Robotization and Labor Market Dynamics in South Korea: Occupation-Level Analysis

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Abstract

We use the rare labor panel data in South Korea to observe the effect of robotization on employment and wages in South Korea. Considering that South Korea has been one of the leading and fastest countries in terms of robot adoption, our analysis has implications not only for the labor market of South Korea but also for countries whose robotization rates are only starting to increase. To establish an association between robotization and labor market dynamics, we use a new robot exposure measure developed by Webb (2020). The method exploits an overlap between the text of job tasks descriptions and the text of robot patents, resulting in the measure of robot exposure at an occupation level. We observe a drop in the overall employment for occupations that are more exposed to robotization. This effect appears after 2010, when the robototization rates in South Korea have accelerated. At the same time, we do not observe any negative effect on the average wage. While our methodology does not allow us to claim causality, the first results set the stage for the future research.

JEL classification: J23, J24, O33

Keywords: Automation, Robotization, Technological change, Robots, Occupation, Patent

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1 Introduction

The aim of the robot ethical charter is to confirm of the human ethics for the co-existence and co-prosperity of the human being and the robot

The statement is reproduced from the Korean Robot Ethics Charter released on October 30, 2007. The charter is significant not only because it was the very first charter to secure the harmonious association between humans and robots in the world, but it also demonstrated the South Korean government's concerns about possible issues arising due to the rapid automation. In 2008, the South Korean government launched the Development and Distribution of Intelligent Robots Act to encourage enterprises to adopt more automation in their production. Based on the act, Basic Robot Industry Plan is formulated every five years to stimulate industrial robots market; for instance, according to the article 24, firms who invest in industry automation will obtain the tax deduction. From 2009 to 2018, the South Korean government invested over 17 billion NT dollars to support the research and development technologies related to robotics industry. Nonetheless, in 2017 South Korea became the first country to impose a robot tax.[1] The main reason behind of this imposition was to compensate potential losers from automation. Transitioning from their traditional production method to advanced robots are costly. Therefore, technological improvement occurs mostly in corporations while SMEs are lagged behind. The rapidity gap increases the productive capacity between the corporations and others. To grasp the other potential issues caused by this productivity difference, the government executed the tax law in exchange of abating the robotization. The mixed signals that the Korean government has been sending align with the countervailing economic forces on the labor market, rooted from the robotization.

The explanation from a substantial body of research notwithstanding, understanding the causes and consequences of the automation is still puzzling. Automation in labor and product markets can enhance the productivity, therefore induce higher market production resulting in higher labor demand (Acemoglu and Restrepo 2018; Aghion et al. 2020; Autor 2015); however, this productivity effect can be offset by displacement effect, as robots replace the humans' tasks, raising the possibility of technical unemployment. (Brynjolfsson and McAfee (2014), Acemoglu and Restrepo (2015)).

To construct proper policies regarding the possible issues caused by automation, monitoring the precedent cases can play a crucial role. Based on this aspect, our paper delves into South Korea's automation status and its consequences on the labor market with the following reasons. First, as reported by International Federation of Robot (IFR), South Korea is a leading country in terms of robot density followed by Singapore, Japan and Germany in 2015 (Cho and Kim (2018)).[2] The operational stock of industrial robots has increased almost eightfold, from 3.8 million in 2000 to 30 million in 2018. With its high accumulation in robots stock, the Korean data can exemplify for other countries whose robotic industries are growing.

[1] In 2017, South Korean government announced two percent drop in the tax reduction to slow down the growth of automation.(Vigliarolo (2017))

[2] According to IFR, robot density is defined as the number of industrial robots per 10,000 manufacturing employees

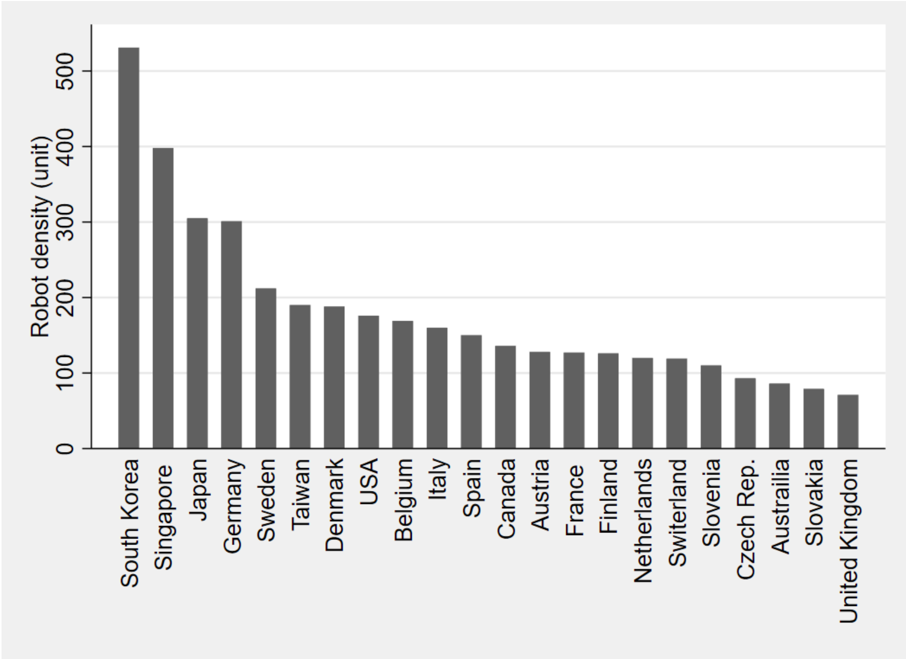

Figure 1: **Robot density by country, 2015 (unit); per 10,000 employees in the manufacturing industry 2015**

Source: Robot density by IFR (2016)

Note: This bar graph shows the robot density (the number of robot units per 10,000 employees) in the manufacturing industry in 2015 by country.

Second, the South Korean case provides us with a proper empirical environment to analyze how the state intervention in terms of automation alters the labor market demand. Figure 2 exhibits the high absorbance of robots in South Korea as well as its rapid growth of it. Owing to the acceleration happened after 2005, it provides us with an opportunity to investigate the role of policies in terms of robot usage at each industry as well as its consequence.

Third, Arntz et al. (2016), point out that South Korea has the lowest percent of workers at risk due to the automaton[3]; they believe that it is because a large share of Korean workers achieved educational levels that are associated with fewer automatable tasks. Expressly, the South Korean education system is likely to mediate the labour market effects of automation. This feature should be paid attention with reasons as below. The global gross enrollment ratio in tertiary education is consistently an increasing trend; since 1970s, the gross enrollment rate has increased more than fourfold (WorldBank (2020)).[4] With the high share of tertiary educated individuals and hence the high share of high skilled workers, South Korea can be a pathfinder to present the forthcoming labor market consequences of automation to the world.[5]

Lastly, considering that South Korea is an aging society, the political decision of state in terms of

[3]According to Arntz et al. (2016), in terms of share of workers with high automatibility by OECD countries, the highest countries are Germany and Austria (12%) and the lowest is South Korea and Estonia (6%)

[4]According to the World Bank micro data, the gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown.

[5]In the OECD publication, Education at a glance: Educational attainment and labour-force status (2021), South Korea has the highest share of tertiary-educated among individuals between 24-34 years old

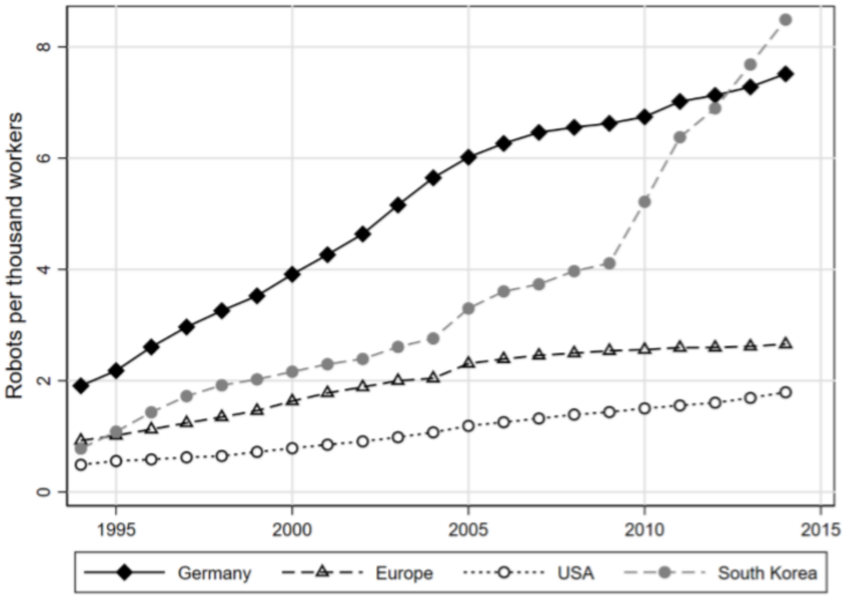

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Figure 2: **Robot penetration, 1994-2014; Robot penetration is the robot stock relative to the dependent employment in full-time equivalents (FTE), Dauth et al. (2021)**

Source: Robot penetration data by Dauth et al. (2021)

dealing with automation could illustrate the method to coordinate the labor market with inevitable robot adoption. In order to solve the possible issues caused by the deficiency in workforce in the near future, the government has announced several plans to replenish the workforce with robots in diverse sectors.(Maonline (2020)) While it is inevitable for South Korea to face the further robot adoption, the government has its duty to protect workers from unemployment. Attempts of Korean government to get a balance between the consistent adoption of robots and labor protection give us an opportunity to see the role of policy to govern the degree of automation impact on the labor market. In spite of its advanced robot usage, the study on the effect of automation in South Korea has relatively lagged behind, comparing to other developed countries.

Kim and Lee (2021) investigate the effect of automation on the employment rate in South Korea. For their identification, they used a task-based approach, employing industrial level of the adjusted penetration of robots (hereafter APR) from Acemoglu and Restrepo (2015) with the robot data provided by IFR. Using APR of European countries, the study estimates a two-stage fixed effects model. They discover that during the financial crisis (2010-2018), a single-unit increase in the APR led the employee growth rate and real wage growth in a given industry to decline by 0.1% and 0.3%, respectively. Even though the paper succeeds to demonstrate the displacement effect mentioned above, it has critical limitations as the study restricts itself only to explore the outcomes from the labor demand sides. The study overlooked that the changes in demographics and skill composition of workers could affect the labor market adjustment after the adoption of robots. In contrast to Kim and Lee (2021), there are studies standing on the positive side of spectrum (Jeong (2017), Huh (2017), Kim (2017)). They declare that the industries depending heavily on the automation will increase their productivity; after an adjustment period, demand for labor will escalate. Due to the lack of their empirical confirmations for their theories and political recommendations, however, those papers are limited as subjective statements. Cho and Kim (2018) illustrates the impact of robotization on the labor market with the industrial robot data from Work Environment Assessment Survey published by Korea Occupational Safety and Health Agency and the business level data from the Survey on Labor Conditions by Employment Type publised by the Ministry of Employment and Labor. Their inquiry brings an interesting perspective as they consider the robotization as an endogenous occurrence. They computed the robotization indicator based on the actual number of industrial robots currently deployed in workplaces and performed a multiple regression analysis. Exploring the triangular relationship of employment-working hours-wages, their results show the complementary relation between employment and robotization but the substituting relation between working hours and robotization. Notwithdstanding their recognizable contribution to a body of literature, there is a significant aspect that their study has not taken account of the possible distinct consequences of automation depending on the industries or tasks conducted by different occupations.

By improving the previous methodologies employed the literature mentioned above, our paper contributes to the current stream of automation studies with the following novelties. First, our data extracted from Korean Labor Income and Panel Survey (KLIPS) allows us to scrutinize the effect of automation on the labor market as the data includes the chronological information on wages, employment rate as well as workers' employed status and working condition based on the survey's meticulous questionnaires. Furthermore, the current study enhances the accuracy of analysis by conducting the robustness checks with Workplace Panel Survey (WPS) data, which not only consists of comparable variables with data from KLIPS but also provides further financial information on firms. Second, our analysis of impact of automation is based on occupation level of employees, following the method established by Webb (2020)[6]. Classifying the employees by the occupation level has been already exploited by previous studies. Frey and Osborne (2017), who are the pioneers to utilize the occupational information to investigate the effect of computerisation on the employment estimate the probability of risk at which the total US employment will be in the near future. Following Frey and Osborne (2017), Kim (2015) estimates the substitutability between the task of occupations and computerization; and deduce the number of occupations at risk. The author concludes that the impact of technology in South Korea is less than in the United States because higher number of workers participate in the sales field which has lower propensity to be substituted by automation. Another paper, Park (2016), exploring the South Korean case based on Frey and Osborne (2017), also states that sales as well as managerial and specialized tasks will be less exposed to the automation. With the perspective that our paper utilizes the job classification, their studies have an affinity; however, their studies have only delved into the aspect of technical substitution between the automation and labor demand based on the task-compatibility; in other words, the papers do not take account of economic utility formed by automation. By merging the occupation data with KLIPS, we manage to pronounce the relationship between the automation and each occupation with more economic outcome such as employment rate and wages. In Webb (2020), the author reports that the moving from the 25th to the 75th percentile of exposure to robots has a negative effect on the wage and employment share. Aligned with his findings, our result also presents the decline in employment of each occupation when its task are exposed to higher automation.

The rest of current paper is organized as follow. In section 2, we describe the databases we used and

[6] This method will be discussed further in the next chapter

the method to compute the exposure score. Section 3 presents the impacts of robot exposure on the changes in employment and wages. Section 4 provides and outlook for future research and concludes.

2 Data Variable Description and Summary Statistics

2.1 Administrative Labor Market Data

As mentioned in the previous section, our main labor data provided by the Korean Labor Income and Panel Study (KLIPS). KLIPS is the only longitudinal survey existing in South Korea, conducted once every year. KLIPS collects information of consuming behavior, labor market participation, education, social activities from 5,000 households, including each family member from the household. The data is updated to 2020; our study observes the data from 1998 to 2019 based on the assumption that South Korea had a massive wave of automation was conducted during this period. We use an individual panel data variables which is released for the annual conference held by KLIPS.[7] The data contains information on gender, age, their residential locations educational attainment, 3-digit occupation codes, 3-digit industrial affiliation codes, as well as labor market outcomes, such as employed year, wages and working hours. The comprehensive individual level information from KLIPS allows us to understand overall changes in average employment rate and wages change depending on the workers' demographic information, occupations and working industry without merging with other dataset. Furthermore, KLIPS comprises a detailed questions on workers' working/health conditions: exposed rate of job training, wished job training, reasons for leaving, level of stress caused by works, difficulties of obtaining a new job, etc. We particularly pay attention on the feature of this database that the effect of job training combined with automaton is able to be demonstrated.[8] For our analysis, we use the 3-digit occupation codes. The occupation codes from KLIPS follows the Korean Standard Classification of Occupations (KSCO) formulated by Statistics Korea. To merge with the automation penetration score for each occupation in Webb (2021), we, first, convert the KSCO to International Standard Classification of Occupation (ISCO); then match the converted code with codes from David Dorn's Occupational Schema.[9] To merge with the robot penetration rate of each occupation, following Webb (2020).[10] To enhance the accuracy our analysis, we check the impact of automation on the industrial level as well, using the task-based approach. In order to conduct this, we excavate the Korean Working Condition Survey which contains questions inquiring the level of repetitiveness of workers' tasks, provided by Occupational Safety and Health Research Institute of Korea.[11]

Table 1 describes the descriptive summary of our labor data. We did not conduct the regional comparison since the KILPS does not provide us with a less than state level.[12] Also, KLIPS does not have any observation of workers at public sector. The average employment percentage as well as the the

[7]As mentioned above, those individuals are the members of the households.

[8]We will discuss in our extended study.

[9]Again, all the procedure will be described in the following chapter.

[10]The more detailed description of Webb (2020) is in the following section.

[11]The survey contains the individual level information including gender, age, educational attainment, wages, working hours as well as other questions related to their working conditions; many variables from this data is synchronized with KLIPS; the survey, however, has been conducted irregularly (in 2006, 2010, 2011, 2014, 2017) and the occupational codes were dropped in 2006, 2010 and 2014. Therefore, we only utilize the survey result on the repetitiveness in industrial level; and our main analysis is based on the KILPS data.

[12]South Korea has only nine different states; we find out the employment differences within those nine states are very trivial since most of jobs are crowded in metropolitan including Seoul.

percentage of employees in manufacturing and non-manufacturing industries increase from 1998 to 2020. Weighted it by the total number of population of each year, those percentage changes increase marginally. We can also confirm that the non-manufacturing sector is growing faster than the manufacturing sector. This aligns with Kim (2015) which points out that the automation in South Korea has a weaker effect on its labor market than in the United States because higher ratio of workers to the total population is involved in the non-manufacturing sectors, more specifically, sales /sales-related service sectors. The trend of ratio of workers to total employees in manufacturing sectors and service sectors is more clearly presented by figure 3. The decline before 2000 stems from the financial crisis in 1997. South Korea economy highly depends on exporting the manufacturing goods; therefore, lower decline and faster recovery of employees at the manufacturing sector accords with the growth rate of the industry in the late 1990s. Service industry starts to expand as the growing manufacturing industry created the demand for services; by the 2010s, the service industry has become the highest source of employment in the nation (Ministry of Land Infrastructure and Transport (2017)). The gap between the employment ratio of manufacturing and service sectors particularly started to be widen after the 2008 financial crisis.

Table S1: **Summary Statistics, individual level, 1998-2020**

0bservations	unweight		weighted	
	mean	(sd)	mean	(sd)
[A]**Outcomes**				
% change in total employment	3.807	14.029	3.940	.072
% change in manuf. employment	2.492	12.230	2.395	.114
% change in non-manuf. employment	3.483	15.735	3.683	.073
100xln-change in average wage	3.658	4.042	3.845	.011
100xln-change in average wage, manuf	3.684	4.021	3.955	.034
100xln-change in average wage, non-manuf	3.650	4.023	3.828	.011
%-point change in emp/pop-ratio	0.160	1.136	.237	.005
%-point change emp/pop-ratio, manuf	-0.068	0.337	-.048	.003
%-point change emp/pop-ratio, non-manuf	0.067	0.337	.057	.001
[B]**Control Variables**				
% female	40.764	1.012	40.652	.006
% age $\geq$ 50 years	78.963	13.894	76.606	.074
% unskilled	9.638	2.354	9.914	.077
% vocational training	18.297	2.760	18.124	.027
% university degree	34.101	5.398	33.633	.051
% manufacturing	18.574	1.270	18.724	.009
% food products	1.493	0.096	1.486	.003
% consumer goods	4.958	1.712	4.988	.024
% industrial goods	12.632	0.622	26.027	.011
% construction	1.389	0.303	1.378	.012
% maintenance; hotel & catering	9.992	0.285	9.971	.003
% services	20.157	0.664	20.103	.006
% public sector	.	.	.	.

Considering South Korea's fast recovery from the crisis, this divergence demonstrates further than the tardy growth of manufacturing sector. In the following chapters, we investigate this difference, ascribing it to the higher robotization in manufacturing sector.[13]

[13]After colonization and war, the industrialized gap between South Korea and other developed countries was tremendous.

Other graphs demonstrating the overall trend of labor market outcomes are included in Appendix (A.1-7).

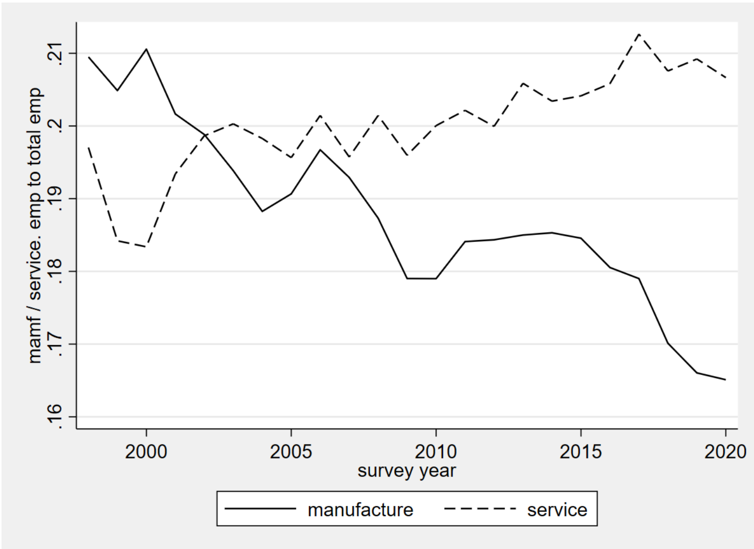

Figure 3: **Manufacturing/service employees to total employees**

Source: Labor data by, KLIPS
Note: The sample is limited to the full workers in the manufacturing sector and service sector. We did not include the workers who are engaged in both sectors.

2.2 Occupation and robot exposure data

Our primary data to measure the robotization of each occupation follows the Webb (2020). In Webb (2020), the author develops a new method to measure the new technology exposure scores depending on each occupation with patents of technology and job descriptions: Using a dependency parsing algorithm (Honnibal and Johnson (2015)), the author utilize the overlapping text between the patent and job descriptions. In this paper, the effect of three different technologies are investigated: software, robot, and artificial intelligence. To fit into our study purpose, we only use the exposure scores of robot from this study.[14] To compute the robot exposure scores of each occupation, the author extracted patent data IFI CLAIMS Patent Services; the job description data from O∗NET.

2.3 Exposure Score

The process of constructing the exposure score employed by Webb is as follow. First, he extracted the verb-noun pairs which might describe the functions of a certain technology from the patent title collected from IFI CLAIMS Patent Services. In terms of the job description, he uses the O∗NET database,

In order to catch up with other industrialized countries, the state intervened the economy actively with a unique approach. The government supports firms with massive subsidies to distort relative prices in order to stimulate economic activity. (Amsden, 1992) The investment especially aimed to expand the manufacturing sector and technology. Owing to the aid from International Monetary Fund, the creditors in South Korea were bailed out; following the tutelage from IMF, the government created the alternative funding sources payment rescheduling, a flexible labor market which contributed its fast recovery from the crisis (Koo and Kiser (2001)). These reforms eventually played a significant role during the 2008 financial crisis.

[14]The method invented by Webb(2020) will be discussed in the following chapter.

produced by the US Department of Labor and collects the pairs of verb-noun which capture the characters of each occupation. Next, the author computes the final exposure score based on the set of aggregated set of verb-noun pairs. Measuring the exposure of occupations is summarized with two equations presented as below:

$$rf_c^t = \frac{f_c^t}{\Sigma_{c \in C^t} f_c^t} \ldots (1)$$

For a certain technology (in our case, robot), t, is defined to be encompassed within T, the set of technology. f_c^t is the raw counts of incidents of aggregated verb-noun pair c extracted from technology t patent titles. Therefore, equation (1) denotes the relative frequency of aggregated verb-noun pair c in technology t patent title. This relative frequency, then, is given to each of the task-level aggregated verb-noun pairs. The final exposure rate is defined:

$$Exposure_{i,t} = \frac{\Sigma_{k \in K_i}[w_{k,i} \cdot \Sigma_{c \in S_k} rf_c^t]}{{}_{k \in K_i}[w_{k,i} \cdot \mid \{c : c \in S_k\}]} \ldots (2)$$

In the equation (2), i indicates each occupation; K_i is the set of tasks in occupation i, and S_k is the set of verb-noun pairs extracted from task $k \in K_i$; $w_{k,i}$ is a weight of task k within occupation i.[15] In other words, the $Exposure_{i,t}$ is translated as the intensity of patenting activity in technology t which is related to the tasks in that occupation. A challenge of following Webb (2020) is applicability of the method to the Korean case. As explained above, the exposure rate is computed based on the US data. After constructing the exposure scores to each technology, Webb (2020)) merges it to IPUMS data to obtain the individual level of demographic information as well as labor market outcomes. In order to conduct this procedure, the author matches the O∗NET occupation classification codes with David Dorn's Occupational Schema which uses the job task data from Dictionary of Occupational Titles (DOT) released by U.S. Department of Labor[16](Dorn (2009)). DOT released the job description based on Functional Job Analysis; Human Resources Development Services of Korea (HRDSK), which is a subordinate body of Ministry of Labor and Employment of South Korea, regulates the job description follows the functional job analysis as well; HRDSK released a standard job description heavily based on the U.S. system.(Joo et al. (2011)) Furthermore, due to the global movement and the influence of culture, the job description from O∗NET is likely to transport for the same job overseas. (Taylor et al. (2008)) With recognition of the caveat that the transportability of job description across the countries should be conducted, taking into account of the detailed situation of each firm, we still believe that the similarity of the job description and the method to construct the job description allows us to use Webb (2020)'s exposure scores.

Figure 5 compares employee characteristics depending on the occupations' exposure to robotization as of 2019. Figure 5.A shows average exposure score of occupations (weighted by employment in 2019) across different education groups. The graph confirms a canonical trend: the workers categorized in the lower education level (low skill) are more exposed to robotization. This has been proved by many previous studies that used data from other countries (Dauth et al. (2021), Acemoglu and Restrepo (2015), Aghion et al. (2020), Webb (2020)). Figure 5.B plots occupations' exposure percentile against average wage (in logs) .[17] The graph shows that the most exposed occupations have the lowest wages while high wage

[15] $w_{k,i}$ is an average of the frequency and the relevance of task k to occupation i, as in the O∗ database
[16] This was the previous platform of O∗NET
[17] marker size is proportional to the number of employed in a given occupation.

occupation are less exposed. Nonetheless, for the largest mass of employed there is no clear relationship between the wage and the exposure score of their occupation. Figure 5.C plots the occupations' exposure percentile against the average age of the employed. Overall, the graph illustrates that older workers are more exposed to robotization than younger ones. Interestingly, the graph shows the reversed result from Webb (2020), who conducted a similar analysis for the US labor market. We view this divergence from the U.S labor market as a consequence of the combined effect of a stereotype in manual work and high education boom. Since the early 1990s, the general conception of the occupations related to manual task or manufacturing sector have been transit from 'typical work of the breadwinner' to 'inferior work for non-educated workers.' With an increasing trend in pursuing the high education in South Korea, the workforce newly enters into labor market has a strong preference to work at non-manual sectors where requires more analytic tasks.[18] Furthermore, with the economic boom after the late 1990s, South Korea presents a rapid growth in producing high skilled workers. The proportion of 25-64 year-olds who have attained a general degree at the upper secondary or post-secondary level is higher than the proportion of 55-64. Considering that lower educated workers are more associated with the higher robot exposure percentile, the graph C is possible to be translated as a result reflecting the educational attainment gap between the different generation.

Figure 5.D plots average exposure percentile for occupations by percent of female workers. This shows that occupations where the female share is high are less exposed to robots than occupations with more male workforce. Being consistent with figure 4, the current graph exhibits that men are more clustered into the manufacturing sector that faces more robot adoption while females are more dominant in the sector less exposed to robot such as secretary, call center agent, etc.

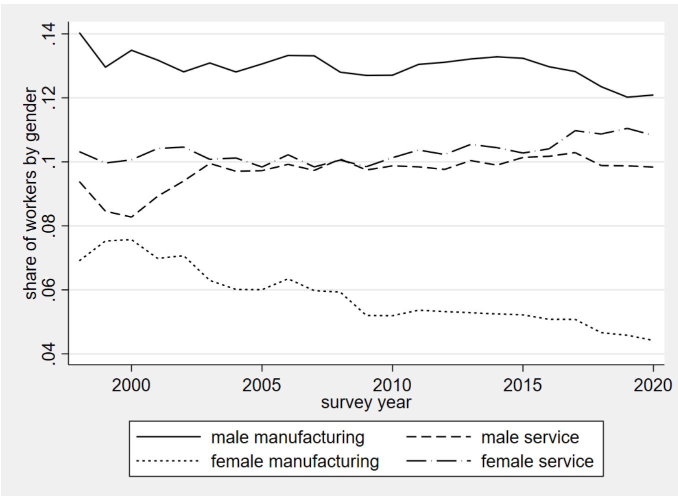

Figure 4: **Manufacturing and service sector workers by gender**

Source: Labor data by KLIPS

Note: The graph shows the share of workers of manufacturing and service sectors based on the total number of employed workers each year.

[18]According to the survey,which was conducted in 2018 by Cho (2021), the youth have a strong occupational preference for services or other career paths than manual works or manufacturing sector

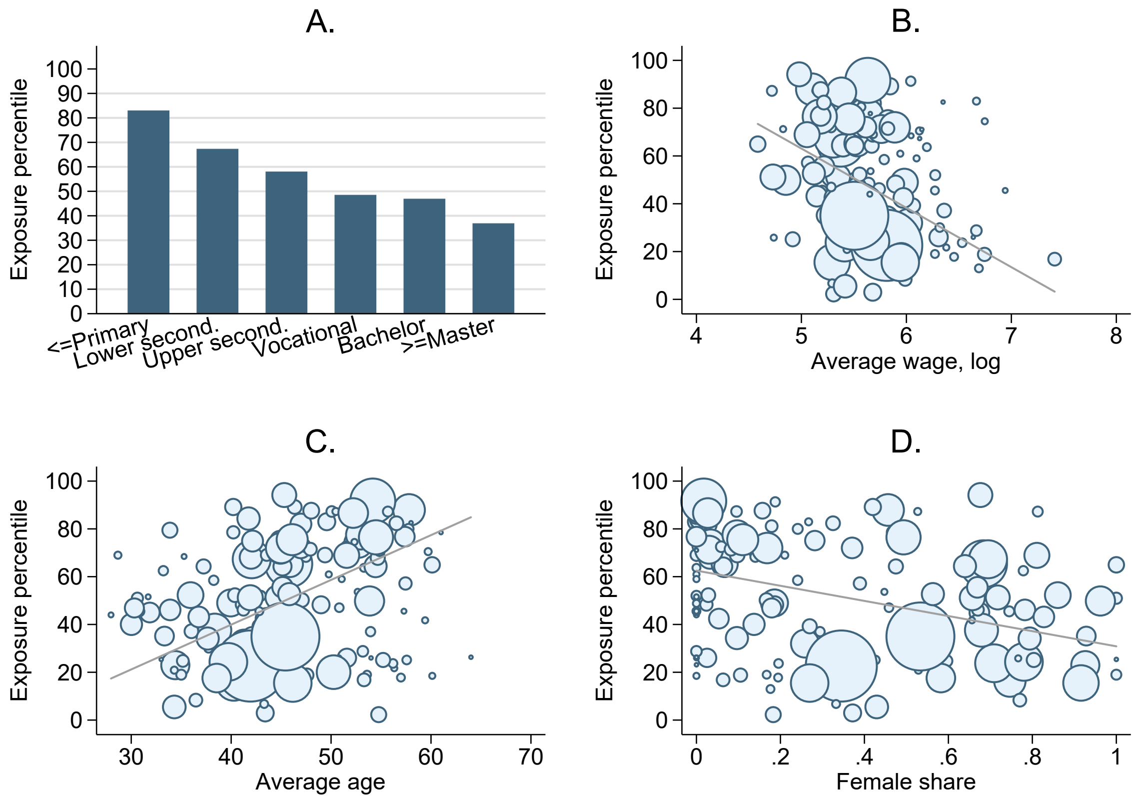

Figure 5: **Robot Exposure and Employees' Characteristics in Korea, 2019**

Source: Robot exposure data by Webb (2020), KLIPS 2019 *Note:* The sample is limited to observations in 2019, employed individuals between 20 and 65 years old. Unit of observation - occupation, 3-digit code. Marker size is proportional to the number of employed in a given occupation. Cross-sectional weights for 2019 are applied.

2.4 Additional Robot Adoption data

We also conduct an empirical analysis, following the Dauth et al.(2020). For this, we employ robot database including the robot installations and the operational stock of robots at the industry level provided by the International Federation of Robot (IFR). We adopt the definition of robot from IFR: automatically controlled, reprogrammable, and multipurpose machines (IFR., (2016)). The industrial classification of this database is following the 3-digit ISIC Rev.4 codes in which the information is available for manufacturing equipment. The drawback of using the robotic data from IFR is lack of information on robot adoption in non-manufacturing sector; to investigate the Korean case, robotic data on non-manufacturing sector should be paid more attention. In 2017, the President of South Korea established the 4th Industrial Revolution Committee directly under the President, and declared the 4th Industrial Revolution Response Plan (I-Korea 4.0, hereafter). The core purpose of this plan is to invest in high technology to promote smart robots, smart factories, smart cities, etc. The expected consequence of this investment is to ensure global competitiveness of Korean firms based on their enhanced productivity and innovation. The government includes a strategy to expand the development and usage of service robot within this plan in order to prevent the issues caused by aging population. Believing that the service robot usage will improve the quality of life; and therefore the productivity of workers, the government selects three local governments to import 1,150 service robots within two years through a demonstration plan, which will formally across the country after 2020 (Market Prospect, (2020)). Our main empirical analysis allows us to iron out the limit of database from IFR; yet we include our test based on IFR information in order to compare the outcome with other previous studies.[19]

3 Baseline Effect

In this section, we displays our baseline results for the impact of robot exposure on employment and wages.

Before turning to the regression analysis, we characterise general trends. Figure 6 plots employment levels and average wages (normalized to 1999) in manufacturing for two groups of occupations: those with robot exposure above or equal to the median (high exposure) and those below the median (low exposure). First, we confirm that employment of the high exposure group declines faster than that of the low exposure group (employment in manufacturing has been decreasing in general). The divergence between high and low exposure groups starts to widen after 2009, which corresponds with the acceleration in robot adoption following the financial crisis, as can Figure 2. Furthermore, the difference persists and widens after 2012. On the other hand, the wage changes of high and low exposed occupations follow a similar upward pattern. In general, high exposed occupations have higher wages until 2019; after 2019, the wage of low exposed occupation has outstripped the high exposed. This is an opposite result from the US wage changes observed by Webb (2020). In the U.S case, the higher occupations are exposed to robotization, the lower wages are given to the workers. To estimate the effect of automation on the employment and wages in Korean labor market, we follow the empirical strategy from the Webb (20020) as below.

$$\Delta y_{o,i,t} = \alpha_i + \beta Exp_o + \gamma Z_o + \epsilon_{o,i,t}$$

[19]Due to the limited data access that we face currently, our IFR data usage is restricted only to present the relationship between the penetration rate and changes in working hours.

Our outcome variables are changes in total employment and manufacturing employment, or the log changes in wage, on the predicted robot exposure scores, with o indicating occupation (3-digit level KSCO 7), i industry (2-digit level KSIC 10), and t year, from 2000 to 2019. The employment change is measured according to DHS changes. DHS is a symmetric measure of the growth rate defined as the difference of two values divided by their average (Honnibal and Johnson (2015)). In terms of constructing a wage estimation, we use the log change in real monthly wages of workers in each occupation-industry cell. On the right-hand side, we include Exp_o which is the exposure of the occupation to robots. In the vector of Z_o, we control for female shares, age and education structure, and log wages as of 1999. We also include the industry fixed effects to ensure that our results are not driven by contemporaneous industry-specific shocks such as change in trade or offshoring. Hence, our results exploit only within-industry variation in occupations' exposure to robotization.

Including our control variables, we attempt to address several endogeneity issues in which our model possibly has. First, we concern the changes on the labor supply side which might affect our results. During our observation periods, the Korean government executed two significant educational reforms which could affect the changes in workers' skill upgrades (Lee et al. (2006)).[20]; this could reduce the supply of low skill workers. In order to attribute the results of our empirical specifications solely to robot exposure, we address this issue by controlling for the share of education of workers in 1999.

Second, as another concern of the change in labor supply side, we concern the large changes in demographics of workers. We pay attention on the female labor and ages of labors. As we demonstrate previously[21], the female labor supply steadily increases during our observation period. Furthermore, age could be a significant factor affecting the South Korean labor outcomes since the society is categorized as a hyper-aging society(Kim and Kim (2020)). Lastly, we consider other circumstances unrelated to robotization which might cause the fluctuation in wages. To relax on this issue, we control for a log wage and its square of occupation.

The result of our empirical approach is summarized in Table S2. To interpret the result of our regression correctly, one should remember that these results are not simply showing that the employment in occupations exposed to robots has decreased; the result shows that the particular occupations exposed to robots more than others within each industry receive negative impact by robotization than those that are less exposed.

Column 1 shows the employment change from 2000 to 2019 with the presence of all control variables. We find that the employment difference from 2000 to 2019 has a negative association with exposure to robot which is consistent with the Figure 6. We also look at the employment change only in manufacturing sector as well; we figure that robot adoption leads a declining employment share with a slightly larger impact than it has for the total employment rate change. With the spirit of Frey and Osborne (2017), we attribute the larger impact of robot exposure at manufacturing sector to higher compatibility of its tasks with robots. Unlike non-manufacturing tasks, which requires interpersonal skills or analytic mind, manufacturing sector consists of repetitive tasks. The result gives us a point that the displacement effect is stronger in manufacturing sector than non-manufacturing sector.

In column 2, we repeat the analysis using the difference in monthly log wages as the outcome variable. In contrast to the employment, we have a very small and statistically insignificant effect. This result

[20] The 6th (applied for the elementary and high school students who were registered in 1995-1998 school system) and 7th (applied for all primary and secondary students registered in 2000-2002 school system) reforms are conducted; one of the aims of the reforms is to enhance students' IT related skills

[21] Also, refer to the appendix

Table S2: **Association between employment and wages and robot exposure**

VARIABLES	(1) Employment change 2019 - 2000 all industries	(2) Difference in log wage 2019 - 2000 all industries	(3) Employment change 2019 - 2000 only manufacturing	(4) Difference in log wage 2019 - 2000 only manufacturing
Exposure pct	-0.008*	-0.001	-0.009*	-0.002
	(0.004)	(0.002)	(0.005)	(0.002)
Female share, 1999	-0.681***	0.160	-0.760*	0.047
	(0.224)	(0.117)	(0.418)	(0.136)
Average age, 1999	-0.012	-0.001	-0.016	-0.022**
	(0.011)	(0.006)	(0.013)	(0.009)
Share of medium-edu, 1999	0.009	0.110	-0.573	-0.387
	(0.310)	(0.200)	(0.506)	(0.257)
Share of high-edu, 1999	0.052	0.105	-0.352	-0.385
	(0.341)	(0.215)	(0.475)	(0.319)
Log wage, 1999	-2.849**	-0.887	-2.858**	-1.376
	(1.070)	(1.005)	(1.155)	(1.291)
Log wage sq., 1999	0.238**	0.057	0.263*	0.109
	(0.117)	(0.099)	(0.140)	(0.129)
Observations	296	271	107	99
R-squared	0.259	0.326	0.338	0.441
Clusters	53	51	21	21
FE	Industry	Industry	Industry	Industry

Notes: The table presents the association between changes in employment/wages and robot exposure in South Korea. The sample is limited to individuals between 20 and 65 years old. Two-way standard errors (in parentheses) at occupation and industry level. *** p<0.01, ** p<0.05, * p<0.1

suggests that stayers in more exposed occupations were on average more positively selected, as higher skilled individuals are more likely to be complements rather than substitutes to robots.

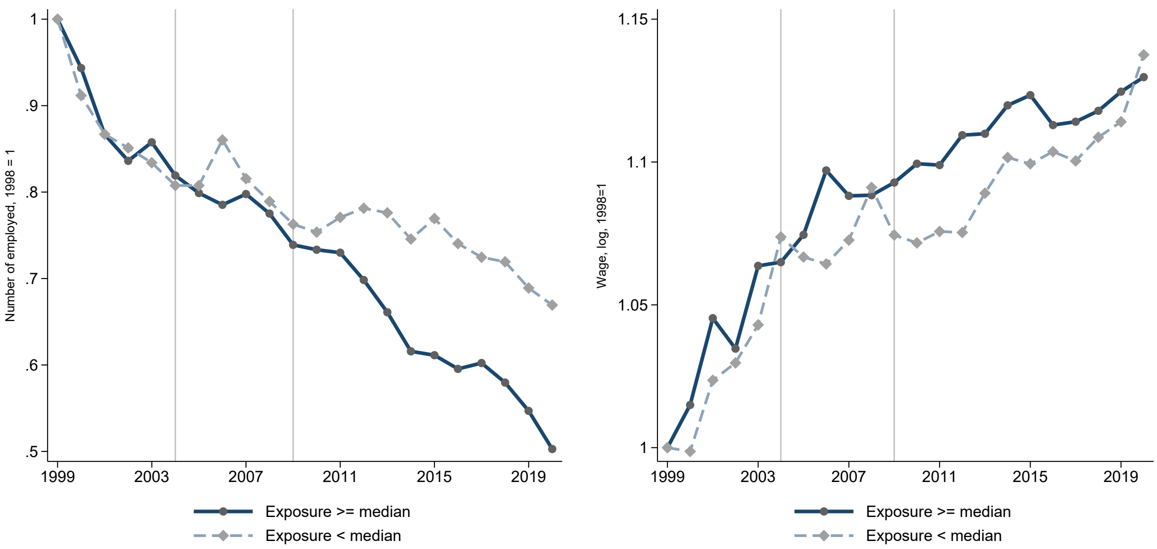

Figure 6: **Employment and wages vs. exposure to robots**

Source: Robot exposure data by Webb (2020), KLIPS

Note: The sample is limited to individuals between 20 and 65 years old, working in the manufacturing sector. Workers are divided into high- vs. low-exposure groups based on the robot exposure percentile in their occupation. Employment level and wages are normalized to 1999 - the first available year. Panel weights for 1999-2020 are applied.

4 Conclusion

Previously many studies have investigated the effect of automation on the labor market. South Korea is one of the leading countries in terms of robot industry developments notwithstanding only small empirical study pays attention to the Korean labor market movement caused by the robot adoption. This paper has focused on the labor adjustment as a consequence of automation. Based on the newly developed method to compute the exposure of occupations to robots, we observe the longitudinal labor market data from 1999 to 2019, provided by KLIPS. Aligning with other previous study, we confirm that low-skill occupations are more exposed to robots than high-skill occupations. The observed effect is rather small but our result reports that the occupations exposed to higher robot adoption receives more negative impact in terms of their employment and wage changes than the occupations less exposed to robot within the same industry. Our analysis has a novelty that the current empirical analysis is based on a new method which has not been conducted for the Korean labor market study. Despite of the possible improvement/extension of the study, our result provides a political implication for the countries whose robot adoption is lagged, therefore, at its fundamental stage to construct a policy to establish the well adjusted labor market to the automation: the massive investment by has been generated by the government to boost the robot adoption in each industry and more investments are planned for promoting the robot adoption by Korean firms. Contradicting to their bolstering plan for the technology, South Korea is also the very first country who introduced 'Robot tax' in 2017 to reduce the tax incentive that each firm had been benefited by employing more robots for their production[22]; the government has announced the law with the acknowledgement of possible displacement effect caused by robots. We look at those government's effort to support labor market to function harmonically with robotization as a cause of weak effect of robotization on employment change in occupational level. This suggests the possibility that appropriate policies can generate an economy where firms and workers both are benefited from automation. Therefore, developing an advanced model which allows us to understand more comprehensive role of policies related to the automation and its consequence of labor market will be a promising direction of the current study.

[22] In 2017, Moon administration officially announced the two percent drop in the available deduction to slow down the growth of automation (Vigliarolo (2017)).

A Appendix

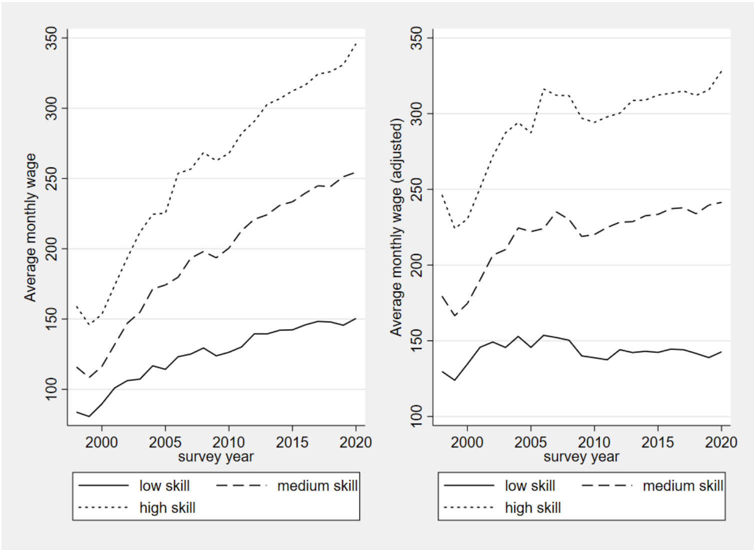

Figure A.1: **(adjusted)Average monthly wage per skill (in 10,000 won)**

Source: Labor data by KLIPS

Note: The skill level is divided into three level: high, medium and low according to the International Standard Classification of Education (ISCED). The price is adjusted with CPI base year 2015, from the Statistics Korea.

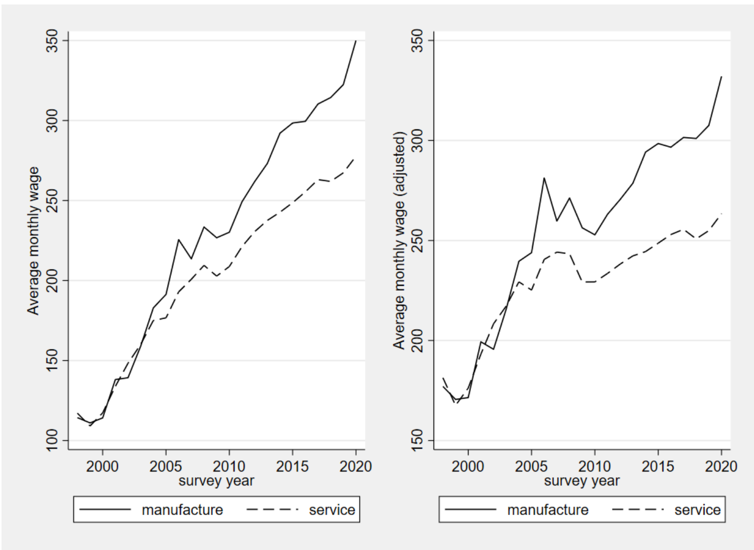

Figure A.2: **(adjusted)Average monthly wage by manufacturing and service workers (in 10,000 won)**

Source: Labor data by KLIPS

Note: The price is adjusted with CPI base year 2015, from the Statistics Korea. The sample is limited to the full workers in the manufacturing sector and service sector. We did not include the workers who are engaged in both sectors.

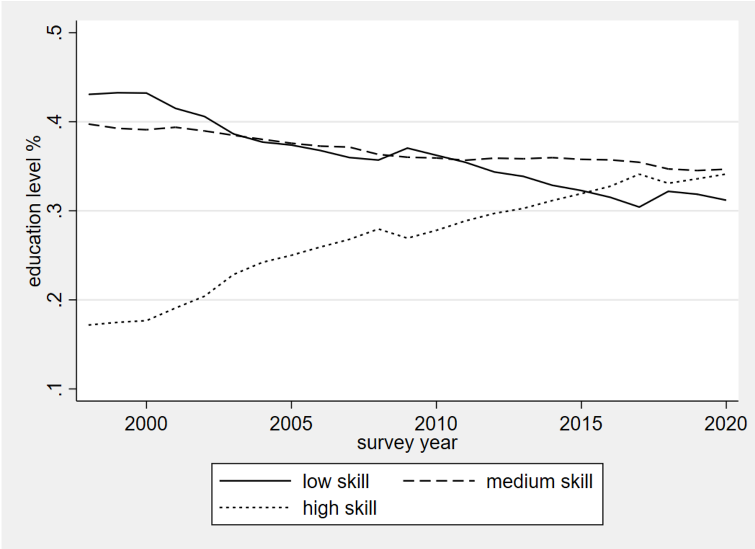

Figure A.3: **Education level growth**
Source: Labor data by KLIPS

Note: education levels are classified into six levels: no education, less than high school, high school graduated, university drop-out or in progress, job college graduated and university graduated or higher than university. According to the International Standard Classification of Education, we categorize the 6 education level into three: low, medium, high skill.

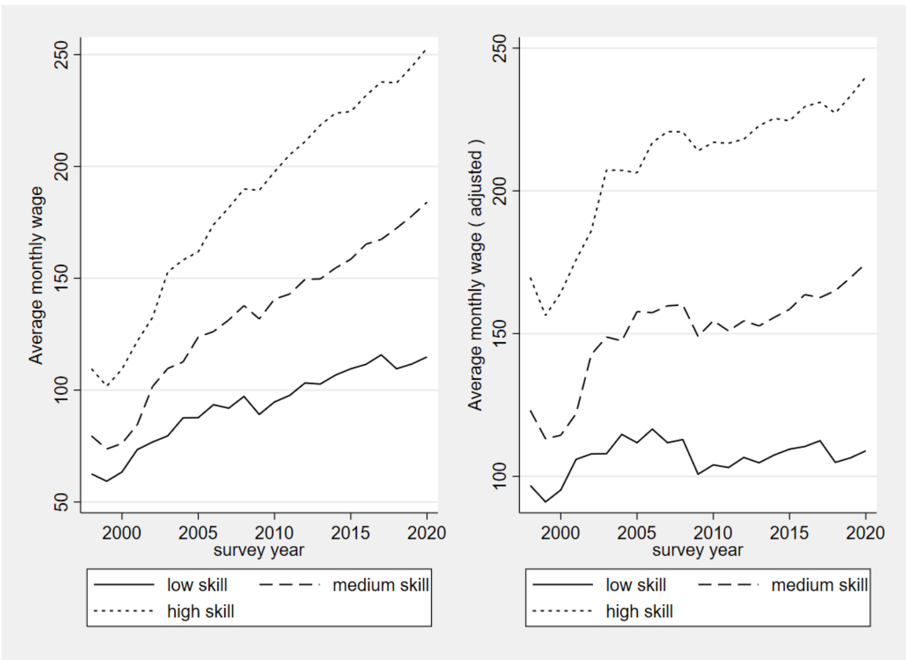

Figure A.4: **(adjusted)Average wage per female skill level(in 10,000 won)**

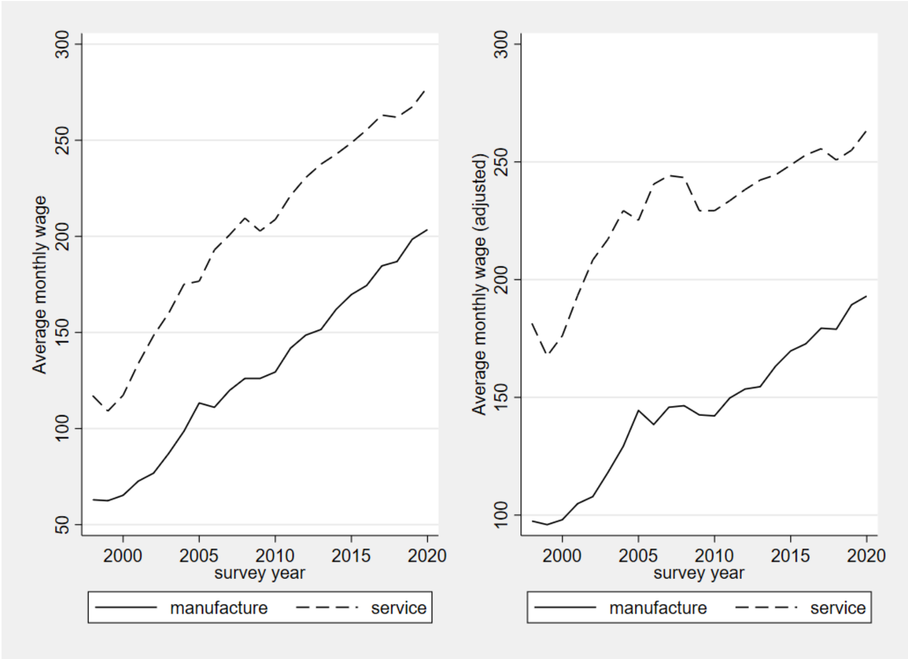

Figure A.5: **(adjusted)Average monthly wage by manufacturing and service female workers (in 10,000 won)**

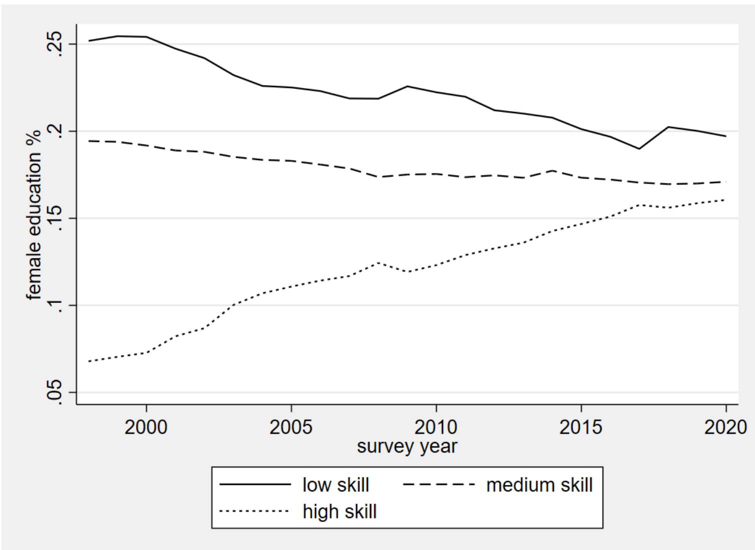

Figure A.6: **Female education level to total female**

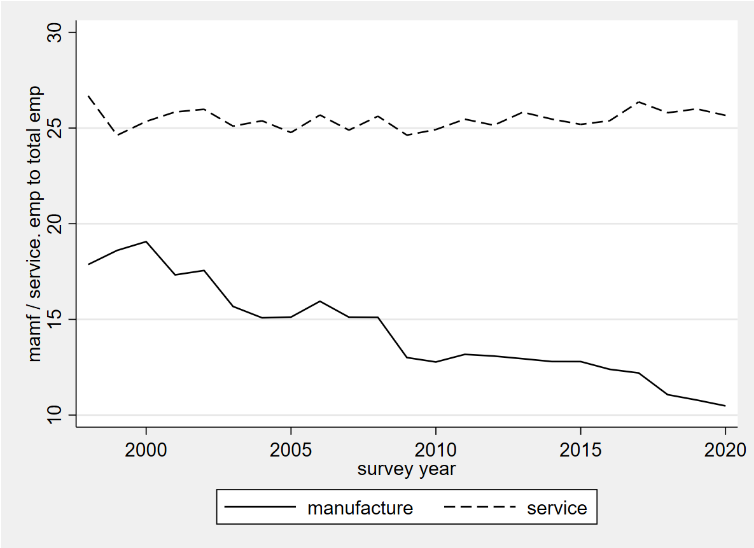

Figure A.7: **Manufacturing/service employees to total employees**

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2021
한국노동패널
학술대회

[제3주제]

노동조합

1. Anti-Authoritarian Attitudes after Democratic Movements : Evidence from the June Struggle of 1987 in South Korea

2. 노조도구성과 노동조합 가입의사의 관계에 대한 종단연구 : 잠재성장모형을 중심으로

3. 노동조합을 통한 근로자간접참여의식과 인사관리유형 및 조직몰입 사이의 종단적 관계