.04	-0.08	0.09

**Note:* Skill quintiles are based on the predicted wage in the standard jobs. The quintile share of non-standard represents the percentage of all non-standard workers in the skill quintile. The wage/hour gap is the difference in mean log wages/hours between non-standard and standard workers in the skill quintile. The variance gap is the difference in the variance of log wages/hour between non-standard and standard workers in the skill quintile. See Table2. 1 for the sample definition.

Figure2. A4. Non-standard Gaps of Wage and Working Hours across Skill Groups



The mean difference between nonstandard and standard jobs in wage and working hour and their variance gaps are shown by skill level in Table2. A1.[40] The wage difference enlarges as the skill level increase. From 2004 to 2016, the hourly wage difference widened across the skill group. In particular, this phenomenon is pronounced in the upper skill groups. In the second panel in Table2. 5, the higher the level of skill, the smaller the working hour difference. Also, in the case of working hours, for the analysis periods, the gap widened, and this was noticeable, especially in the lowest group.

The variance difference of hourly wage shows a U-shape pattern like the labor income case. From 2004 to 2016, as the gap in the middle-skill group decreased and the gap in the 5th skill groups increased, the U-shape is getting closer to V-shape. The variance gap of working hours shows a negative relation to skill level. Recently, in the 1st and the 5th skill group, the gap is widened. In particular, the increase in the dispersion of the 5th skill group in the two factors means that non-regular workers who disappeared from group 5 during this period had relatively high wages and long working hours. As they disappeared, the average wage and working hours of the remaining non-regular workers' groups were lowered, and the variance gap between regular and non-regular workers seems to have increased in the 5th skill group.

All the changes related to the job type stood out in the 5th skills and 1st skill groups. From this, we can infer there would be a structural change in the wage and working hours in each job type as well as the change in rate of non-standard jobs. A relatively large reduction in the non-standard ratio of highly skilled groups moves the income distribution of non-regular workers to the left and taper the right tail of the distribution. In addition, the wage gap and the time gap between the upper groups widened at the same time, deepening the left-leaning average for non-regular workers.

[40] The skill group is same as the group used in the analysis of labor income.

Table2. A2. Income Decomposition and Effect of Non-standard Jobs

		Var(ln•)				
		Total	Effect	Effect/Total	Within	Between
2004	Var(lnWH)	0.294	0.070	0.24	0.007	0.063
2004	Var(lnW)	0.367	0.026	0.07	-0.006	0.031
2004	Var(lnH)	0.103	0.033	0.32	-0.001	0.034
2004	2Cov(lnW,lnH)	-0.176	0.011	-0.06	0.014	-0.003
2009	Var(lnWH)	0.336	0.092	0.27	0.011	0.080
2009	Var(lnW)	0.380	0.033	0.09	-0.003	0.036
2009	Var(lnH)	0.101	0.030	0.30	-0.001	0.031
2009	2Cov(lnW,lnH)	-0.145	0.029	-0.20	0.015	0.014
2016	Var(lnWH)	0.318	0.090	0.28	0.014	0.076
2016	Var(lnW)	0.298	0.030	0.10	-0.001	0.031
2016	Var(lnH)	0.067	0.034	0.51	0.000	0.034
2016	2Cov(lnW,lnH)	-0.047	0.026	-0.553	0.015	0.012

Table2. A2-1. Effect Decomposition for 2004-2016

	Total change	Effect	Within	Between
△Var(lnWH)	0.024	0.020	0.007	0.014
△Var(lnW)	-0.069	0.004	0.005	-0.001
△Var(lnH)	-0.036	0.001	0.002	-0.001
△Cov(lnW,lnH)	0.129	0.015	0.001	0.015

It can be interpreted that, among the top skilled group, workers with high incomes disappeared from non-regular jobs for analysis periods. At the same time, the significant reduction of working time in the lowest skill group occupying the largest portion of non-standard jobs could further lower the average income of non-regular workers.

Table2. A2 reports the estimated results of non-standard jobs' effects in each component: hourly wage, working hours, and their covariance in 2004, 2009 and 2016 and Table2.2-1 shows how the effect of non-standard jobs on inequality change from

2004 to 2016. In Table2. A2, the first column represents the variance of each factor and the second column shows the non-standard employment's effects on each element's variance. The value in the third column, $Effect/Total$, is how much non-regular jobs account for each variance. In columns 4 and 5, within-effects and between-effects are calculated, respectively.

In the first column of Table2.A2-1, despite a decrease in the spread of wages and working hours. It is confirmed again that the change in income inequality was increased by an increase in covariance. The second column of Table2.2-1 shows that about 60% of the contribution of non-regular jobs to rising labor income inequality is explained by that's effects on covariance. While the influence of decrease of the proportion of the nonstandard job cancels out the impact of the increase in mean and variance difference at each element, the simultaneous increase in wage and working hours gap, which might be mainly influenced by the lower skill group with high nonstandard rate and large gap, cause the nonstandard job to largely influence the rising labor income inequality.

4. Interpretation

In summary, although the rate of nonstandard has decreased, the labor income inequality rather has increased and the nonstandard jobs cause the part of the increase. That's because, in the process of decline in the proportion of nonstandard jobs, the within inequality in nonstandard jobs increased and the gap between standard and nonstandard jobs increased. To put it another way, for the analysis period, the nonstandard jobs were driven to relatively less-worked and less paid positions, which can be inferred by the simultaneous wage and working hours gap, as seen in A3. Consequently, the pattern of the change increased covariance between hourly wage and working hours, rising inequality.

The covariance between hourly wage and working hours has shown a negative sign and historically eased the overall labor income inequality; high-wage earners work less and low-wage earners work more. However, recently the covariance value is approaching zero. It can be interpreted in two ways on the increase in covariance between wages and working hours. First, the elasticity of labor supply to wages can increase from 2004 to 2016; workers increase working hours more than in the past as the wage increases. Second, some pressure or environment may have changed the way firms offer jobs in the form with “low wages-low working hours” and with “high wages-high working hours”.

Figure2. A5. The ratio of 'hour-wage' type to total employment in 2004, 2009 and 2016

Note. 4 refers 2004, 12 refers 2009 and 26 refers 2016. We divide the samples into four types ‘hour-wage’ group based on the mean of working hours and the mean of hourly wage. If a worker’s working hour and hourly wage are less than the mean of each, the worker is included in type1, less-working and less-paid, LL type. If a worker’s working hour is less than the mean and hourly wage is larger than the mean, the worker is in type 2, less-working and higher-paid, LH type. Type 3, HL type, is more-working and less paid workers and type 4, HH type, is more-working and higher-paid workers.

A2. Non-standard Jobs and Labor Income Inequality in Manufacturing and Service Industries

The increase in inequality contribution by non-regular workers, despite the decrease in the ratio of non-regular workers, does not mean that the decrease of the non-standard jobs' ratio does not have equalizing effects. Rather, if the ratio of irregular workers had not decreased, it means that overall inequality has increased more.

In this section, we analyze the effect of non-regular jobs on income inequality by industry, focusing on the manufacturing industry and service one. The manufacturing industry featured the relatively low rate of non-standard jobs and experienced the biggest drop in the rate of non-regular workers, while the service industry has a larger percentage of non-regular workers compared to other industries and a smaller decrease in the ratio of non-regular workers.

Looking at the pattern of reduction of the proportion of non-regular jobs in the two industries by education, age, occupations and firm sizes, we can see that the pattern of decline is similar, but the size of the decrease is different.

Table2. A3 shows the non-standard rate, the variance and the estimated results of the effect of non-standard jobs on labor income inequality in the manufacturing industry during the sample periods. In Table2. A3-1, the detail of the estimated results is described.

Table2. A3. Estimates of the Contribution of Non-standard Jobs to Income Inequality in the Manufacturing Industry, 2004-2016

	2004	2016	Change(16-04)
Male Workers			
Non-standard Rate	0.194	0.092	-0.102
Variance in Log Income	0.205	0.212	0.007
Effect of Non-standard Job Using Raw Wage Differentials (Equation 5)	0.023	0.009	-0.013

Table2. A3-1. Details on Estimates of the Contribution of Non-standard Jobs to Income Inequality in the Manufacturing Industry, 2004-2016

Male	Var[n(c)△w(c)]	2Cov[Ws(c), n(c)△w(c)]	E[r(c)△v(c)]	E[n(c)*(1-n(c)) *(△w(c))^2]	Total	Within	Between
2004	0.000	0.003	0.016	0.003	0.023	0.003	0.019
2016	0.000	0.001	0.005	0.003	0.009	0.001	0.008

Table2. A4 shows the non-standard rate, the variance and the estimated results of the effect of non-standard jobs on labor income inequality in the service industry during the sample periods. In Table2. A4-1, the detail of the estimated results is described

In the manufacturing sector, where the ratio of non-regular workers decreased significantly, the impact of the ratio of non-regular workers on income inequality decreased, while the service sector, which had a small decrease in the proportion of non-regular workers, saw its contribution to income inequality increase. In the manufacturing industry, it seems that the equalizing effect of reduction in the proportion of non-regular workers is large enough to offset the effect of other unequalizing factors.

Table2. A4. Estimates of the Contribution of Non-standard Jobs to Income Inequality in the Service Industry, 20042016\

Description	2004	2016	Change(16-04)
Male Workers			
Non-standard Rate	0.290	0.238	-0.053
Variance in Log Income	0.340	0.348	0.008
Effect of Non-standard Job Using Raw Wage Differentials (Equation 5)	0.090	0.106	0.016

Table2. A4-1. Details on Estimates of the Contribution of Non-standard Jobs to Income Inequality in the Service Industry, 2004-2016

Male	Var[n(c)△w(c)]	2Cov[Ws(c), n(c)△w(c)]	E[r(c)△v(c)]	E[n(c)*(1-n(c)) *(△w(c))^2]	Total	Within	Between
2004	0.001	0.012	0.055	0.022	0.090	0.013	0.077
2016	0.003	0.017	0.045	0.041	0.106	0.020	0.086

Chapter3. Technology, Routinization and Wage Inequality in South Korea[41][42]

I. Introduction

With entering a fast food store, kiosks, not store employees, are welcoming us, and, at a manufacturing factory, robots are working hard. As technology, represented by ICT, has been developed, it has changed the appearance of the labor market a lot. In studying the relationship between technology and the labor market, the traditional literature represented by the Skill Biased Technology Change -henceforth, SBTC- explains that technology development increases the demand for highly skilled workers and decreases the demand for low skilled workers (Katz & Murphy, 1992; Goldin & Katz, 2008). However, recently, as technology has matured more, it has influenced the labor market in different ways depending on the task types. According to the Routine Biased Technology hypothesis,-hence force, RBTC (Autor, Levy, & Murnane, 2003; Goos & Manning, 2007; Acemoglu & Autor, 2011; Autor & Handel, 2013, Lago & Biagi, 2018), the impact of technological change depends on the task types, not the skill; they move the unit of analysis from the skill base to the task base. The task is divided into abstract (analytical and interpersonal task), routine(repetitive and structured tasks), and non-routine manual task. While ICT development increases the productivity of abstract tasks and complements the abstract task, it rather substitutes the routine tasks. On non-routine manual tasks, technology has little effects.

The task-based literature (Autor, Levy, & Murnane, 2003) suggests that Routine Biased Technology Change explains job polarization, which has been observed across

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[41] JEL classification: J23 J31 O33
Keywords: Technological change, Routinization, Employment, Wages
[42] *Part of this paper is based on the results of a joint research with Jung-Min, Lee, PhD candidate at Seoul National University.

Western countries (Goos & Manning, 2007; Reenen, 2011; Michaels et al., 2014; Fonseca, Lima, & Pereira, 2018; Sebastian, 2018). The job polarization is the pattern of the employment share change that the share of middle-skilled occupations declined compared to the share of highly skilled and less-skilled occupations. Besides, Autor, Katz, and Kearney (2006) say the RBTC also explains the wage polarization pattern that the wage growth rate in the middle-wage percentile group is lower than in low and high wage percentile groups.

This study focuses on the South Korea case. South Korea experienced drastic economic growth after the 1970s, and technical progress was fast during the 80s-2000 and especially ICT investment sharply increased by the late 1980s. With technology development, many studies analyze the effect of technology on labor markets and most of the studies are based on the SBTC hypothesis. These studies suggest that ICT technology improvement increases the demand for high-skilled workers relative to low-skilled workers (Koh, 2019) and widen the wage gap between high-low skilled workers (Seo et al., 2004; Choi & Jeong, 2005). However, not only have few studies analyzed the effects of technology on labor market outcomes from the routinization perspective but also the existing studies on routinization do not address the impact of routinization on wage inequality. Kim (2014) suggested that South Korea had experienced RBTC for 2000-2008 using the Korea Dictionary Of Task (KDOT). But they measured only the routine task score excluding abstract and non-routine manual task and have a limitation on measuring the service sector. Their measure could not be consistently compared to other countries' task measures. Our study uses the KNOW data, which is the same content as the O*NET in the U.S. Using the KNOW data, we construct all task measures (abstract; analytic and interpersonal, routine; cognitive and manual, non-routine manual), identify the change of the RBTC pattern and check whether job polarization induced by RBTC occurs. Finally, we analyze the effect of RBTC on wage inequality in South Korea.

This study shows that, in South Korea, RBTC has influenced since the 1990s. The abstract tasks have increased, the routine tasks have decreased, and non-routine manual tasks have also decreased at a slower rate than the routine tasks. This pattern of task change is consistent with the U.S. and other Western countries. In addition, we confirm that the task scores are one of the significant factors to influence the wage. The task score trend seems to contribute to the wage inequality pattern since the 1990s. Notably, the pattern of wage inequality in the 90s is well explained by the task score.

It is worthy to note that because the non-manual task is located in medium education and wage level, which is distinct from other Western countries, the routinization pattern appears to coexist with SBTC in South Korea. However, given that the returns of routine tasks and non-routine tasks show substantially different ones, the routine task and non-routine task have their own characteristic and should not be considered as one. Thus, the task-based analysis has unique contribution distinct from skill-based analysis.

This paper is organized as follows. Section 2 introduces the RBTC literature in U.S. and EU and then South Korea. In Section 3, data for analyzing tasks and labor market outcomes are described and South Korea's employment share and wage inequality patterns for the 90s-2010s are shown. Section4 describes the task measures in detail and Section 5 shows the routinization patterns in South Korea. In section 6, the effect of task score on wage inequality pattern is analyzed. Section 7 summarizes the main conclusion of the paper and discussion for future research.

II. Literature Review

A. RBTC

In the U.S. and other Western countries, the wage gap between high-skilled and low-skilled workers had risen and the employment share of high-skilled workers had

increased relative to low-skilled workers since the 1980s. This change in the distribution of wage and employment induced a large literature to analyze the relationship between technical change and labor demand. The Skill Biased Technology Change is the standard explanation in labor economics to account for these wage and employment patterns. The basic idea behind SBTC is that new technologies that foster productivity are "skill-biased", meaning that high-skilled workers are more able to use new technologies than low-skilled workers (Tinbergen,1974, 1975), who, in fact, are at risk of being substituted by them. This non-neutral technological change increases the relative productivity of high-skilled workers to low-skilled workers and therefore increases relative labor demand for high-skilled workers.

However, SBTC cannot account for the wage and employment patterns observed in the U.S. after 1990. After 1990, the U.S. has undergone a U-shape change in jobs with decreasing proportion of middle wage(skill) jobs compared to high and low wage(skill) jobs, called “job polarization”(Goos & Manning, 2007) and in addition wage polarization also occurred which means the upper-tail wage inequality has continued to rise, while lower-tail inequality has stayed relatively flat from around 1990. To explain the wage and employment patterns after 1990, the Routine Biased Technology Change hypothesis was suggested by Autor, Levy, & Murnane (2003).

One of the key differences of the RBTC from the SBTC is the distinction between tasks and skill; contents of the job and endowment of workers. The RBTC classifies the task into the abstract, routine and non-routine manual. The definition of each task is as follows.

Abstract: Analytic and interpersonal works which are not only difficult to replace with machines but also even considered as a complementary role with technologies.

Routine: Repetitive and codifiable works. These tasks are programmable, expressible in rules and imply a methodological repetition of the procedure.

Non-routine manual: Activities that require situational adaptability, visual and language recognition, and in-person interactions.

Source: Acemoglu & Autor (2011)

The RBTC hypothesis predicts that ICT development and digitalization lead to a decline in jobs that are rich in the routine component and an increase in the number of jobs that are rich in the cognitive non-routine characteristics(abstract). The theory gives a rather ambiguous prediction about the employment of jobs with non-routine characteristics, because these jobs are not directly related to ICT technology change.

Autor, Levy, & Murnane (2003), Acemoglu & Autor (2011), and Goos & Manning (2007) show the RBTC captures quite well the changes in the employment distribution in the U.S. and the U.K. Michaels et al. (2014) support that, given the monotone relation between skill level and the task level(in order of non-routine, routine and abstract), RBTC well explain the job polarization in Japan and nine EU countries as well as the U.S. However, the assessment of whether the RBTC can account for the wage distribution for the 90s is inconsistent across studies (Autor et al., 2006; Firpo et al., 2011; Mishel et al., 2013). Autor et al. (2006) suggest the wage polarization can be explained by the RBTC hypothesis. Mishel et al. (2013) show the opposite opinion. Because the wage pattern is the outcome of the interaction between labor supply and labor demand, the job polarization would not necessarily lead to wage polarization.

B. Korea

The studies on the effect of the technology on the Korean labor market were mainly focused on skill-based research that is in line with SBTC (Kwon et al., 2002; Seo et al., 2004; Ahn, 2007; Shin, 2007). They suggest, for the 90-2000s in South Korea, the technology development contributed to the increased demand for high-skilled workers and the increased wage inequality between high-skilled workers and low-skilled workers.

As the overall technology-related studies move from SBTC to RBTC, job polarization pattern was examined in several ways by defining “job" as a combination of occupation and industry like Acemoglu (1999) or as a cluster composed of small unit of occupations with similar task characteristics (Cheon, 2007; Kim, 2015; Cheon, 2017). Kim (2014) directly measures routine tasks using the Korean Dictionary of Occupation(KDOT) based on a task-based approach and shows the routinization pattern have shown in South Korea. However, because KDOT provides limited information to categorize the characteristic of each occupation based on the traditional task approach: abstract, routine, and non-routine manual (Autor, Levy, & Murnane, 2003; Acemoglu & Autor, 2011). Thus, Kim (2014) measures the only routine degree of each occupation.

To complement the measuring issue, this study uses KNOW data which is constructed based on the U.S. O*NET structure and useful to measure abstract, routine, and non-routine tasks. To our knowledge, KNOW data is firstly used in the task-based analysis in this study. Using KNOW data, we examine the routinization hypothesis that can explain South Korea’s employment. Furthermore, we anlayse the effects of the routinization on wage distribution for 1993-2018, which has not been addressed before.

III. DATA for Employment and Wage

A. Structure of Earning Survey

This paper's primary data source is the Wage Structure Survey (WSS) created by the Korea Ministry of Employment and Labor in the 1980s. Employers answer a yearly survey with information on employee and firm characteristics. The dataset excludes self-employed workers. WSS only survey firms with at least ten employees before 1999, firms with at least five employees from 1999 to 2008, and all firms with at least one employee since 2009. Because this exclusion of small firms of this dataset can undermine the representation of the population, we additionally use Occupation Employment Statistics (OES) in Korea Employment Information Service for 2000-2008 which includes firms of all sizes. Local Area Labour Force Survey (LAFS), which is surveyed by Statistics Korea[43] for 2009-2018, is also used to ensure the robustness of the WSS's employment and wage outcomes.

We restrict our sample to paid workers aged between 16 and 65. Wages are deflated to the year 2015 using the Consumer Price Index. The monthly wage is the sum of base wage and regular bonuses, and hourly wage is calculated by dividing the monthly wage to weekly working hours multiplied by 4.35. We cover periods from 1993 to 2018. During this period, the Korean Standard Classification of Occupation had undergone two revisions in 1999 and 2008. Using occupation crosswalks for linking the occupation classification across all periods makes the classification of occupation coarse. Thereby, this study divides the analysis period based on KSCO revision year for 1993-1999, 2000-2008, and 2009-2018 and use occupational code at 2digit and 3digit[44], comprising 65, 88, and 95 occupations respectively.

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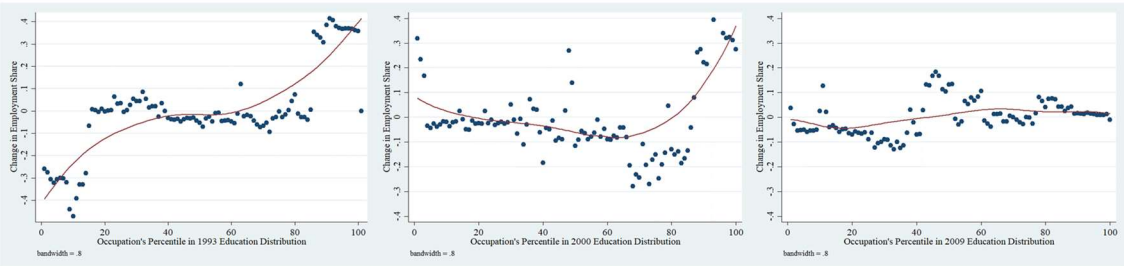
[43] OES was incorporated into Local Area Labour Force Survey after 2008.

[44] Wage Structure Survey provide KSCO code as 2 digit for manager, professional and related workers, service/sales workers, skilled agricultural, forestry and fishery workers and 3 digit for clerks, craft and related trades workers, equipment, machine operation and assembling workers,

B. Korea's Employment and Wage Change

In this paper, Figure3.1 shows 1993-1999, 2000-2008 and 2009-2018 changes in employment share at each occupational skill percentile in the same way as Autor, Katz, and Kearney (2006). These occupations are ranked on the x-axis by their skill level from lowest to highest, where an occupation's skill rank is approximated by the median education years of workers in the occupation in 1993.[45]

Figure3. 1. The Change of Employment in Korea



Note : Smoothed changes in employment in Korea(1993-1998, 2000-2008, 2009-2018). The figure plots a locally weighted non-parametric smoothing regression (bandwidth 0.8 with 100 observations). The jobs are defined at 2digit or 3digit KSCO level. Jobs are ranked by the WSS 1993 median education year for the period 1993-1998, WSS 2000 median education year for the period 2000-2008, and WSS 2009 median education year for the period 2009-2018. *Sources* : Wage Structure Survey (1993-2018)

Figure3.1 shows that South Korea's employment structure does not present the typical job polarization pattern shown in the U.S. and other EU countries. During the 1990s (1993-1999), employment growth was nearly monotone in occupational skill; the relative employment growth was negative at low percentiles (20th percentile and down), rapid at high percentiles (80th percentile and up) and modest at the middle percentiles, which seems to be in line with the SBTC hypothesis. In the subsequent period (1999-2008), the employment share for high-skilled occupations still highly increased, for low-skilled occupations below 50 percentiles had little change, and for the upper-middle group (50-80 percentile) decreased. This employment pattern is a little different from the job polarization found in other countries in that the decline occurs in the upper-middle

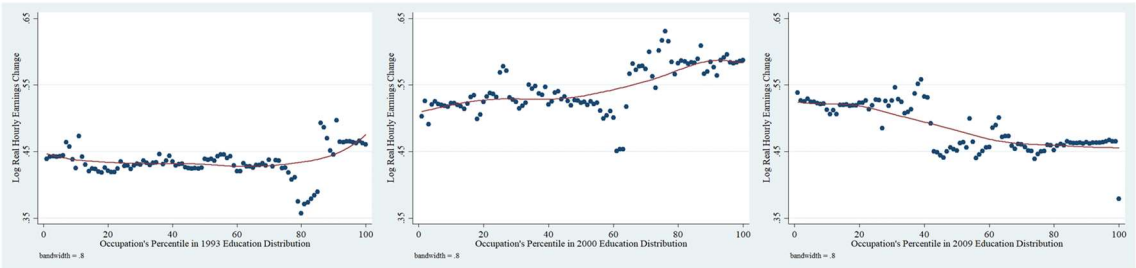
and elementary workers.

[45] For the proxy for occupation's skill, we also use mean log hourly wage instead of median education years. The results are not different from the results using education years.

group rather than the middle one. In the most recent period, since the financial crisis (2009-2018), there is no clear pattern according to skill level compared to the previous periods, but there is a slight decrease in the bottom percentile and an increase in the medium-skilled groups.

Overall, before the financial crisis, there was a steady increase in employment of upper skilled groups, the lower groups had declined and the change slowed, and the middle-skilled groups lacked clarity in the employment share pattern. After the financial crisis, overall changes have weakened. There is no clear trend of job polarization at all periods when occupations are classified by skill level.

Figure3. 2.The Change of Wage in Korea



Note : Smoothed changes in wage in Korea(1993-1998, 2000-2008, 2009-2018). The figure plots a locally weighted non-parametric smoothing regression (bandwidth 0.8 with 100 observations). The jobs are defined at 2digit or 3digit KSCO level. Jobs are ranked by the WSS 1993 median education year for the period 1993-1998, WSS 2000 median education year for the period 2000-2008, and WSS 2009 median education year for the period 2009-2018. *Sources* : Wage Structure Survey (1993-2018)

Figure3.2 shows the log real hourly wage distribution change for three periods. Before the financial crisis, wage growth was monotone in occupational skill; thus, wage inequality had enlarged steadily. This wage pattern for these periods can be interpreted that the increase in demand for high-skilled workers and the decrease in demand for low-skilled workers shown in Figure3. 1 affect the wage structure. After the financial crisis, the wage growth pattern reversed; the bottom-skill occupations experienced higher wage growth relative to other groups. According to the distribution based on the skill level, there has been no wage polarization like there has been no job polarization in the share of employment.

IV. Measuring the Task Content of Jobs

A. Task Score

From the employment and wage pattern for analysis periods, job polarization has not been found in South Korea, which could imply the routinization (or the RBTC) has not occurred in South Korea. However, to precisely investigate whether the routinization influences the South Korea labor market, we analyze the employment pattern from a task-based approach. We construct the task score (abstract, routine, and non-routine manual) to measure the degree of each task intensity of each occupation and present the task scores' trend for the analysis period.

We use the Korea Network for Occupations & Workers (KNOW)[46] data to measure the task score of each occupation. Because the KNOW data was constructed following the O*NET in the U.S., using KNOW data helps make a comparable task measure with other studies (Acemoglu & Autor, 2011; Autor & Dorn, 2013). Following Acemoglu & Autor (2011)'s task measure, we select the KNOW descriptor that has importance and context scale 1 and 5.[47] The abstract task is composed of non-routine analytic and non-routine interpersonal. The routine task is made up of routine cognitive and routine manual. Each task score is normalized with zero mean and one standard deviation based on the initial year of each three periods.

[46] KNOW, which benchmark O*NET in the U.S., has investigated key knowledge, work styles, job performance abilities, work values, work context, interests and job prospects, qualifications and training that are actually required at our industrial sites since 2001 by the Employment Information Service. Every year, KNOW survey workers who work in the job subject to the survey. We use 2014-2017 KNOW survey to measure the task score. The detail of KNOW can be found in Employment Information Service (2017)

[47] Table A.1 shows a detailed list of the contents by task type. Based on Acemoglu & Autor (2011)'s task measure, we additionally use four more indices to complement non-routine manual task measure. The detailed description is summarized in Appendix 1.

Table3. 1. Examples of KNOW Task Score

Occupation	Abstract		Routine		Non-routine	Median Edu Years	Mean Log Hourly Wage
	Analytic	Interpersonal	Cognitive	Manual	Manual		
Expert in Physics,	1.84	1.41	-0.70	-0.66	-0.57	16	1.77
Corporate Manager	1.54	2.44	-0.89	-0.90	-0.80	16	2.18
Counting Clerk	0.81	0.73	1.98	-1.05	-1.44	12	1.59
Mechanical Operators	-0.29	-0.40	1.39	1.79	0.60	12	1.27
Motor Vehicle Operator	-1.16	-1.03	-0.69	1.26	1.95	12	1.36

**Note*: Task measure is calculated as the same way in Autor et al.(2011) using KNOW measures. The scores are standardized to mean 0 and standard deviation 1. Expert in Physics, Mathematics and Engineering, Mechanical Operators for Printing, Binding and Paper Products

Table3.1 enumerates the representative occupation of each task score and their task scores in the order of analytic, interpersonal, routine cognitive, routine manual and non-routine manual. Each occupation has the five task scores. An expert in physics, mathematics, and engineering and a corporate manager shows a high score in the abstract task and low score in both the routine and non-routine manual. A counting clerk shows high marks in the routine cognitive task which can be more likely to be substituted with a computer. Although both a machine operator and a motor vehicle operator show a relatively high score in the routine task, a motor vehicle operator tends to be more non-routine manual task intensive. The results support that the five task scores assigned to each occupation are quite consistent with general intuition.

Table3. 2. Correlation between KNOW and O*NET

		O*NET				
		Analytic	Interpersonal	Routine Cognitive	Routine Manual	Non-routine Manual
KNOW	Analytic	0.6143*	0.4211*	-0.0289	-0.6023*	-0.5043*
	Interpersonal	0.6170*	0.5060*	-0.1563	-0.6179*	-0.4722*
	Routine Cognitive	-0.2297*	-0.2334*	0.4111*	0.4667*	0.3518*
	Routine Manual	-0.3557*	-0.1837	0.1617	0.7552*	0.6960*
	Non-routine Manual	-0.1497	0.0245	-0.0356	0.5530*	0.7621*

		KNOW				
		Analytic	Interpersonal	Routine Cognitive	Routine Manual	Non-routine Manual
KNOW	Analytic	1				
	Interpersonal	0.8576*	1			
	Routine Cognitive	-0.3084*	-0.3246*	1		
	Routine Manual	-0.5157*	-0.4786*	0.5255*	1	
	Non-routine Manual	-0.3781*	-0.3084*	0.3372*	0.7804*	1

		O*NET				
		Analytic	Interpersonal	Routine Cognitive	Routine Manual	Non-routine Manual
O*NET	Analytic	1				
	Interpersonal	0.6595*	1			
	Routine Cognitive	-0.1995	-0.3427*	1		
	Routine Manual	-0.4917*	-0.4419*	0.3384*	1	
	Non-routine Manual	-0.3121*	-0.3028*	0.0673	0.6805*	1

**Note*: Correlation is computed following the WSS occupation classification. *Sources*: Author's analysis from KNOW and O*Net data.

To confirm the robustness of the task score, we check the relation between our task score made with KNOW and the task score made with O*NET in Acemoglu & Autor (2011). The first panel in Table3.2 presents the correlation of task measures between KNOW and O*Net.[48] Considering that both use the same questions to make the task measures[49], the level of correlation shows the similarity of each task level in the same job between South Korea and the U.S. As seen in the diagonal of the Table3.2, each task score of the two surveys is positively correlated. The second and third panel in Table3. 2 shows the correlation between inter-task variables in South Korea and the U.S. The correlation between inter-task variables also have the same sign and similar magnitude between KNOW and O*NET. The results indicate that both surveys are close enough, meaning that the KNOW is a suitable measure for tasks.[50]

B. The Relation between Skill Level and Task Score

Task-based analysis has a difference from the existing skill-based analysis (SBTC) in that it distinguishes skill from the task. The skill is a worker's endowed ability to perform a job, and a task is a job's contents workers have to perform. Through a specific allocation mechanism, a worker with certain skills is allocated to a job with specific tasks. In general, confirmed in other literature, abstract jobs are filled with high-skilled workers, the routine task with middle-skilled workers, and non-routine manual jobs with low-skilled workers (Michaels et al., 2014)

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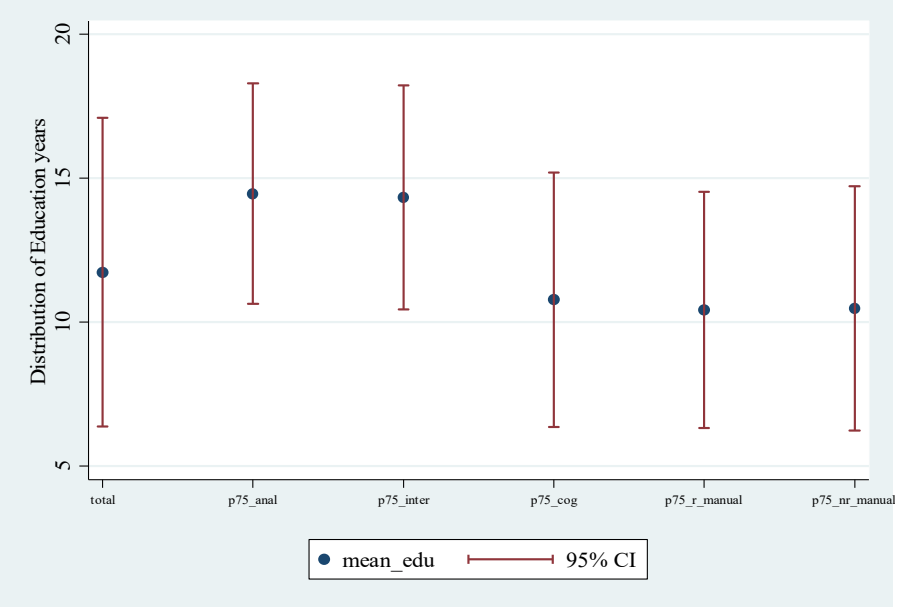
[48] The task scores made with O*NET measure each task intensity of occupations based on US census 1980. US Census 1980 codes are matched to the International Standard Classification of Occupations. Linking the same occ using ISOC, we calculated the task scores' correlation in same occ.

[49] For non-routine manual task, we used four additional questions that seemed appropriated for the characteristics of the task. By using four additional question for non-routine manual, the correlation between KWOW and O*NET in non-routine manual variable rather increase.

[50] We also construct task measure using Korean Dictionary of Occupation; we adopt similar method as Kim (2014) and but complement Kim (2014)'s method. The task measure between DOT and KNOW are highly correlated. In this paper, our main task measure is KNOW. The data and detail are available upon request.

Figure3. 3. Education Year Distribution by Task



Note : The worker's education year distribution of the top 25% occupation in each task score. In the figure, the blue point represents the average education year of each distribution in the top 25% occupation, and the red line means the 95% level confidence interval.

To clarify the relationship between skill and task in South Korea, we select the top 25% occupations in each task score and draw the education years distribution of the individuals in the top 25% occupations of each task in Figure3. 3.[51] In South Korea, while the abstract task-intensive group has a distinctly high level of the education than other task-intensive groups, there is no apparent difference in the distribution of education levels between workers with the routine task-intensive job and workers with non-routine manual task- intensive job.

[51] To use more detailed occupations classification, we use OES data (2007) which provides 4-digit occupation code for this analysis.

Table3. 3. Mean Standardized Scores by Skill Group, South Korea Data

		CLG	SMC	HSG	HSD
Abstract		0.78	0.09	-0.67	-1.09
	Analytic	0.85	0.05	-0.75	-1.20
	Interpersonal	0.71	0.12	-0.59	-0.97
Routine		-0.50	0.15	0.81	0.47
	Cognitive	-0.72	0.08	0.76	0.21
	Manual	-0.28	0.23	0.87	0.73
Non-routine Manual		-0.24	-0.13	0.55	0.41

**Note*: Mean standardized scores by skill group is computed using 2007 OES data in South Korea. The occupation classification is 4-digit. CLG is college graduate, SMC is some college graduate, HSG is high school graduate and HSD is high school drop out. After selecting the top 10 occupations with high fraction of each skill group and we calculate the occupations' mean task score from the individual task score. Then, mean standard scores in a skill group is obtained by averaging the task score of top 10 occupations in a skill group.

In Table3. 3, for a more accurate analysis, we select the top 10 occupations[52] with the highest fraction of each education level and average their task scores as in Michaels et al., (2014). Unlike the U.S. case[53], in South Korea, the non-routine manual task score is not highest in the lowest education group; the non-routine manual task score is the highest in high school graduates that are the middle-skill group, although the level of non-routine manual task score is similar between high school graduates and high school dropout.

Putting the results in Figure3.3 and Table3.3 together, in South Korea, non-routine manual jobs are composed of similar skill level workers with routine manual jobs[54]. Given the monotone relation between education level and wage, this pattern also

[52] In appendix 3, the specific list of occupations and their task score can be found.
[53] The table for U.S. case (Michaels et al., 2014) is in appendix 2.
[54] It may be the results of Korea's average high education level, but the same result is true of older people, who do not have a high average level of education. The results imply that the industrial structure or other factors causes the education level similarity between routine and

can be observed in the distribution of wages[55]. Under the indivisibility of the education level between the routine and non-routine task-intensive occupations, the change in tasks is hard to be recognized if the employment change is analyzed based on skill distribution. Considering the skill and task the same can lead some errors in analysis. For these reasons, the task-based analysis is essential for figuring out the RBTC pattern.

V. Routinization

A. Task-based Analysis

For examining the routinization trend, using the task score measured by KNOW, we plot the trend of task score based on the initial year of each three periods in Figure3 .4. The change of task score along the year reflects the change of employment share of the task-intensive occupations; each year's task score is calculated by averaging each occupations' task score weighted by the occupations share.[56] For example, if the share of the occupation with high abstract task score and low routine task score increases along the time, the abstract score increases and routine task score decreases relative to the first-year score.

During the first phase (1993-1999), the abstract task score had increased, the routine task score had declined, and the non-routine manual task score had decreased, but at a slower rate than the routine task score. In the second phase (2000-2008), initially, there was little change, and then each task score started to move back to the previous trend shown in phase 1. From 2000 to 2004, all tasks scores' movements became week. From 2004, the trend of the first period is followed again. For about five years after

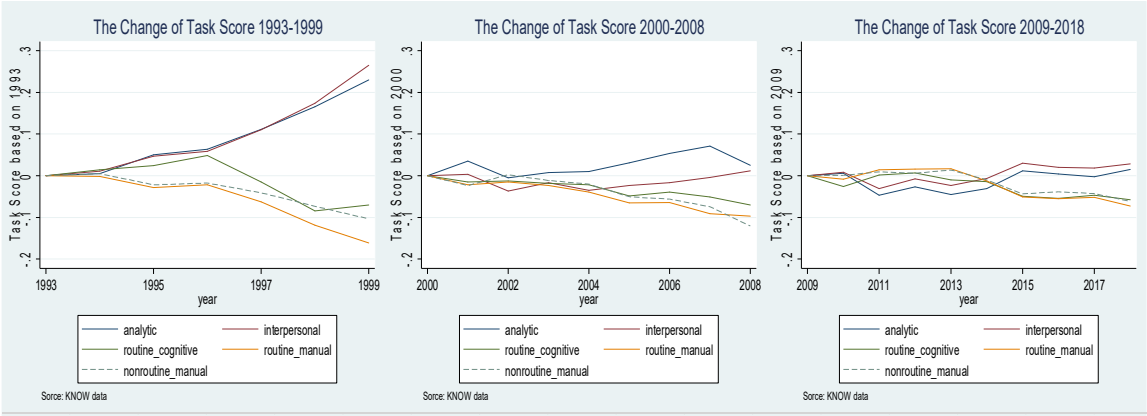
non-routine task jobs.

[55] We plot hourly wage distribution as in Figure2, we confirm that wage distribution is very similar with education distribution.

[56] The initial task score is fixed in each occupation. By changing the share of each occupation, the task score changes by year.

financial crisis in 2008, there was a tendency to reverse the main trend.[57] Then again, from 2013, the abstract score increase, the routine score decrease, and non-routine score moves with routine task score

Figure3. 4. The Trend of Task Score



Note : Trends of routine and non-routine tasks (1993-1999, 2000-2008, 2009-2018). Figures are constructed using KNOW task measures by occupation paired to employment data for 1993-2018 WSS data. Data are aggregated to 65, 88, and 95 occupations by year for each period, and each occupation is assigned a value corresponding to its task scores. Plotted values depict the empolyment-weighted mean of each assigned percentile in the indicated year. *Sources* : Wage Structure Survey (1993-2018), Korea Network for Occupations & Workers (2014-2017)

According to the RBTC hypothesis, the technology advance fosters the demand for the abstract tasks and substitute the routine tasks and has ambiguous effects on the non-routine manual tasks. The trend of abstract and routine task score in South Korea are generally consistent with the RBTC hypothesis except for a few years immediately after two crises. The non-routine manual score shows a similar pattern with the routine score even though the rate of change of the non-routine manual task score is not higher than that of the routine task score. Given that RBTC hypothesis does not give clear prediction on the trend of non-routine task, this trend of non-routine manual cannot be sees as contrary to RBTC. However, it is necessary to analyze the reason for the trend for non-routine manual. Specifically, considering that non-routine manual task score

[57] It seems to be due to the large number of unemployment in the finance-related abstract jobs shortly after the financial crisis.

shows the high correlation with routine task score in Table 3.2, the similar trend between routine and non-routine manual task can be expected. However, in case of the US, even though it has also a fairly high correlation between routine and non-routine manual, it does not show the same pattern as Korea. It is necessary to figure out the fundamental factors which makes this difference between South Korea and other countries.

From the skill dimension, because the routine tasks and non-routine manual tasks are located in middle-low skill distribution, the decrease in two task scores (in Figure3.4) is interpreted that the decrease in the share of low-middle skill group. Thus, the routinization pattern coexists with the STBC in south Korea. From the skill-based analysis, South Korea's employment share pattern can be seen as SBTC, but if analyzed in detail from a task-based perspective, the RBTC pattern also have occurred.

B. Technology and Task

To confirm whether ICT technology development induces the RBTC pattern shown in South Korea (Figure3. 4), we examine the effect of ICT technology on the task scores. The degree of ICT technology development is approximated by the ICT investment growth rate by industries. We use the value-added growth accounting data announced by KISDI (2018), which is available from 1991 and by 38 industries. We analyze the impact of the ICT investment growth rate in the early 90s on each task score for all and by education level.

$$(1)\ Task_{kt} = \alpha + \beta_1 * ICT\ investment\ rate_{1991_k} + \mathrm{d.year} + \Gamma Z + \epsilon_{jt}$$

Table3.4 shows that the higher the ICT investment rate, the higher the abstract task score is. In contrast, the increase in ICT investment rate decreases both the routine and the non-routine manual task scores: a higher decrease in the routine manual task than

the non-routine manual task. In case of the routine cognitive score, even though the sign of the coefficient is negative but insignificant. The results are in accordance with RBTC.

Table3. 4. Regression Task Scores on ICT Investment Growth Rate

		Analytic	Interpersonal	Routine Cognitive	Routine Manual	Non-routine Manual
		coef/t	coef/t	coef/t	coef/t	coef/t
ICT (t=1991)	Total	0.203***	0.122***	-0.063	-0.136***	-0.104***
		(4.500)	(2.820)	(-1.501)	(-3.672)	(-2.636)
	HSD	0.127***	0.069**	-0.087*	-0.099***	-0.053
		(4.056)	(2.488)	(-1.717)	(-3.228)	(-0.989)
	HSG	0.185***	0.112***	-0.058	-0.151***	-0.118***
		(5.471)	(3.432)	(-1.278)	(-4.045)	(-2.700)
	SMC	0.132***	0.062*	-0.047	-0.067**	-0.047
		(3.664)	(1.845)	(-1.392)	(-2.233)	(-1.532)
	CLG	0.090***	0.020	-0.019	-0.028	-0.025
		(3.471)	(0.696)	(-0.771)	(-1.599)	(-1.026)
	N	804	804	804	804	804

**Note*: t-statistics in parentheses. Coefficients are estimated by random effect model. We control each industry's growth rate of installation capital, construction capital and input of labor and year fixed effects. N is the number of observations. *** p<0.01, ** p<0.05, * p<0.1

In specific, looking at the results by education level, in case of the routine manual task, the negative effect of ICT investment on the routine task score is not seen in the college graduate group. For the college graduate group, ICT technology has influence only on the analytic task score and does not decrease both the routine and non-routine manual task scores. These results imply that one task can have different levels of complexity internally across skill levels. For example, routine task's complexity can increase as the skill level increases. Thereby, the routine task charged by high-skill group can be hard to be substituted by machines. Considering the influence of the technology is evident in the high school graduation group, the task charged b high school graduates

(HSD) seems to be located at a certain complexity level suitable for replacement or complement by technology.

In summary, as a result of the task-based analysis, in South Korea, Routine Biased Technology Change has influenced labor demand. However, the RBTC is not connected to job polarization because, in Korea, the relationship between skill and task is different from the general monotone relationship seen in the Western countries (Goos & Mannig, 2007; Michaels et al., 2014). As seen in Figure3. 3 and Table3. 3, routine manual jobs and non-routine manual jobs are not distinguished from each other in the skill distribution; both are mixed in the middle and bottom of the skill distribution. Rather, this relationship between skill and task lead to the coexistence of routinization and SBTC.

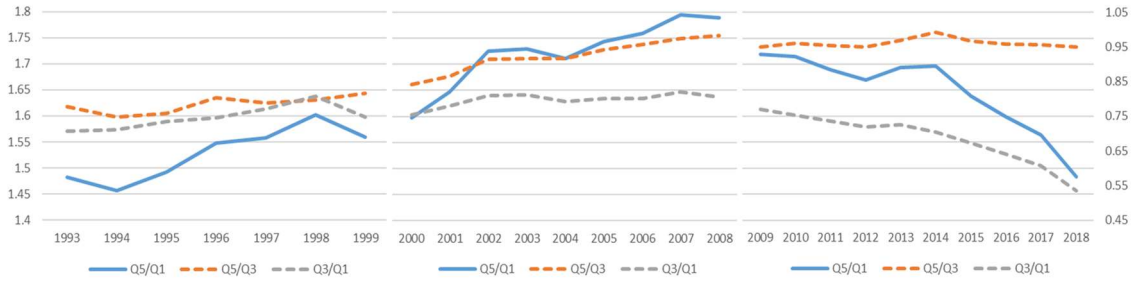
VI.Routinization and Wage Inequality

In this section, we examine whether the routinization presented in the employment share can explain the wage inequality pattern.

We divide the sample into quintiles based on a log real hourly wage by each year using WSS. Figure3.5 shows the log real hourly wage inequality pattern, Q5/Q1, Q5/Q3, and Q3/Q1 from 1993 to 2018 in South Korea.

Before the financial crisis, the overall wage inequality had increased regardless of the upper-tail and lower-tail. After the financial crisis, the upper-tail inequality has stayed at the same level as before. However, wage inequality of Q5/Q1 and Q3/Q1 has declined.

Figure3. 5. Quintile Wage Inequality Trend



Note : Wage inequality trend represents log real hourly wage gap between different quintiles (1993-1999, 2000-2008, 2009-2018). The sample is divided into quintiles based on a log real hourly wage by each year using WSS and the figures show the wage gap between Q5 and Q1, Q5 and Q3, and Q3 and Q1. For example, Q5/Q1 shows trend of relative hourly wage ratio of quintile 5 (top 20%) to quintile 1 (bottom 20%). Relative wage ratio of Q5/Q1 uses scale on the left y-axis and that of Q5/Q3 and Q3/Q1 uses scale on the right y-axis. *Sources* : Wage Structure Survey (1993-2018)

Under the assumption the impact of labor demand is dominant than that of labor supply, while the enlarged inequality during the pre-crisis period is consistent with the prediction based on the change in the task distribution of the period, the alleviation of the wage inequality during the post-crisis periods is hard to be explained by the task trend change- increasing abstract and decreasing routine/non-routine manual.

To elaborately analyze whether the task composition of each wage quintile can explain the wage inequality pattern, we do regression analysis and calculate the contribution of each task to wage inequality.

A. Wage Analysis

At first, we estimate the effect of the abstract, routine and non-routine manual task on log real hourly wage. We use not only each task score but also its interaction with year dummy variables for catching out the trend of the task's effect following Equation (2). The coefficients of each task measure can be seen as the return of each task on the base year and the coefficients of the interaction between tasks and year dummies reflect the time variation of the return. We control individual characteristics (sex, education years, labor market experience), and workers' job characteristics (firm size, industry, occupation). Besides, we control the interaction terms between most of the

control variables and year dummy variables, except for industry and occupation dummies, because there are possibilities the coefficients of the trend of the effects of task scores include other variables' trend.

The RBTC explains that ICT technology development enhances the demand for abstract task- intensive jobs and reduces the demand for routine task-intensive jobs by substituting the routine task with a machine. However, because the wage structure is the outcome of the interaction between labor demand and supply, only under the premise that demand had a more significant impact than supply, the wage structure can reflect RBTC. Under the demand-dominant situation, the increased demand for abstract tasks further enhances the wage premium of the abstract score, the declined demand for routine tasks enhances the routine tasks' adverse effects on the wages, and the effects of non-routine manual tasks on wages are ambiguous.

$$(2)\ lnw_{ijt} = \alpha + \beta_1 * Task_{i(j)} + \beta_{2t} * Task_{i(j)} * d.year + \zeta_1 * eduyears_i$$

$$+\zeta_{1t} * eduyears_i * d.year + \beta_{3t} d.year + \Gamma X + \eta_j + \epsilon_{it}$$

$$i: individual$$

$$j: individual\ i's\ occupation\ j$$

$$t: year$$

$$d.year: year\ dummy$$

$$lnw: log\ hourly\ wage$$

$$X: characteristic\ vetor(age, exp, sex, industry, firmsize).$$

In Table3.5, the three tasks all significantly influence the workers' wages. The abstract task has a positive effect on wages at every base year. In contrast, the routine

task negatively influences wages at every base year. In the case of the non-routine manual task, the sign of the impact on wages varies depending on periods.[58] It is noteworthy that the task variables have significant effects on wages even after controlling all other factors, especially education, industry, and occupation. In the next section, considering the time trend of the tasks' return, we calculate the tasks' contribution to the wage inequality trend.

[58] While the non-routine tasks had shown inverted U-shape along the wage distribution until the early 2000, it have shown downward sloping pattern recently, which is the unique case considering other tasks' composition have relatively remained. The change of the non-routine tasks' pattern imply the change of its intrinsic characteristics in labor market. We suggest that the large variation of the coefficient is related with the pattern change in wage distribution. However, we have not yet revealed the reason for the change.

Table3. 5. Regression Log Real Hourly Wage on Task Score

VARIABLES	Log Real Hourly Wage			VARIABLES	Log Real Hourly Wage			VARIABLES	Log Real Hourly Wage		
	Abstract	Routine	NR_manual		Abstract	Routine	NR_manual		Abstract	Routine	NR_manual
task	0.020***	-0.031***	0.058***	task	0.051***	-0.043***	0.079***	task	0.056***	-0.023***	-0.005***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1993b.year*.task	0.000	0.000	0.000	2000b.year*.task	0.000	0.000	0.000	2009b.year*.task	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
1994.year*.task	0.001	0.002*	-0.005***	2001.year*.task	0.014***	0.013***	-0.004***	2010.year*.task	0.003***	-0.011***	0.006***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1995.year*.task	0.009***	0.011***	-0.010***	2002.year*.task	-0.009***	0.022***	-0.036***	2011.year*.task	0.003***	-0.003***	0.004***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1996.year*.task	0.033***	0.029***	-0.022***	2003.year*.task	-0.004***	0.023***	-0.040***	2012.year*.task	-0.006***	-0.006***	0.003***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1997.year*.task	0.050***	0.033***	-0.022***	2004.year*.task	-0.012***	0.022***	-0.035***	2013.year*.task	0.002	0.006***	-0.007***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1998.year*.task	0.054***	0.041***	-0.021***	2005.year*.task	-0.024***	0.026***	-0.058***	2014.year*.task	0.015***	0.022***	-0.008***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
1999.year*.task	0.028***	-0.006***	0.003***	2006.year*.task	-0.003**	0.032***	-0.045***	2015.year*.task	0.001	0.028***	-0.006***
	(0.001)	(0.001)	(0.001)		-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
				2007.year*.task	-0.006***	0.041***	-0.074***	2016.year*.task	0.009***	0.031***	-0.007***
					-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
				2008.year*.task	0.015***	0.056***	-0.079***	2017.year*.task	-0.003***	0.022***	0.009***
					-0.001	-0.001	-0.001		(0.001)	(0.001)	(0.001)
								2018.year*.task	-0.009***	0.017***	0.006***
									(0.001)	(0.001)	(0.001)
Constant		0.125***		Constant		0.325***		Constant		0.761***	
		(0.006)				-0.006				(0.006)	
Observations		2,935,474		Observations		4,078,035		Observations		6,748,374	
R-squared		0.700		R-squared		0.674		R-squared		0.610	

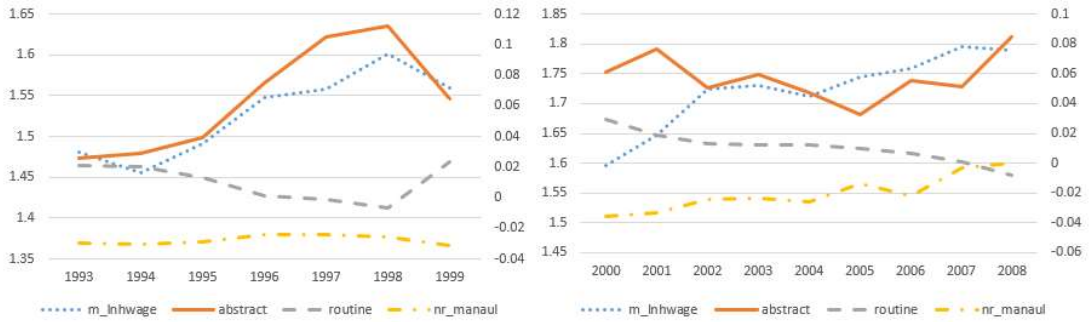
Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.0

B. Results

Before 2008, the overall wage inequality pattern, regardless of upper-tail and lower-tail, shows a similar pattern, so, for 1993-2008, we show the Q5/Q1 wage inequality only. Figure3.6 shows the contribution of each task scores on Q5/Q1 wage inequality for 1993-1999 and 2000-2008.

During the first phase (1993-1999), the abstract task substantially explains the wage inequality trend. The trend of abstract task contribution and wage inequality move almost together, and the abstract score accounts for about 10% of the predicted wage. In the second phase (2000-2008), although the first two years are not well explained, the abstract scores had explained well the increase of wage inequality since 2004. The non-routine manual task score also contributes the wage inequality with the enlarged gap of the non-routine manual task intensity between Q5 and Q1 and the enhanced negative effect of the non-routine manual task. But the size of the contribution decreases relative to the first phase.

Figure3. 6. Contribution of Task to Wage Inequality (1993-1999, 2000-2008)



Note: The figures plot the contribution of each task scores on Q5/Q1 wage inequality (1993-1999, 2000-2008). The contribution of a task to quintile k consits of the product of the coefficient of the task and the mean value of the task of the quintile k.Figures are constructed using KNOW task measures and wage data for 1993-2008 WSS data.
Sources: Wage Structure Survey (1993-2008), Korea Network for Occupations & Workers (2014-2017)

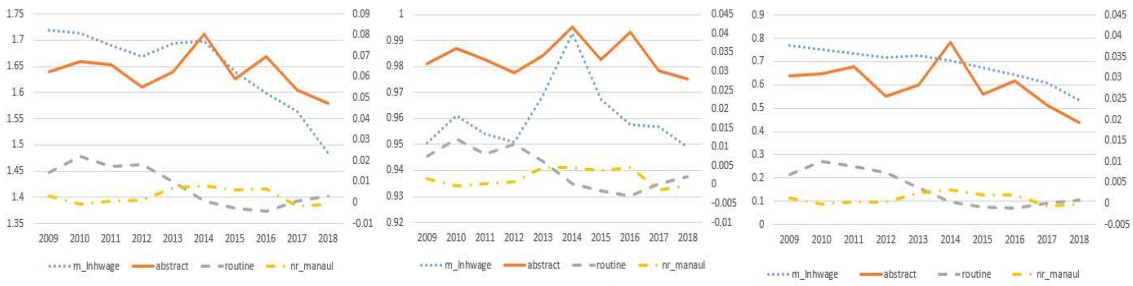
Figure3.7 shows the Q5/Q3 and Q5/Q1 wage inequality patterns and each task's contribution after the financial crisis (2009-2018). While the Q5/Q3 wage inequality has stayed at a similar level with the previous phase, the wage inequality of Q5/Q1 and

Q3/Q1 decrease. The contribution of the abstract premium and the routine disadvantage also flowed in a way that explains the alleviation of wage inequality of Q5/Q1 and Q3/Q1. In detail, during this period, the trend of the coefficient of each task and the gap of task between quintile move toward easing the wage inequality. The size of the positive effects of the abstract task declines and the size of the negative effects of the routine task decreases. In the task score, the relative abstract score of Q1 increases and the relative routine and non-routine manual score decrease. That is, Q1 becomes more abstract and less routine/non-routine intensive group than before, seen as "task upgrading".

If the RBTC effects were dominant and enhanced, the decline in the return of the abstract score and the rise in the return of the routine score would not be observed. Also, the task upgrading in Q1 could not be inferred from the RBTC hypothesis. That implies that supply-side effects occur or some other factor eases the effect of the technical change on wages especially in a way that the factor can mainly have effects on Q1.

To figure out what happens to Q1, in Table.3.6, we summarize the change of each quintile's mean value of job-related characteristics for the third period (2009-2018). Q1 experienced about 30% higher wage growth rate than the other quintiles. In the task scores, the relative abstract score of Q1 increases and the relative routine and non-routine manual scores decrease. It seems that the Q1 group has experienced a task-skill upgrading during the third period.

Figure3. 7. Figure 5-2. Contribution of Task to Wage Inequality (2009-2018)



Note: The figures plot the contribution of each task scores on Q5/Q1,Q5/Q3, andQ3/Q1 wage inequality (2009-2018). For the details, see note to Figure 3.6.
Sources: Wage Structure Survey (2009-2018), Korea Network for Occupations & Workers (2014-2017)

For 2009-2018, the overall education level increased. Notably, the decrease of the fraction of HSD and the increase of the fraction of CLG is dramatic in 1st quintile relative to other quintiles. Besides, while South Korea has been experiencing a fast-aging population, Q1 shows a relatively slow pace of aging.

Considering the change of the occupation composition, the noticeable change in Q1 compared to other quintiles is that, at first, the share of professional and related workers and service and sales workers has increased. Second, in contrast, the share of the equipment, machines operating and assembling workers, which has the largest share in Q1, has declined relatively much. The change in industry composition is in line with the change in occupation composition. While, in Q1, the service industry has increased, the share of the manufacturing and transportation industry has declined.

To sum up, Q1 has experienced a faster pace of education level upgrade, a slower pace of aging, and a more rapid increase in the portion of the service industry rather than manufacturing and transportation-related work. The increase in the abstract score and the decrease in the routine and non-routine manual scores can be related to the above industrial composition change and the increased education level.[59] It can be suggested that the industrial and demographic changes may have occurred asymmetrically to Q1. That results in a kind of task-skill upgrading in the lowest wage group.

[59] Manufacturing and transportation industries are relatively routine and non-routine intensive sectors. In contrast, service sector is abstract intensive sector.

Table3. 6. Summary Statistics by Wage Quintiles

Wage Quintile	1Q			1Q			3Q			3Q			5Q			5Q		
Year	2009	2014	2018	18/09	14/09	18/14	2009	2014	2018	18/09	14/09	18/14	2009	2014	2018	18/09	14/09	18/14
Log Hourly Wage	1.63	1.94	2.27	0.65	0.32	0.33	2.39	2.65	2.81	0.41	0.25	0.16	3.35	3.64	3.76	0.41	0.30	0.12
Abstract Score	-0.56	-0.56	-0.44	0.12	-0.01	0.12	-0.01	-0.02	-0.03	-0.02	-0.01	-0.01	0.56	0.57	0.57	0.01	0.01	0.00
Routine Score	0.31	0.25	0.13	-0.18	-0.07	-0.11	0.01	-0.01	0.00	-0.01	-0.02	0.01	-0.32	-0.32	-0.36	-0.04	-0.01	-0.04
Non Routine Manual Score	0.29	0.28	0.15	-0.13	-0.01	-0.12	0.03	0.02	0.00	-0.03	-0.01	-0.02	-0.30	-0.34	-0.36	-0.06	-0.04	-0.02
Ratio of Male	49.6%	47.1%	41.6%	0.84	0.95	0.88	69.9%	67.1%	65.7%	0.94	0.96	0.98	87.2%	83.1%	81.7%	0.94	0.95	0.98
Education Years	12.38	12.56	12.90	1.04	1.01	1.03	13.62	13.85	13.99	1.03	1.02	1.01	14.99	15.15	15.33	1.02	1.01	1.01
HSD	13.2%	10.3%	5.5%	0.42	0.78	0.53	4.5%	2.9%	2.0%	0.45	0.64	0.70	2.1%	1.0%	0.8%	0.38	0.48	0.80
HSG	60.0%	61.0%	60.7%	1.01	1.02	0.99	40.7%	38.7%	38.0%	0.94	0.95	0.98	23.7%	20.4%	17.8%	0.75	0.86	0.87
SMC	15.3%	14.5%	15.4%	1.01	0.95	1.06	24.2%	22.4%	20.1%	0.83	0.93	0.89	11.4%	12.9%	11.4%	1.00	1.13	0.88
CLG+	11.5%	14.1%	18.4%	1.60	1.22	1.31	30.6%	36.0%	39.9%	1.30	1.18	1.11	62.7%	65.7%	70.0%	1.12	1.05	1.06
Age	39.76	41.96	42.76	1.08	1.06	1.02	36.08	37.74	39.31	1.09	1.05	1.04	41.85	42.58	44.61	1.07	1.02	1.05
16-25	15.3%	13.8%	14.2%	0.93	0.90	1.03	7.8%	7.5%	6.5%	0.84	0.96	0.88	0.6%	1.5%	0.5%	0.83	2.51	0.33
26-35	25.7%	21.0%	19.5%	0.76	0.82	0.93	48.6%	42.9%	36.8%	0.76	0.88	0.86	21.3%	21.4%	15.4%	0.72	1.01	0.72
36-45	23.9%	22.1%	18.9%	0.79	0.92	0.86	25.2%	26.1%	27.5%	1.09	1.04	1.05	45.4%	40.3%	37.0%	0.82	0.89	0.92
46-55	21.6%	25.6%	25.6%	1.19	1.19	1.00	14.4%	17.0%	19.6%	1.36	1.19	1.15	28.4%	29.8%	35.9%	1.26	1.05	1.20
56-65	13.5%	17.6%	21.8%	1.62	1.31	1.24	4.1%	6.5%	9.7%	2.36	1.58	1.49	4.3%	6.9%	11.2%	2.59	1.59	1.62
Firm Size																		
1-5	24.4%	25.7%	28.7%	1.18	1.06	1.12	15.7%	16.4%	15.7%	1.01	1.05	0.96	6.1%	6.7%	7.5%	1.23	1.10	1.12
10-29	30.3%	30.8%	31.5%	1.04	1.02	1.02	25.6%	25.5%	25.5%	0.99	0.99	1.00	14.6%	15.4%	15.7%	1.07	1.06	1.01
30-99	25.3%	24.9%	22.6%	0.89	0.98	0.91	25.2%	26.8%	25.6%	1.01	1.06	0.95	19.0%	17.7%	16.6%	0.87	0.93	0.94
100-299	13.3%	13.8%	10.6%	0.79	1.04	0.77	18.1%	18.7%	19.4%	1.07	1.03	1.04	16.3%	14.8%	14.9%	0.92	0.91	1.01
300-499	3.3%	2.0%	2.2%	0.65	0.60	1.09	4.7%	5.1%	4.9%	1.05	1.09	0.96	7.5%	6.3%	7.0%	0.92	0.83	1.11
500+	3.3%	2.8%	4.5%	1.35	0.84	1.61	10.7%	7.5%	8.8%	0.83	0.70	1.18	36.5%	39.1%	38.3%	1.05	1.07	0.98

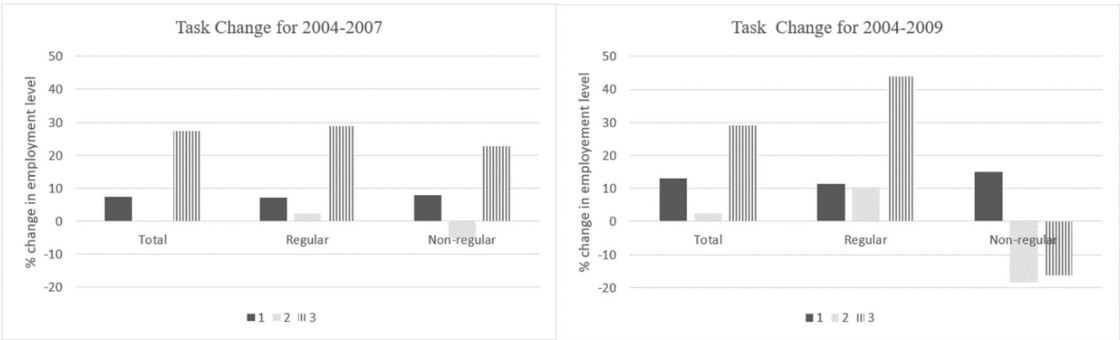
Wage Quintile	1Q			1Q			3Q			3Q			5Q			5Q		
Year	2009	2014	2018	18/09	14/09	18/14	2009	2014	2018	18/09	14/09	18/14	2009	2014	2018	18/09	14/09	18/14
Occupation																		
Manager	0.2%	0.2%	0.0%	0.22	1.06	0.21	0.9%	0.7%	0.3%	0.31	0.76	0.40	5.8%	6.5%	4.7%	0.81	1.11	0.73
Professionals and Related Workers	12.6%	14.2%	17.8%	1.41	1.13	1.25	24.1%	24.2%	23.7%	0.99	1.00	0.98	37.5%	36.0%	37.7%	1.01	0.96	1.04
Clerks	16.2%	13.5%	15.1%	0.93	0.83	1.12	28.2%	28.4%	29.2%	1.04	1.01	1.03	32.3%	35.1%	36.7%	1.13	1.09	1.04
Service	5.5%	9.7%	12.5%	2.28	1.77	1.29	2.1%	3.4%	2.7%	1.28	1.59	0.81	0.7%	0.7%	0.9%	1.22	0.98	1.24
Sale Workers	5.1%	6.7%	7.6%	1.49	1.32	1.13	6.0%	5.9%	6.0%	1.00	0.98	1.02	4.8%	4.5%	4.4%	0.90	0.94	0.96
Skilled Agricultural, Foresty and Fishery Workers	0.3%	0.5%	0.3%	1.16	1.64	0.71	0.2%	0.2%	0.2%	0.79	1.13	0.70	0.1%	0.0%	0.0%	0.48	0.69	0.69
Craft and Related Trades Workers	9.2%	7.3%	6.9%	0.75	0.79	0.94	9.6%	9.4%	8.9%	0.92	0.98	0.94	5.3%	6.4%	4.3%	0.81	1.20	0.68
Equipment, Machine Operating and Assembling Workers	30.0%	25.7%	20.1%	0.67	0.86	0.78	24.5%	22.9%	23.4%	0.95	0.93	1.02	12.7%	10.1%	10.9%	0.85	0.79	1.08
Elementary Workers	21.0%	22.2%	19.6%	0.93	1.06	0.88	4.4%	5.0%	5.7%	1.30	1.15	1.13	0.7%	0.6%	0.5%	0.77	0.84	0.91
Industry																		
Agriculture, Forestry and Fishing	0.2%	0.3%	0.4%	2.54	1.98	1.28	0.2%	0.2%	0.2%	1.15	0.87	1.31	0.3%	0.3%	0.2%	0.92	1.01	0.91
Mining and Quarrying	0.1%	0.1%	0.1%	0.75	1.02	0.73	0.2%	0.2%	0.2%	0.78	0.84	0.92	0.2%	0.1%	0.1%	0.58	0.62	0.93
Manufacturing	33.9%	30.3%	25.7%	0.76	0.89	0.85	38.1%	36.6%	36.4%	0.96	0.96	1.00	30.4%	34.2%	29.8%	0.98	1.13	0.87
Electricity, Gas, Steam and Water Supply	0.1%	0.0%	0.1%	0.50	0.42	1.19	0.1%	0.3%	0.3%	2.10	2.15	0.98	2.4%	1.8%	1.9%	0.80	0.75	1.07
Construction	5.0%	4.5%	4.3%	0.86	0.89	0.97	6.3%	5.6%	5.2%	0.83	0.89	0.93	5.1%	5.0%	4.9%	0.96	0.98	0.98
Wholesale and Retail Trade	8.8%	11.3%	11.2%	1.28	1.29	0.99	10.0%	9.8%	10.1%	1.01	0.98	1.03	7.7%	7.8%	8.5%	1.10	1.01	1.09
Accommodation and food service activities	5.5%	7.3%	8.2%	1.49	1.33	1.12	1.6%	1.7%	1.9%	1.16	1.05	1.11	0.4%	0.3%	0.3%	0.77	0.88	0.88
Transportation / Publishing, Visual Entertainment, Information and Communication	11.2%	8.4%	6.2%	0.55	0.75	0.74	10.0%	9.7%	9.2%	0.92	0.97	0.95	12.0%	10.6%	11.5%	0.95	0.88	1.08
Financial Institutions and Insurance	0.8%	0.6%	0.6%	0.75	0.83	0.91	3.2%	2.3%	2.1%	0.66	0.72	0.92	11.6%	10.7%	10.2%	0.88	0.92	0.95
Real Estate Activities, Rental and Leasing / Business Facilities Management and Business Support Services	14.7%	13.6%	12.6%	0.85	0.92	0.92	7.9%	10.4%	10.9%	1.37	1.32	1.04	5.8%	4.3%	5.3%	0.91	0.74	1.23
Service*	15.9%	19.3%	25.9%	1.62	1.21	1.34	18.3%	19.6%	19.9%	1.09	1.07	1.01	22.5%	23.0%	25.4%	1.13	1.02	1.11
Other Service*	3.9%	4.2%	4.8%	1.24	1.09	1.14	3.9%	3.6%	3.6%	0.92	0.92	0.99	1.5%	1.8%	1.7%	1.17	1.20	0.97

Note : Based on samples derived from 2009,2014,2018 WSS. Sample include individuals age 16-65 who are not self-employed. Sample is wieghted by WWS sample weight. The quintile groups are divided on log real hourly wage of each year. Service industry* includes Public administration and denfence; compulsory social security, Education service, Human health and social work activities, Arts, sports and recreation related services and Professional, scientific and technical activities. Other Service industry** includes Membership Organizations, Repair and Other Personal Services and Sewerage, Waste Management, Materials Recovery and Remediation Activities.

VII. Technology and Non-regular Workers

When analyzing the routinization trend by dividing it into non-regular and regular workers, after 2007 in which the Non-regular Protection law forced, it can be seen that the decline in the routine task in Korea was mainly absorbed by non-regular workers. Figure3. 8 shows how employment has changed in each task in the 2004-2009 period. The tendency to decrease routine jobs had been continuing since the 2000s and until 2007, it had been affecting both regular and non-regular workers in proportion. However, with the implementation of the Non-regular Workers Protection Act after 2007, it seems that most of the non-regular workers have absorbed the tendency to decrease the number of jobs in the routine task. The law on the protection of non-regular workers increases the relative cost of non-regular workers, so the number of routine tasks that firms need to reduce during this period is covered by the reduction in non-regular jobs while maintaining regular routine jobs, which are relatively important. If the drop in this route task has moved to a lower level of the task, on average, non-regular workers will be more distributed to lower task.

Figure3. 8. Task Change by Job Type for 2004-2009



Note:1,2,3 indicate the level of tasks' complexity. As the number increases, the task become complex.
Source: SSEAP 2004-2009, Author's calculation

In addition, with the relatively large distribution of regular workers in abstract jobs and the relatively large distribution of non-regular workers in less abstract jobs, the

increase in return due to rising demand for abstract tasks shows that the wage gap between regular and non-regular workers could widen further. For 2004-2009, the return of the abstract task score had increased (.034 to .068).

The significant decrease of the share of the non-regular job in the complex task induced the concentration of non-regular jobs on the low skill and the low (simple, non-routine manual) task. In addition, non-regular workers are also being pushed out of the routine task. This distributional change in skill dimension between job types has a negative composition effect on income inequality. However, beyond the composition effect, the skill and task separation between non-regular and regular jobs make an environment in which the benefits of technological advancement are inevitably disproportionately received depending on the type of employment; high return for regular jobs and low return for non-regular jobs. Technology development can further widen the income inequality between regular and non-regular workers.

VIII. Conclusion and Discussion

The RBTC hypothesis predicts that ICT development and digitalization lead to a decline in jobs that are rich in the routine component and an increase in the number of jobs that are rich in the abstract component. The theory does not make clear predictions about employment in jobs that are mostly non-routine manual, as these are not directly affected by the digital revolution.

The task-based literature (Autor, Levy, & Murnane, 2003) suggests that RBTC explains job polarization, which has been observed across Western countries (Goos & Manning, 2007; Reenen, 2011; Michaels et al., 2014; Fonseca, Lima, & Pereira, 2018; Sebastian, 2018). In addition, Autor, Katz, and Kearney (2006) say the RBTC also explains the wage polarization patterns that the middle-wage percentile group's wage growth rate is lower than low and high wage percentile groups.

This study focuses on the South Korea case. There is no clear trend of job polarization and wage polarization at all periods when occupations are classified by skill level. We analyze the employment pattern from a task-based approach. We construct the task score to measure the abstract, routine, and non-routine manual degree of each occupation using the Korea Network for Occupations & Workers (KNOW) data and present the task scores' trend for the analysis period.

According to the result of the task-based analysis, in South Korea, RBTC has influenced labor demand. Overall, except for the period right after the financial crisis, the abstract score had increased, the routine score had declined, and the non-routine manual score had decreased, but at a slower rate than the routine score.

However, the RBTC is not connected to job polarization because the relationship between skill and task in Korea is different from the general relationship seen in Western countries. In South Korea, non-routine manual jobs are composed of similar skill level workers with routine manual jobs. Under the indivisibility of the education level between the routine and non-routine task-intensive occupations, the change in tasks is hard to be recognized if the employment change is analyzed based on skill distribution. Therefore, task-based analysis is essential for figuring out the RBTC pattern in South Korea. On the other hand, a similar skill level between routine and non-routine manual task lead the coexistence of RBTC and SBTC in South Korea. If the employment pattern analyzed based on skill level, the demand for higher education increase and the demand for lower education decrease, as predicted by SBTC.

In addition, we confirm that the task scores are one of the significant factors to influence the wage. The three tasks all significantly influence the workers' wages. It is noteworthy that the task variables have significant effects on wages even after controlling all other factors.

The task score trend also seems to contribute to the wage inequality pattern since the 1990s. During the first phase (1993-1999), the abstract task substantially explains

the wage inequality trend. In the second phase (2000-2008), the abstract scores had explained well the increase of wage inequality since 2004. The non-routine manual task score also contributes the wage inequality. After the financial crisis (2009-2018), the trend of the coefficient of each task and the gap of task between quintile move toward easing wage inequality. Especially for the Q1 group, the relative abstract score increases and the relative routine and non-routine manual scores decrease. That is, Q1 becomes more abstract and less routine/non-routine manual intensive group than before, seen as "task upgrading", which contribute to easing the wage inequality.

In a further study, it is necessary to analyze why, in South Korea, the relationship between skill and task does not show the general pattern reported in other Western countries – abstract task-intensive in high-skill, routine task-intensive in middle-skill, and non-routine manual task-intensive in low-skill. In South Korea, the non-routine manual task score is not highest in the low-skill(education) group. There may exist a specific industry in which the demand for the non-routine manual task is high and the productivity is also high. Thus, that bring middle-skill workers into non-manual tasks. On the other hand, the wage-setting system in the non-routine manual task intensive sector may be strongly protected by the union, which causes the wage in the sector to be higher than the wage set in the market. This point leads the middle-skill workers to be injected in the non-routine manual task jobs.

For 2009-2018, the premium of abstract tasks decreases and the disadvantage of the routine tasks is eased, which move in the way of easing wage inequality. In this paper, we do not provide the reason for the change in the tasks' return for these periods. The task's return is determined by the interaction between the demand and supply for the task. The demand for the task depends on the industrial structure, technology advancement, and business cycle. The supply for the task is closely linked to the supply of the skill because the labor supply is provided as the labor with specific skills to jobs with specific tasks. To figure out what factors to influence the trend of return of tasks, the allocation

mechanism from skill to the task should be studied as well as the task-demand side factors. In the process of analyzing the return of task, we think, that fundamental for the relation between non-routine manual task and skill distribution mentioned above will also be revealed.

The technology effects on task scores need to be more specifically analyzed. In this study, we analyze the effects of ICT technology investment growth rate in the early 90s on the task scores by industry. It is necessary to find out a variable that can catch the degree of technological advancement. In particular, we need to come up with the measure for the technology which is more likely to substitute the labor or more likely to complement the labor.

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Appendix

Appendix 1. Task Score Descriptor

Table A.1. KNOW Decriptor and Scale Type by Task

KNOW Descriptor		Scale Type
Abstract		
A. Analytical		
	Analyizing data/ information	importance
	Thinking creatively	importance
	Interpreting information for others	importance
B. Interpersonal		
	Estabilishing and maintaining personal relationship	importance
	Guiding, directing, and motivating	importance
	Coaching and developing others	importance
Routine		
A.Cognitive		
	Importance of repeating the same task	content
	being exact of accurate	content
	structured vs unstructuctured work (reverse)	content
B. Manual		
	Controlloing machines and process	importance
	Keeping a pace set by machinery or equipment	content
	Time spent making repetitive motions	content
Non-routine Manual		
	Operating vehicles, mechanized devices	importance
	knowledge of transportation	importance
	Time spent using hands to handle, control	content
	data processing(reverse)	importance
	Manual dexterity	importance
	static stregnth	importance
	Spatial orientation	importance
	Spend Time Keeping or Regaining Balance	content

Note : KNOW measures selected for construction of each task measures following Acemoglu and Atuor(2011). 2014-2017 KNOW data is used for the measure.

Based on Acemoglu & Autor (2011)'s task measure, we additionally use four more indices to complement non-routine manual task measure. For descriptor of ‘Operating vehicles, mechanized devices’, we add ‘knowledge of transportation’, because operating devices may include characteristics of routine manual tasks. Considering that one of the representative occupations of the non-routine manual task is truck driving, transportation descriptor can reinforce the non-routine manual characteristics.‘Time spent using hands to handle, control’ is used together with reversed rating of ‘data processing’. Data processing is also required to use hands a lot to deal with computers or calculators, but it is close to routine task. Therefore using a reversed rating of `data processing’ helps to eliminate

the routine factors. For ‘Manual dexterity’, we additionally consider ‘Static Strength’and for ‘Spatial orientation’, ‘Spend Time Keeping or Regaining Balance’ is added. Static Strength and Keeping or Regaining Balance can emphasize the importance of physical abilities, which are essential for non-routine manual tasks, such as janitorial services, street sweepers, and drivers.

Appendix 2. Mean Standardized Scores by Skill Group for U.S.

TABLE 2.—MEAN STANDARDIZED SCORES BY SKILL GROUP, 1980 U.S. DATA

			High Skilled	Middle Skilled	Low Skilled
Routine tasks	Cognitive	Set limits, tolerances, or standards	−0.32	0.06	0.07
	Manual	Finger dexterity	−0.21	0.13	−0.14
Nonroutine tasks	Cognitive	Quantitative reasoning requirements	0.79	−0.02	−0.43
		Direction, control, and planning	0.90	−0.11	−0.32
	Manual	Eye-hand-foot coordination	−0.36	−0.04	0.29

This table reports the mean standardized task measures by skill group, using 1980 U.S. Census microdata and the occ8090 classification from Autor et al. (2003). For each task measure, the standardized measure is derived by subtracting from each occupation's task score the weighted mean task score across all occupations, and then dividing the difference by the standard deviation of the task measure across the 453 occupations.

Source: Michaels et al. (2014), Table3. 2, p65.

Appendix 3. Top Occupations by Share of Worker's of Different Education Levels With Task Measures

Table A.3. Top Occupations by Share of Workers of Differecnt Education Levels With Task Measures

							Task Score						
							Abstract			Routine			Non-routine
	Occupation	Employment Share in 2007	Fraction HSD	Fraction HSG	Fraction SMC	Fraction CLG	Abstract	Analytic	Interpersonal	Routine	Cognitive	Manual	Manual
Top ten occupation ranked by share of CLG workers													
512	Lawyer	0.08	0.00	0.00	0.00	1.00	1.40	1.38	1.41	-1.32	-1.60	-1.04	-0.50
2229	Science, engeering and technology associate professionals	0.02	0.00	0.00	0.00	1.00	1.37	1.62	1.11	-0.23	-0.40	-0.06	-1.44
311	Investment and credit analyst	0.05	0.00	0.00	0.00	1.00	1.31	1.68	0.94	-0.93	-0.78	-1.08	0.16
611	Internist	0.29	0.00	0.00	0.00	1.00	1.07	1.11	1.03	0.15	-0.33	0.62	0.36
313	Insurance and financial product developer	0.04	0.00	0.00	0.00	1.00	0.84	0.63	1.04	-0.54	-0.47	-0.61	-0.77
664	Articifial limb technician	0.00	0.00	0.00	0.00	1.00	0.59	0.47	0.70	0.32	-0.57	1.21	0.75
612	Doctor	0.10	0.00	0.00	0.00	1.00	0.52	0.27	0.77	-0.76	-1.22	-0.30	-0.40
411	University professor	0.67	0.00	0.00	0.00	1.00	0.38	0.37	0.39	-1.10	-1.58	-0.62	0.18
421	Education specialist	0.06	0.00	0.00	0.00	1.00	0.29	0.83	-0.26	-0.05	0.14	-0.24	0.17
2221	Gas & Energy technician and researcher	0.00	0.00	0.00	0.00	1.00	0.04	0.11	-0.03	-0.52	-0.40	-0.64	-0.91
Top ten occupation ranked by share of SMC workers													
2225	Energy inspector	0.00	0.00	0.00	1.00	0.00	0.59	0.85	0.33	0.34	-0.12	0.81	-0.42
663	Dental technician	0.12	0.01	0.09	0.79	0.11	-0.68	-0.91	-0.44	-0.34	-0.87	0.19	-0.02
665	Optician	0.11	0.00	0.13	0.77	0.10	-0.52	-0.25	-0.78	1.42	1.25	1.59	0.51
1812	Textile engineering inspector	0.02	0.00	0.28	0.70	0.02	-0.15	0.01	-0.32	0.37	0.70	0.05	-0.42
651	Physical therapist	0.17	0.00	0.03	0.65	0.32	0.15	-0.03	0.34	-0.54	-1.11	0.03	0.66
662	Radiologist	0.12	0.00	0.00	0.64	0.36	-0.30	-0.33	-0.28	0.46	-0.11	1.03	0.65
661	Clinical pathologist	0.14	0.00	0.00	0.64	0.36	0.55	0.35	0.75	0.21	0.31	0.11	-0.23
674	Medical recorder	0.02	0.00	0.00	0.50	0.50	-0.28	-0.64	0.09	0.43	0.90	-0.03	-0.85
721	Care teacher	1.21	0.00	0.18	0.49	0.33	0.19	-0.14	0.52	-1.02	-0.47	-1.58	-1.12
856	Draftsperson	0.41	0.00	0.26	0.49	0.25	0.60	0.81	0.39	0.85	1.10	0.60	0.09

Table A.3. Top Occupations by Share of Workers of Differecnt Education Levels With Task Measures

	Occupation	Employment Share in 2007	Fraction HSD	Fraction HSG	Fraction SMC	Fraction CLG	Task Score: Abstract: Abstract	Abstract: Analytic	Abstract: Interpersonal	Routine: Routine	Routine: Cognitive	Routine: Manual	Non-routine: Manual
Top ten occupation ranked by share of HSG workers													
671	Masseur	0.01	0.11	0.89	0.00	0.00	-0.45	-0.37	-0.54	0.41	0.47	0.36	0.14
1621	Sheet metal technician	0.07	0.14	0.81	0.05	0.00	-0.19	-0.27	-0.11	0.58	0.10	1.05	0.94
1622	Sheet metal operator	0.04	0.14	0.81	0.05	0.00	-0.98	-1.09	-0.88	1.21	1.02	1.40	1.58
1623	Machine tool operator	0.05	0.14	0.78	0.05	0.02	-0.84	-1.25	-0.44	0.67	0.61	0.72	1.31
1450	Construction and mining machine operator	0.89	0.13	0.77	0.06	0.04	-0.91	-0.87	-0.95	0.80	0.38	1.22	1.57
1442	Industrial plumber	0.12	0.07	0.72	0.10	0.10	-1.30	-1.72	-0.88	0.88	0.78	0.98	0.98
1662	Machine operator for metal processing	0.37	0.10	0.71	0.12	0.06	-1.22	-1.33	-1.11	0.99	0.90	1.08	0.83
1962	Electronic parts and products manufacturing machine ope	0.40	0.05	0.71	0.17	0.07	-1.96	-1.92	-2.00	1.55	1.90	1.20	0.03
2252	Pulp and paper manufacturer operator	0.05	0.05	0.70	0.12	0.13	-1.06	-0.85	-1.28	1.77	1.90	1.64	0.20
1582	Car parts aseembler	0.62	0.10	0.70	0.15	0.05	-0.69	-0.80	-0.58	1.76	1.14	2.37	0.71
Top ten occupation ranked by share of HSD workers													
2350	Fishing and other elementary acricultrue occupations	0.74	0.85	0.14	0.01	0.01	-2.23	-2.12	-2.34	-0.42	-1.17	0.33	-0.03
1211	Hairdressor	0.30	0.73	0.26	0.02	0.00	0.02	-0.30	0.33	0.47	-0.04	0.98	1.58
1132	Environmental hygienist	1.27	0.72	0.25	0.02	0.01	-1.66	-1.73	-1.58	0.52	0.60	0.45	-0.72
2342	Fishermen	0.30	0.70	0.27	0.02	0.01	-1.77	-2.05	-1.49	-0.19	-1.12	0.75	1.27
2331	Mamager of forest / logger/ wood cutter	0.05	0.63	0.31	0.00	0.06	-0.87	-1.12	-0.62	0.63	0.58	0.68	1.13
1862	Shoe Manufacturer Operator and assembler	0.07	0.63	0.25	0.00	0.12	-0.76	-0.82	-0.70	1.05	1.00	1.10	0.29
1844	Garment repairman	0.57	0.58	0.37	0.03	0.02	-0.21	-0.39	-0.02	0.19	0.04	0.33	0.42
722	Childcrase and relatied personal service occupation	0.86	0.56	0.32	0.04	0.09	-1.49	-1.65	-1.32	-0.46	0.17	-1.08	-0.50
2322	Livestock breeder	0.40	0.55	0.36	0.03	0.06	-1.38	-1.32	-1.45	0.22	-0.50	0.94	0.44
1323	Kitchen assistant	2.14	0.53	0.41	0.03	0.03	-1.34	-1.73	-0.94	-0.24	-0.68	0.20	0.03

Note : The task score of each occupation and the fraction of each skill group are computed using 2007 OES data in South Korea. The occupation classification is 4-digit. CLG is college graudate, SMC is some college graduate, HSG is high school graduate and HSD is high schoo droup out. After selecting the top 10 occupations with high fraction of each skill group and we calculate the occupations' mean task score from the individual task score.

국문초록

비정규직 노동시장에 대한 경제학

서울대학교 대학원

경제학부 경제학전공

황인영

90 년대 이후 비정규직이 지속적으로 사회문제로 대두되고 있는 상황에서, 비정규직 고용 내면에 흐르는 경제학을 체계적으로 정리하고자 하였다. 근로자에게 비정규직이 어떤 역할을 하는지, 기업이 비정규직을 사용하는 이유는 무엇인지, 기술발전과 함께 변해가는 노동수요의 흐름에서 비정규직은 어떤 영향을 받고 있는지 살펴보았다. 첫 번째 장은 비정규직 거쳐 정규직으로 전환된 근로자들의 임금동학 패턴을 분석하고 일자리 매칭(Job matching)과 고용자 학습(employer learning)의 관점에서 실증분석 결과가 도출되는 메커니즘을 설명하였다. 두 번째 장은 2004 년과 2016 년 사이에 비정규직이 감소함에도

불구하고 소득불평등이 증가했던 현상에 주목하여, 비정규직 규모와 소득불평등의 관계에 대해 체계적으로 분석하고, 기업의 정규직-비정규직 고용원리를 설명하는 모델을 기반으로 위의 결과는 기업의 비정규직 보호법에 대한 반응임을 제시하고 있다. 세 번째 장은 기술발전에 의한 한국노동시장의 수요변화를 RBTC(Routine Biased Technological Change) 관점에서 분석하고, 이 수요변화가 임금불평등에 기여한 바를 분석한다. 더 나아가 이러한 기술발전에 의한 수요변화가 비정규직에 미치는 영향을 보여준다.

첫 번째 논문은 비정규직을 거쳐 정규직으로 옮겨간 근로자들의 임금동학에 대한 연구이다. 첫 직장을 비정규직으로 시작하는 것은 이제 한국에서 약 1/3 가량의 근로자가 경험할 정도로 일반적인 현상으로 자리잡고 있다. 본 연구는 비정규직을 거쳐서 정규직으로 옮겨간 근로자들의 임금동학을 분석함으로써 진입 초기에 경험으로서 비정규직 직업보유가 가지는 경제적 의미를 연구하였다. 비정규직 경험이 정규직 초기 임금 수준에는 부정적인 영향이 있지만, 임금상승률을 증가시켜 처음부터 정규직이었던 근로자들의 임금수준을 추격해가는 현상을 확인하였다. 정규직으로 내부에서 전환되었는지, 직장 이동을 통해서 전환되었는지에 따라 임금상승요인이 다른데, 내부전환자는 재직기간(tenure)을 통해, 직장이동자는 노동시장근로기간(experience)을 통해 임금상승이 반영됨을 보였다. 이는 (i)기업이 정보 불확실성의 대상인 근로자의 능력과 매칭 수준에 대한 평가를 통해 정규직과 비정규직을 구분하고, (ii) 그 다음 생산물을 기초로

신호추출(signal extraction)을 통해 능력과 매칭 수준에 대해 점차 인지해가면서 일정 수준 이상일 경우 정규직으로 전환하고. 근로자들은 현재 직장에서 제대로 인정받지 못할 경우 더 나은 매칭 또는 1 차평가의 불확실성을 감안하여 다른 직장을 탐색하여 직장이동을 통해 더 잘 맞고 더 높이 능력이 인정되는 회사를 찾아간 결과로 해석할 수 있음을 이론모형을 통해 체계적으로 보여주고 있다. 이를 통해 비정규직 근로기간이 생산성에 대한 정보를 업데이트해가는 과정으로서의 기능이 존재함을 보임으로써 기업에게 심사(screening)와 수습 평가 장치(probationary evaluation device)로, 근로자에게 직장 탐색 도구(job search device)로서 함의를 지님을 암시하고 있다.

두 번째 연구는 2004 년에서 2016 년동안 비정규직 비율이 감소함에도 불구하고 소득불평등이 증가하는 Puzzling 한 현상에 주목한다. 이 현상은 상대적으로 열악한 집단인 비정규직이 감소하면 전체 불평등이 감소할 것이라는 상식과 배치되는 내용이다. 본 연구는 분산분해(variance decomposition) 기법을 통해 비정규직 비율이 감소했지만 비정규직 내에서 높은 숙련도를 지닌 그룹에서는 많이 감소하고, 낮은 기술 그룹에서는 적게 감소하는 숙련편향적인(skill-biased) 감소형태를 실증분석을 통해 규명하였다. 이로 인해 정규직과 비정규직의 평균적인 격차가 확대되는 부정적 효과가 비정규직 감소효과를 압도함으로써 소득불평등이 심화된 것임을 보였다 본 논문은 숙련(Skill) 집단 내에 직무의 복잡성(Task complexity) 수준을 구분하여 기업이

각 숙련집단에서 직무(task)의 복잡성에 따라 정규직과 비정규직을 할당하는 모델을 제시함으로써 위의 숙련편향적 비정규직 감소가 비정규직 보호법(2007) 실행에 대한 기업의 반응이라고 해석하고 있다. 비정규직 보호법이 비정규직의 고용의 상대비용을 증가시킴에 따라 기업은 비정규직의 효율이 낮은 고숙련 집단의 복잡도가 높은 직무부를 정규직으로 더 많이 재배분함으로써 위와 같은 숙련편향적인 감소가 발생했음을 설명하고 데이터를 통해 뒷받침하고 있다

세 번째 논문은 기술발전이 노동시장에 미치는 영향에 대해 분석하였다. 본 연구는 기술발전이 노동시장에 미치는 영향이 숙련(skill)을 넘어 직무(task)의 성격에 따라 다르게 영향을 받는다고 설명하는 정향편향적 기술진보(Routine-biased technological change, RBTC) 가설을 검증하였다. 미국 O*Net 을 기반으로 설계된 KNOW 데이터를 이용하여 업무(task) 단위의 분석을 시행한 결과, 1993-2018 년 사이 한국에서도 추상적 직무의 고용 점유율은 증가하고, 정형적 직무의 고용 점유율이 감소한 고용 변화 패턴(routinization)이 나타났다. 또한 본 연구에서는 추상적, 정형적, 비정형적 육체업무의 직무 점수가 임금에 유의한 영향을 미치고, 임금 불평등 추세에 기여함을 확인하였다. 이 추세를 비정규직과 정규직으로 구분해서 분석할 경우, 한국의 정형적 직무 감소현상은 비정규직을 위주로 발생했음을 확인할 수 있다. 이는 정형적 업무에서도 상대적으로 핵심적인 직무를 맡고 있는 정규직은 유지하고, 비정규직을 통해 전체 수요를 감소시키는 방향으로 대응한 것으로 해석된다. 또한 정규직은 상대적으로

추상적 직무에 많이 분포해 있고, 비정규직 직무가 정형적 직무와 비정형적 육체직무에 집중적으로 분포하는 상황에서 추상적 직무 수요 증가에 따른 보상(return)증가는 정규직과 비정규직의 임금격차를 더 확대시킬 수 있음을 보여준다.

주요어: 비정규직, 직장 이동, 직장 매칭 및 탐색, 불평등, 기업의 행동, 기술발전, 루틴화

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