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Is there labor demand shift due to “Routine-biased technological change” in Korea?

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Abstract: Recently routine biased technological change (RBTC) is pervasive in developed countries with the development of technologies which are efficiently possible to replace human labor source. This study find evidence for RBTC in Korea from 1993 to 2015, using panel analysis. The change employment structure shows decline in middle-skilled group and concurrent rise in high-and low-skilled groups. The empirical result confirms that routine intensive occupations are more vulnerable to job loss.

I. Introduction

The development of Information & Communication Technology (ICT) has promised the new era of the smarter and more connected society, but this promise might not be for all. There have been fears that human would be replaced by computer since its appearance. Fear against AI, automation and related job destroying is prevalent in our society. Many studies have dealt with what automation or technology will do to jobs, but no one could make agreement on the numbers or give a clear diagnosis, ranging from optimistic to devastating(Erin Winick, 2018). Some researchers (Boston Consulting Group, 2015; Bowles, 2014; Frey & Osborne, 2013) study how many jobs are to be at risk of automation or computerization. In spite of those pervasive fear, computers or machines do not directly replace an occupation. Instead, the introduction and progress of technology make some tasks of an occupation more favorable to be substituted. Reduction in the cost and promotion in the speed of developing technologies boost replacement of tasks codified (D. H. Autor, Katz, & Kearney, 2009)- including not only computers but machine learning, developments in smart factory with internet of things, artificial intelligence and mobile robotics. New jobs can be created and outdated jobs can be faded over time. But the core

tasks that is essence of an occupation would exist, still performed by human or replaced by machine. Taking into the consideration that, it is important to take task-based or skill-based approach toward forthcoming labor market.

With this task-based approach, an occupation can be regarded as complex of manual, routine and abstract tasks. In a word, development of ICT would affect the labor demand for routine or codifiable task-intensive workers, not affecting directly the certain workers or occupations which are mainly, but not exclusively, performed by middle-skilled workers. This labor shift is explained by “Routine-biased technological change (RBTC)” hypothesis, explaining polarization of work, decreasing the demand for middle-skilled workers relative to high- and low-skilled workers (D. H. Autor, Levy, & Murnane, 2003; Cortes, 2016; Goos & Manning, 2007; Spitz-Oener, 2006). This is an alternative hypothesis for “Skill-biased technological change (SBTC)”, which emphasizes the role of rising wage premiums in growing wage inequality associated with the development of ICT (Card & DiNardo, 2002; Katz & Murphy, 1992; Michaels, Natraj, & Van Reenen, 2014). Because SBTC concentrates on concurrent rising in demand and wage for high-skilled group, it overlooks another rise in low-skilled group and fails to explain the polarizing phenomenon (Acemoglu & Autor, 2011).

Recently RBTC is observed in many developed countries such as US, UK, Germany, Japan and so on. There are considerable researches on wage inequality caused by global trade or outsourcing and SBTC with development of ICT in Korea (Kang & Hong, 1999; Kwack, 2012; H. Lee & Sim, 2016; S. Lee, 2017). But little study has been done in the view of RBTC (Kim, 2015). The aim of this paper is to elaborate the effect of technology spread on labor skill demand change and to figure out RBTC phenomenon between 1993 and 2015 in Korea.

The paper is organized as follows. The next section describes the data and the measure of routineness of occupation. In Section III, before modeling, the general progress of job polarization in Korea is covered and depicted by showing the employment share change and the relationship between the measure of routineness of tasks and wage. The two-stage production model for analyzing the effect of RBTC is explained in the latter part. It presents the polarization of employment structure in Korea and the outcome of analysis.

We discuss the collusion in Section IV. An appendix reports supplement of analysis.

II. Data

A. Employment and Wage

The main source of employment and wage is the ‘Survey Report on Wage Structure’ and ‘Survey on work status by employment type’ released by Ministry of Employment and Labor from 1993 to 2015. For the demand of labor data, the total monthly working hour and the number of workers in each occupation of each industry are used. Total monthly working hour is the sum of normal working hours and overtime working hours. The analysis results are not affected by the measure of labor demand when using the number of persons employed instead of the total monthly working hours. From 1993 to 2015, the classification code for occupation and industry has been changed. For industry, Korean Standard Industrial Classification (KSIC) was revised in 1998, 2000 and 2007 and for occupation, Korean Standard Occupational Classification (KSCO) was revised in 2000 and 2007. For analysis of data across classification system crosswalks are used at major (1 digit) level for industrial classification and sub-major (2 digits) or minor (3 digits) levels for occupational classification.

B. Routineness of Occupations

Autor, Levy, and Murnane (2003) first designed the measure of occupation task requirements from the Dictionary of Occupational Titles (DOT)- nonroutine analytic tasks, nonroutine interactive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks. This model permits to measure the tasks performed in occupation and capture the routineness of each occupation. On their following research, collapse ALM’s original five task measures to three task aggregates for abstract, routine, and manual tasks¹. Combining these three measures, a summary measure of routine task-

¹ Abstract task measure is the average of ‘GED Math (nonroutine analytic tasks)’, measuring general educational development, mathematics and ‘Direction, Control, Planning (nonroutine interactive tasks)’, measuring adaptability to accepting responsibility for the direction, control, or planning of an activity. Routine task measure is the average of ‘Set Limits, Tolerances, or Standards (routine cognitive tasks)’, measuring adaptability to situations requiring the precise attainment of set limits, tolerances, or standards and ‘Finger Dexterity (routine manual tasks)’, measuring ability to move fingers, and manipulate small objects with fingers, rapidly or accurately. Manual task is ‘Eye Hand Foot Coordination (nonroutine manual tasks)’, measuring ability to move the hand and foot coordinately with each other in accordance with visual

intensity RTI by occupation is calculated as the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual and standardized to have unit standard deviation and mean zero.

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

Table 1 RTI measures of 10 major occupational groups

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

RTI is based on the U.S. Census Occupational Classification (COC). To calculate the RTI for KSCO, as Statistics Korea offers a crosswalk between KSOC and International Standard Occupational Code (ISCO) 08, crosswalks between ISCO 08 and US Standard Occupational Classification (SOC) 2010, SOC 2010 and SOC 2000, SOC 2000 and COC 2000 are used. Table 1 is the result of conversion for 10 major occupational groups and

stimuli.

Column 4 in Table 2 is using the n-RTI. As higher value means an occupation is more routine intense therefore more vulnerable to automation.

C. Industry Output, Prices, and Costs

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

III. Understanding and Estimating the employment structure of Korea

A. Job Polarization in Korean Labor Market

Table 2 and Figure 1 show a snapshot of change in the Korean employment structure between 1993 and 2015. Occupations are ranked by skill level, which is approximated by the occupational mean wage in 1993². For the sake of intuitive understanding, low-skilled group means three lowest-paying occupation group, four middling occupations for middle-skilled group, and high-skilled group refers three highest-paying occupations from Table 2. Higher RTI means more routine-intensive occupation and thereby high-skilled groups have relatively low RTI compared to middle-and low-skilled groups. ‘Craft and related trades workers’ and ‘Elementary workers’ have relative higher RTI compared to occupations in the similar wage group, because those are manual-intensive ones apparently from Table 1.

2 Autor and Dorn (2013) regard wage percentile as skill percentile.

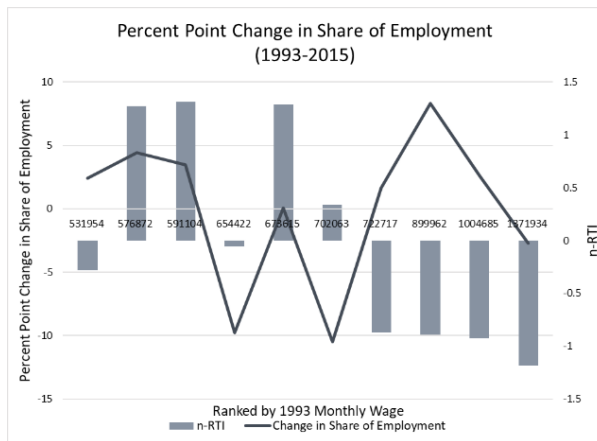
Table 2 Changes in the Share of Employment, 1993-2015

	Occupation ranked by mean monthly wage in 1993	Average employment share in 1993 (%)	Percent point change 1993-2015	Rate of change 1993-2015	RTI
		(1)	(2)	(3)	(4)
High-paying occupations	Administrative, executive and managerial workers	4.47	-2.72	-60.80	-1.18
	Professionals	10.39	2.60	25.05	-0.93
	Technicians and semi-professionals	5.15	8.31	161.40	-0.89
	Clerical Workers	25.23	1.65	6.52	-0.87
	Equipment, machine operating and assembling workers	28.24	-10.46	-37.03	0.34
	Skilled agricultural, forestry and fishery workers	0.17	0.06	33.29	1.29
	Craft and related trades workers	17.27	-9.77	-56.57	-0.06
	Service workers	1.85	3.47	187.06	1.31
Low-paying occupations	Sales workers	1.76	4.45	253.09	1.27
	Elementary workers	5.47	2.42	44.13	-0.28

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

Figure 1 Changes in the Share of Employment, 1993-2015

(a) Percent point change



(b) Rate of change

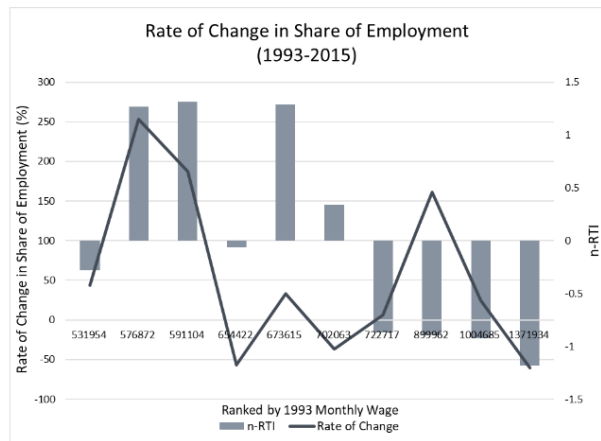


Figure 2 Changes in the Share of Employment in three skill group (1993-2015)

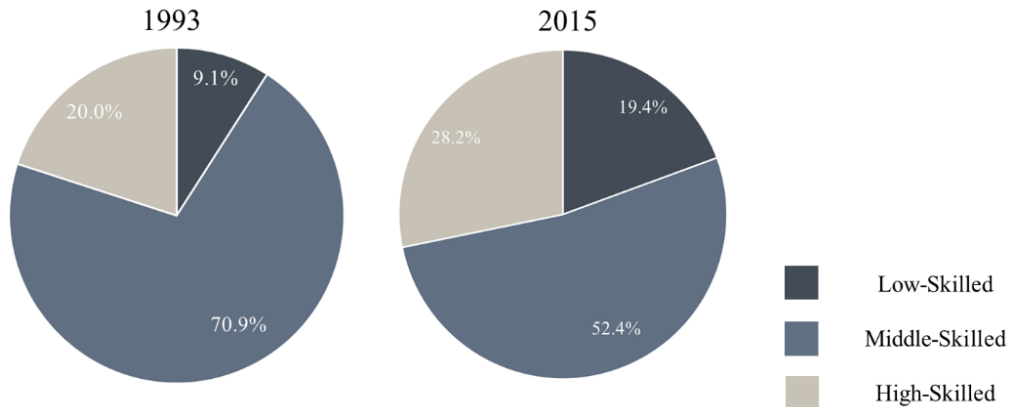


Figure 1 (a) and (b) explains the demand growth change during about two decades for middle-paying group or middle-skilled group is relatively low compared to two ends of wage groups and relatively high for low-skilled group. SBTC argues that the labor demand for high-skilled has risen as technology developed over time, but not in this case. It stands for that the employment structure change in Korea cannot be explained by SBTC. Although the center of Figure 1(a) looks like W-shape, it is just because the center occupation group ‘Skilled agricultural, forestry and fishery workers’ is only 0.17% in employment share, so sensitive in percent point change. From Figure 2, the employment share of the middle-skilled group has decreased in 28.5 percent point while the demand for the low- and high-skilled group has increased 10.3 and 8.2 percent point relatively. There has been significant decrease in ‘Equipment, machine operating and assembling workers’ and ‘Craft and related trades workers’ which covered about half of employment in 1993.

Higher paying occupations seem to have low but RTI is calculated by subtraction of sum of abstract and manual task, lower RTI does not guarantee the higher wage as shown in the case of ‘Craft and related trades workers’ or ‘Elementary workers’. The correlations between components of RTI measure and monthly wage are tested for sub-major or minor occupational groups, 86 groups in 1993 and 87 groups in 2015. This test can reveal the relation between the characteristics of occupations and wage. According to the analysis, although the degree of routineness does not have significant relation to monthly wage,

occupations more intense in abstract tasks have positive relation with higher monthly wage. The negative relation between RTI for manual tasks and wage is also significant in 2015 (Table 3). The result of pairwise correlations of abstract, routine, and manual index confirms that each component has weak correlations (Appendix Table A1). The result of multicollinearity test of RTI components is in Appendix Table A2 which mean variance inflation factors (VIFs) is 1.05 for 1993 and 1.04 for 2015. This implies that the abstract characteristic does have positive relation with wage and the polarization in skill group could lead polarization in wage eventually.

Table 3 Relation between skill characteristic of occupation and wage

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

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

B. Estimating the job polarization: The structure of model

We borrow and modify the model of Goos, Manning, and Salomons (2014). To explain the pervasive job polarization in 16 Western European countries, they estimated the effect of RBTC and offshoring on job polarization, reporting that RBTC plays much more important than offshoring³. Offshoring cannot explain the whole industry level of polarization while suitable for some routine tasks in production but poorly suited to

³ Firpo, Fortin, and Lemieux (2011) also argued technological change and offshorability have different impact on wage polarization.

service occupations (D. H. Autor & Dorn, 2013). So we test whether technological change has impact on job polarization in Korea.

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

$$(1) \quad Y_i(T_{i1}, \dots, T_{ij}, \dots, T_{ij}) = \left[\sum_{j=1}^J [\beta_{ij} T_{ij}]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \text{ with } \eta > 0,$$

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

$$C_i^I(c_1^T, \dots, c_i^T, \dots, c_j^T | Y_i) = Y_i c_i^I(c_1^T, \dots, c_i^T, \dots, c_j^T) \text{ for } j = 1, \dots, J$$

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

$$(2) \quad T_{ij}(c_1^T, \dots, c_i^T, \dots, c_j^T | Y_i) = Y_i t_{ij}(c_1^T, \dots, c_i^T, \dots, c_j^T)$$

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

$$(3) \quad T_{ij}(N_{ij}, K_{ij}) = N_{ij}^\kappa K_{ij}^{1-\kappa} \text{ with } 0 < \kappa < 1,$$

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

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

$$C_{ij}^T(w_j, r_j | T_{ij}) = T_{ij} c_j^T(w_j, r_j),$$

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

$$(4) \quad N_{ij}(w_j, r_j | T_{ij}) = T_{ij} n_j(w_j, r_j),$$

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

In this model, RBTC is assumed to affect the costs of employing an effective unit of the other input which means

$$(5) \quad \frac{\partial \log r_{jt}}{\partial t} = \gamma_R R_j, \text{ with } R_j \text{ the routineness}$$

Substituting equation (2) into (4), taking logs and using equation (5) gives an expression for the log demand of occupation j in industry i conditional on industry output and marginal costs. Time subscripts are added below:

$$(6) \quad \log N_{ijt} = -[(1 - \kappa) + \kappa\eta] \log w_{jt} + [1 - \eta][1 - \kappa]\gamma_R R_j \times \text{time} \\ + \eta \log c_{it}^l + \log Y_{it} + (\eta - 1) \log \beta_{ij} + \varepsilon_{ijt}$$

As routineness of tasks increases the labor demand is to decrease over time. Given that the coefficient γ_R is expected to be negative and if $\eta < 1$, then $[1 - \eta][1 - \kappa]\gamma_R$ is also negative⁴.

C. The result of estimation

In Goos, Manning, and Salomons (2014), Equation (6) predicts job polarization within each industry, using the estimation of coefficient $[1 - \eta][1 - \kappa]\gamma_R$ as RTI measure

⁴ Goos, Manning, and Salomons (2014) set occupational wages by a set of occupation and time dummies because of poor quality of wage data. In this paper wages are included as shown in equation (6).

interacted with a linear time trend regression with occupation-industry fixed effects and year fixed effects. Instead of linear regression for time trend, this paper set data as panel, with 126 occupation-industry groups (14 major industrial groups and 9 major occupational groups). After testing heteroscedasticity and auto-correlation, pooled generalized least squares (GLS) estimation is used to give variation in industry, occupation and time fixed effect. The test results are available in Table A3, all have heteroscedasticity and first order autocorrelation at 1percent significant level, so heteroskedastic and common AR(1) correlation for all panels are assumed for analysis. And the estimation results are reported in Table 4.

Table 4 The result of panel analysis on labor demand, 1993~2015

VARIABLES	(1) log monthly total working hour	(2) log monthly total working hour	(3) log number of persons employed	(4) log number of persons employed
RTI	-0.0285*** (0.00466)	-0.0310*** (0.00423)	-0.0318*** (0.00462)	-0.0326*** (0.00418)
log monthly wage		-0.742*** (0.137)		-0.713*** (0.137)
log industry output		0.643*** (0.0572)		0.646*** (0.0569)
log industry marginal cost		0.646*** (0.117)		0.653*** (0.117)
Constant	12.34*** (0.159)	3.298 (2.383)	7.022*** (0.157)	-2.586 (2.392)
Observations	2,770	2,770	2,770	2,770
Number of ij	126	126	126	126

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The results in column 1 &3 contain occupation-year and industry-year fixed effects and columns 2 &4 contain year fixed effects. Standard errors are clustered by occupation-industry.

Column 1 is the estimation of coefficient of $[1 - \eta][1 - \kappa]\gamma_R$, modeling occupational wages by a set of occupation and time dummies and industry output and industrial marginal costs by industry-year dummies. η is the elasticity of substitution and is larger than 0 and smaller than 1 from equation (3), meaning that $[1 - \eta][1 - \kappa]$ has positive so γ_R would have negative value, if labor demand growth is decreased. As expected, the coefficient has negative value (-0.0285) and statistically significant at the 1 percent level. Table 4 is the result of using both log of total monthly working hour (column 1&2) and

log the number of persons employed (column 3&4) for $\log N_{ijt}$. When the number of persons employed is used instead for $\log N_{ijt}$, the result is similar and also significant at 1% level– RTI coefficient -0.0318.

From the Table 4, it could be interpreted that an occupation with one standard deviation more routinized (higher RTI), the labor demand for it grows 2.85 percent points less fast each year. In column 2 the coefficient of log industry marginal cost, η is positive and significant as predicted. But the coefficient of log industry output is less than unit which assumed to be constant returns to scale in goods production. This might be because two decades are not enough time for industrial output to be reflected by employment⁵. The coefficient of log monthly wage estimates $-\left[(1 - \kappa) + \kappa\eta\right]$ in equation (6), the rise in wage would reduce the labor demand.

Table 5 Relation between Skill Characteristic of Occupation and Labor Demand

VARIABLES	(1) log monthly total working hour	(2) log number of persons employed
RTI_Abstract	0.00302 (0.00915)	0.00337 (0.00923)
RTI_Routine	-0.0268*** (0.0101)	-0.0295*** (0.0103)
RTI_Manual	0.0421*** (0.00599)	0.0415*** (0.00596)
log monthly wage	-0.353** (0.163)	-0.323** (0.163)
log industry output	0.655*** (0.0558)	0.656*** (0.0561)
log industry marginal cost	0.662*** (0.117)	0.668*** (0.117)
Constant	-2.353 (2.657)	-8.156*** (2.673)
Observations	2,770	2,770
Number of ij	126	126

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

⁵ The result of Goos, Manning, and Salomons (2014) shows the same, explaining as: ‘*This is perhaps not surprising given that short-run movements in output are often not reflected in employment*’. As they use linear regression, they constrain the coefficient of industrial output to be 1. This constraint is not allowed for panel analysis so the constrained coefficient is omitted in this paper, but the result of output and marginal cost show comparable, confirming the result of this study.

In the previous part, each component of RTI measure has different impact on wage respectively. Table 5 shows similar relation between skill characteristic of occupation and labor demand change. Replacing R_j to three components of RTI in equation (6), the coefficient of each component explain the relation between the characteristic of occupation task and the labor demand change over time. The results report that labor demand changes for occupations demanding manual tasks have grown from 1993 to 2015, which could be suitable for explaining the increase of low-skilled occupations. At the same time, the demand growth for routine task takes slow. We should not declare that abstract tasks are only for high-skilled and manual ones are exclusively for low-skilled occupations. But putting together Table 1, 2, and 3, high paying occupations are more specialized in abstract tasks, and the labor demand for those grows faster than others from Table 5. The discussion on polarization in wage is beyond scope of this paper but as the employment share of high-skilled has grown shown in Figure 1, the possibility for wage polarization can be also referred based on overall results.

IV. Discussion & Conclusion

This study states the change of employment structure in Korea from 1993 to 2015. For change in employment share, the increase in high- and low-skilled groups are at expense of the decrease in middle-skilled groups. The simultaneous rise in some low-skilled occupations and decline in high-skilled reveals the limitation of skill biased technological change (SBTC) for elucidating changes of labor market in Korea. To figure out more persuasive way for explaining the phenomenon, the framework accounting for how routine-biased technological change has affected the employment structure is applied to Korean case. The analysis confirms the empirical evidence regarding polarization that labor demand for high-skilled (performing abstract tasks) and low-skilled (performing manual tasks) are in rise, on the other hand, for middle-skilled is in decline. By decomposing into three characteristic components of occupation – abstract, routine, and manual–, occupations with more intense in abstract tasks give chance for higher wage and more manual specific occupations for higher employment. The analysis the results for each occupational group are not significant so we couldn't verify the RBTC

empirically for each occupation, although 12 of 14 industries show higher RTI will slow down the labor demand at 1% significant level. Finding the better way for relating each occupational groups remains as further study for us.

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

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Appendix

Figure A 1 Relation between RTI and Monthly Wage

A. Monthly wage in 1993

B. Monthly wage in 2015

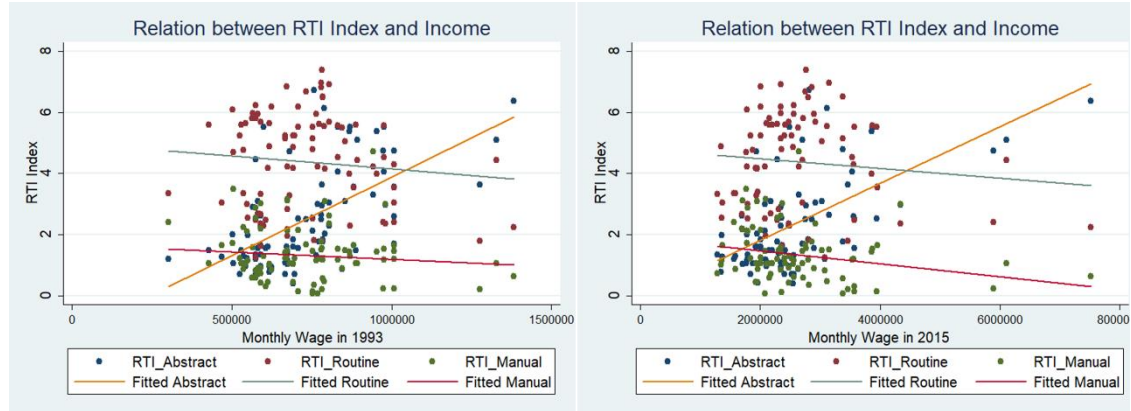


Table A 1 Pairwise correlations of RTI components

	RTI_Abstract	RTI_Routine	RTI_Manual
RTI_Abstract	1		
RTI_Routine	-0.1927	1	
RTI_Manual	-0.1439	0.0089	1
Number of obserbation	87		

Table A 2 Multicollinearity Test Results (VIFs)

Variable	log wage 1993		log wage 2015	
	VIF	1/VIF	VIF	1/VIF
RTI_Abstract	1.07	0.932126	1.06	0.945179
RTI_Routine	1.05	0.954525	1.06	0.946193
RTI_Manual	1.02	0.975845	1.01	0.985747
Mean VIF	1.05		1.04	

Table A 3 Heteroscedasticity and auto-correlation test for Table 4 &5

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

Notes: All have heteroscedasticity and first order autocorrelation at 1percent significant level. Columns 1-4 for Table 4 and 5-6 for Table 5

