Letter

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Unions and Automation Risk: Who Bears the Cost of Automation?

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Abstract: Automation creates winners and losers. By examining establishment-level panel data, we explore how labour unions affect labor adjustment associated with automation. Although automation can increase new hires of junior and unskilled production workers, the presence of labour unions neutralizes these effects. The results suggest that labour unions have incentives to protect incumbent workers negatively affected by automation.

Keywords: robotics, automation, job, union

JEL Classification: O32, O33, J51

1 Introduction

The employment effect of automation is one of the most significant challenges of our time. While countervailing evidence exists on the overall effects, most studies commonly highlight the heterogeneous effects by task, occupation, age, and education (Acemoglu and Restrepo 2022; Arntz, Gregory, and Zierahn 2017; Battisti and Gravina 2021; Blanas, Gancia, and Lee 2019).

This paper adds to the literature by considering an underexplored dimension through which automation can affect employment outcomes: labour unions. The canonical insider-outsider theory states that labour unions tend to protect the incumbent workers (Lindbeck 1988; Lindbeck and Snower 2001; Sanfey 1995).

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If automation threatens the employment of union members, labour unions have incentives to block or bargain over automation. Unions might do so to prevent technical change from weakening the coalition between workers with different skills (Acemoglu, Aghion, and Violante 2001). Therefore, when the management accepts the union's demand to implement automation, the employment cost of automation may fall on those who may benefit from automation, including potential entrants.

However, this question has rarely been addressed by economists. This is surprising given that the role of labour unions has regained research attention despite rapid de-unionization underway over the past three decades (Naidu 2022). To our knowledge, Belloc et al. (2022) is the only study investigating the question of unions and automation. They find that labour unions and automation risk have a negative relationship. However, their analysis does not reveal which group of workers bears the cost of automation risk within nations and firms.

Our paper offers micro-level empirical evidence for how labour unions moderate the effect of automation on employment outcomes. Using a Korean establishment-level panel dataset, we compare the patterns of employment changes due to automation between establishments with and without unions. We find that automation could cause a new hire of young, unskilled workers though labour unions neutralize the effect to protect senior skilled workers. As a result, reallocation through hires and separations is also limited. Our results, consistent with the standard theory of labor unions, provide a useful insight into the effect of automation.

2 Data and Empirical Strategy

We used the Workplace Panel Survey (WPS) for the empirical analysis, a biannual survey conducted by the Korea Labour Institute. The advantage of this panel dataset is that it collects various information from establishments on employment and industrial relations, such as workforce composition, human resources management, labour unions, and conventional firm performance outcomes.

We limit the scope of our analysis to small and medium establishments with less than 300 employees for two reasons. First, small and medium firms account for 99.9 percent of the firms and 81.3 percent of the total employment in the Korean manufacturing sector. Second, automation and unionization may correlate with firm size. While the unions at large workplaces show powerful bargaining power, they do not represent the business population. Table 1 reports the descriptive statistics.

We estimate the effect of automation on employment outcomes using the following specification, separately by union status, and compare the patterns.

Table 1: Descriptive statistics.

Variable	Mean	SD	Min	Max
Hiring rate	0.155	0.243	0	7
Separation rate	0.184	0.491	0	18
Junior workers (age < 35)	0.293	0.208	0	1
Production workers	0.484	0.277	0	1
Unskilled workers	0.068	0.175	0	0.971
New automation	0.181	0.385	0	1
Degree of automation at $t-1$				
0–20%	0.066	0.248	0	1
20–40%	0.118	0.323	0	1
40–60%	0.286	0.452	0	1
60–80%	0.285	0.452	0	1
80–100%	0.245	0.431	0	1
Has a union	0.238	0.426	0	1
Multi-unit status (=1 if part of multi-unit)	0.511	0.5	0	1
ln(wage per worker)	3.864	0.412	2.35	5.173
Ownership (=1 if domestic)	0.957	0.204	0	1
ln(total employment)	4.75	1.076	0	8.808
Observations	1864			

Workplace Panel Survey (2015–2019), South Korea.

$$y_{i,j,t} = \alpha_0 + \alpha_1 A_{i,j,t} + \beta \mathrm{X}'_{i,j,t-1} + \lambda_i + \theta_j + \delta_t + \varepsilon_{it} \quad (1)$$

Measuring automation is the biggest measurement challenge in this literature. Existing studies have employed various proxies, such as automation cost, imports of capital goods related to automation, and answers to survey questions on robot uses (Bessen et al. 2019; Domini et al. 2021; Koch, Manuylov, and Smolka 2021). Considering the high automation rate in South Korea, we focus on *new* automation compared to the previous period rather than automation levels. For automation, the survey includes a question that asks whether the establishment automated a part of the production process ("Compared to the previous year, is there any new automation that occurred in the product/service process?"). Using this question, we define $A_{i,j,t}$ as a binary variable equal to 1 if there was new automation at establishment i.

For employment outcome y_{it}, we consider the hiring and separation rates, the share of junior workers under 35 years old as well as skilled and unskilled production workers in wave t. Our outcome variables parallel Domini et al. (2021), who likewise examine the employment dynamics of automation.

We also include several establishment characteristics in wave $t-1$ as control variables, denoted by $\mathrm{X}'_{i,j,t-1}$. Since new automation has different impacts depending on the initial automation level, we used a dummy variable for each automation level category (0–20%; 20–40%; 40–60%; 60–80% and; 80–100%). We also include a multi-unit dummy, log wage per worker, ownership (domestic/foreign) dummy, and log employment. λ_i, θ_j, and δ_t are the establishment, industry, and year fixed effects, respectively.

Our results from the simple fixed-effects identification may not be sufficient to draw causal interpretations. In particular, the probability of automation may correlate with characteristics of firms such as sales or productivity. To deal with the issue of non-random selection of firms into automation, we follow Guadalupe et al. (2012), Koch, Manuylov, and Smolka (2021), and Domini et al. (2021) that combine a fixed-effect approach with a propensity score reweighting estimation. This allows us to control for time-varying characteristics through the propensity score (Guadalupe et al. (2012)). We suppose that the decision to automate is an outcome of a latent (unobserved) variable A^*_{ijt} so that $\text{Automation}_{ijt} = 1$ if $A^*_{ijt} \geq 0$ and $\text{Automation}_{ijt} = 0$ if $A^*_{ijt} < 0$. Therefore, we first estimate the probability ($\hat{p}$) of observing new automation at time t, in the following pooled logit regression:

$$\text{Automation}_{ijt} = \alpha + \beta \mathrm{X}_{it-1} + \gamma_t + \theta_j + \varepsilon_{it} \tag{2}$$

where X and other variables are defined the same as Eq. (1). Those variables closely match the ones used by Domini et al. (2021) and should control for the relevant observable differences in performance among firms. We find that all these variables positively impact the probability of automation. We then use the propensity scores obtained from the logit regressions to construct firm-specific weights: each automating (treated) firm has a weight equal to $1/\hat{p}$, and each non-automating (control) firm has a weight equal to $1/(1-\hat{p})$, where $\hat{p}$ is the estimated propensity score. Finally, we estimate Eq. (2) using these weights.

3 Results

Table 2 presents the fixed-effect estimation results. Column 3 shows that automation is associated with increases in the separation rate by about 6.1 percentage point, and Column 4 indicate that unions neutralize such effect.

Table 2 also indicates that automation may cause an occupational shift. Columns 5 shows that automation could give opportunities to junior workers below 35 years old. Among production workers, it appears to be related to a reduction in the share of skilled, likely senior, workers (Column 7) and an increase in unskilled workers that are likely junior (Column 9). However, such effects are not found at establishments with labour unions that have incentives to protect senior workers.

Table 3 presents the estimation results from the propensity score reweighting. Controlling for observable and unobservable differences among firms that

Table 2: Effects of automation and union on employment: fixed effect estimation.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Hiring rate		Separation rate		Junior workers (under age < 35)		Skilled production workers		Unskilled production workers	
	No union	Union	No union	Union	No union	Union	No union	Union	No union	Union
New automation	0.047	−0.025	0.061[b]	0.029	0.086[b]	−0.035	−0.170[a]	0.037	0.121[b]	−0.060
	(0.029)	(0.028)	(0.031)	(0.051)	(0.044)	(0.043)	(0.051)	(0.047)	(0.052)	(0.056)
Control variable	o	o	o	o	o	o	o	o	o	o
Year fixed effect	o	o	o	o	o	o	o	o	o	o
Region fixed effect	o	o	o	o	o	o	o	o	o	o
Observations	1063	254	1063	254	1063	254	1063	254	1063	254
R-squared	0.067	0.122	0.077	0.110	0.065	0.053	0.117	0.228	0.102	0.113

[a, b,] and [c] denote significance at 1%, 5%, and 10%, respectively. Workplace Panel Survey (2015–2019), South Korea. Standard errors are reported in parentheses. The following control variables are included but not reported to save space: the degree of automation at $t-1$(0–20%; 20–40%; 40–60%; 60–80%; 80–100%), establishment age, multi-unit status (=1 if part of multi-unit), ln(wage per worker), ownership (= 1 if domestic), and log employment.

Table 3: Effects of automation and union: propensity score reweighting estimation.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Hiring rate		Separation rate		Junior workers (under age < 35)		Skilled production workers		Unskilled production workers	
	No union	Union	No union	Union	No union	Union	No union	Union	No union	Union
New automation	0.056[c]	−0.009	0.068[b]	0.028	0.082[c]	−0.031	−0.154[a]	0.027	0.111[b]	−0.045
	(0.030)	(0.023)	(0.031)	(0.042)	(0.045)	(0.037)	(0.050)	(0.038)	(0.048)	(0.043)
Control variable	o	o	o	o	o	o	o	o	o	o
Year fixed effect	o	o	o	o	o	o	o	o	o	o
Region fixed effect	o	o	o	o	o	o	o	o	o	o
Observations	1063	254	1063	254	1063	254	1063	254	1063	254
R-squared	0.081	0.165	0.096	0.087	0.126	0.101	0.155	0.289	0.145	0.212

[a], [b], and [c] denote significance at 1%, 5%, and 10%, respectively. Workplace Panel Survey (2015–2019), South Korea. Standard errors are reported in parentheses. The following control variables are included but not reported to save space: the degree of automation at $t-1$(0–20%; 20–40%; 40–60%; 60–80%; 80–100%), establishment age, multi-unit status (=1 if part of multi-unit), ln(wage per worker), ownership (=1 if domestic), and log employment.

affect automation, we obtain consistent results; we find sharp differences in the employment outcome of automation again by union status. Columns 1 to 4 show that the unions suppress worker reallocation caused by automation. Without labour unions, automation is associated with an increase in the hiring rate (Column 1) and a decrease in the separation rate (Column 3) by about 5–6 percentage points. However, we do not find such patterns from establishments with unions (Columns 2 and 4).

Similar to the fixed-effect analysis results, Columns 5 to 10 show that automation is associated with an increase in the shares of junior and unskilled production workers and a decrease in the share of skilled, mostly senior, workers at non-union establishments. At unionized establishments, automation does not induce such compositional changes.

Our results are consistent with the insider-outsider theory; it predicts that labour unions would protect incumbent workers, thus impede the creation of new jobs for potential labour market entrants (Lindbeck and Snower 2001; Sanfey 1995). Our analysis demonstrates that automation favors young, less experienced workers and reduce the importance of skilled production workers.

South Korea provides a good example for the union's impact in moderating the automation effect on employment. It has one of the highest robot density in the world (International Federation of Robots 2020). Labour unions are known to be militant and make strong demands (Bae et al. 2008). However, the union membership rate in Korea is still low, 14.2 percent in 2020, which contrasts with European countries, such as Germany (16.3%) or Norway (50.4%). This indicates that labour unions do not represent the overall workforce. Korean scholars have pointed out that senior male workers constitute the largest and powerful group in labour unions and put their interest first – retaining jobs at the cost of new labour market entrants' job opportunities. The widening gap in idea between generations keep young workers from joining unions, accelerating the aging of unions (Chung 2015). Our results corroborate these observations.

4 Conclusion

Policymakers and scholars are constantly faced with the question of who indeed bears the costs of automation. The existing literature has shown a negative correlation between automation and the employment levels of some groups, such as younger workers. Using establishment-level panel data, we investigated how the employment effects of automation differ by labour unions. We obtained a result that is consistent with the insider-outsider theory. While automation can cause reallocation within establishment, replacing senior skilled workers with junior unskilled workers, labour unions neutralize such effects to protect their member workers. Therefore, younger entrants are more likely to bear automation costs. Our results echo the claim that decisions regarding hiring and replacement are not solely driven by technical efficiency (Belloc et al. 2022). We suggest that researchers should pay more attention to the role of labour institutions in assessing the effect of technology on employment.

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References

Acemoglu, D., and P. Restrepo. 2022. "Demographics and Automation." *The Review of Economic Studies* 89: 1–44.

Acemoglu, D., P. Aghion, and G. L. Violante. 2001. "Deunionization, Technical Change, and Inequality." *Carnegie-Rochester Conference Series On Public Policy* 55 (1): 229–64.

Arntz, G., T. Gregory, and U. Zierahn. 2017. "Revisiting the Risk of Automation." *Economics Letters* 159 (2017): 157–60.

Bae, K., J. Yoon, H. Cho, and J. Lee. 2008. "Korean Labour Unions and Labour Movement Since 1987 (in Korean)." In *KLI Research Paper*. Korea Labor Institute.

Battisti, M., and A. F. Gravina. 2021. "Do Robots Complement or Substitute for Older Workers?" *Economics Letters* 208 (2021): 110064.

Belloc, B., G. Burdin, L. Cattani, W. Ellis, and F. Landini. 2022. "Coevolution of Job Automation Risk and Work Place Governance." *Research Policy* 51 (3): 1–18.

Bessen, J., M. Goos, A. Salomons, and W. Berge. 2019. "Automatic Reaction – What Happens to Workers at Firms that Automate? No. 19-2." In *Law and Economics Research Paper*. Boston University School of Law.

Blanas, S., G. Gancia, and S. Lee. 2019. "Who is Afraid of Machines?" *Economic Policy* 34 (100): 627–90.

Chung, J. W. 2015. "The Aging of Labor Unions and Young Employment (in Korean)." In *Labor Review*. Korea Labor Institute.

Domini, G., M. Grazzi, D. Moschella, and T. Treibich. 2021. "Threats and Opportunities in the Digital Era: Automation Spikes and Employment Dynamics." *Research Policy* 50 (7): 104–37.

Guadalupe, M., O. Kuzmina, and C. Thomas. 2012. "Innovation and Foreign Ownership." *American Economic Review* 102 (7): 3594–627.

International Federation of Robot. 2020. *World Robotics Report*.
Koch, M., I. Manuylov, and M. Smolka. 2021. “Robots and Firms.” *The Economic Journal* 131 (638): 2553–84.
Lindbeck, A., and D. J. Snower. 1988. *The Insider-Outsider Theory of Employment and Unemployment*. Cambridge: MIT Press.
Lindbeck, A., and D. J. Snower. 2001. “Insiders versus Outsiders.” *The Journal of Economic Perspectives* 15 (1): 165–88.
Naidu, S. 2022. “Is There Any Future for a US Labour Movement?” *The Journal of Economic Perspectives* 36 (4): 3–28.
Sanfey, P. J. 1995. “Insiders and Outsiders in Union Models.” *Journal of Economic Surveys* 9 (3): 255–84.