Industrial Robots and Job Satisfaction

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Despite the recent surge in the empirical literature about the effects of robotization on labor market outcomes, most studies focus on aggregate labor market outcomes. By employing the conventional method of constructing Bartik-type regional robot exposure and combining with KLIPS, we find that robotization is associated with a reduction in job satisfaction. While the panel analysis shows somewhat greater negative effects, the long-difference analysis suggests that the negative effects might be attenuated over the long run. However, it shows that robotizaton since 2012 made young workers feel less satisfaction, particularly about worsening employment stability and workplace communication.

Key Words : robotization, automation, job satisfaction

Ⅰ. Introduction

Since the "rise of robots" generated widespread fears of technological job destruction, economists have investigated how automation affects labor markets. Much of the existing studies take the local labor market approach. Using the information about the robot installation at workplaces, they construct synthetic measures of the exposure to automation risk at the local labor market (metropolitan statistical area (MSA) for the United States) and associate with the observed changes in employment outcomes. Acemoglu and Restrepo (2020) is one of the seminary studies in this vein of research. They find that robotization suppressed employment and wages.

The literature has developed in the direction of examining more micro-level data to better understand how firms determine technology adoption and employment adjustment. Firm-level studies also show more subtle nature of automation that it is driven by not only cost-saving but more strategic motivation, implying that job destruction may not be a natural consequence.

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They also reveal much heterogeneity across firms. For example, Koch et al.(2021) use Spanish manufacturing data from 1990 to 2016 and present that robot-adopting firms tend to be larger, more productive, and exporters. They also find that robot adoption increases the employment and performance of firms probably because they had plans for work redesign, task reassignment, and worker training and reallocation. Similarly, Domini et al.(2021) analyze French manufacturing firms from 2002 to 2015 and found that the net employment rate of automating firms has increased. Other works also suggest that job-related concers about automation may be overestimated (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Borjas and Freeman, 2019; Mokyr et al., 2015; Bessen et al., 2019).

Recent studies give more focus to various aspects of individual life, including education, voting decision, family formation, and health. (Giuntella et al. 2022; Anelle et al. 2021a, Anelli et al. 2021b) Giuntella et al. (2022) explore how Chinese individuals and families responded to increased exposure to robots. They find that more exposed workers increased their participation in technical training and were significantly more likely to retire earlier. While there was no evidence of an effect on marital behavior, they document that robot exposure led to a small decline in the number of children. In addition, they find that robot exposure increased family time investment in the education of children as well as the investment in children's after-school academic and extra-curricular activities. In the US case, Anelli et al. (2021a) show that changes in labor market structures that affect the absolute and relative prospects of men may reduce their marriage-market value and affect marital and fertility behavior.

Some scholars investigate how automationis related to political orientaton and voting behaviors.

Colantone and Stanig (2019) introduce notable works. Anelli et al.(2021b) investigate the impact of industrial robot adoption on individual voting behavior in 13 western European countries between 1999 and 2015. They argue that a higher exposure to robot adoption pushes voters toward nationalist and radical-right parties and away from mainstream parties on both the left and right sides of the political spectrum. Likewise, Thewissen and Rueda(2019) find vulnerability to automation to be an important determinant of the demand for redistribution. Im et al.(2019) argue that automation threat is most likely to increase support for radical right parties. Dal Bò et al. (2023) find that the share of automation vulnerable workers in a municipality is positively associated with support for the Sweden Democrats radical-right party. Frey et al.(2018) document that the support for Donald Trump was significantly higher in local labour markets more exposed to the adoption of robots.

This paper extends the literature by examining how automation and job satisfaction. Despite recent studies, still little is known about how workers and households may adjust to these labor market shocks (Dauth et al., 2021b). Using the Korean Labor and Income Panel Study (KLIPS), we evaluate how past automation is associated with subjective well-being of survey respondents.

Ⅱ. Literature

How automation would affect job satisfaction? The existing literature suggests various channels including the nature of the work, individual preferences, and the overall context in which automation is implemented.

1) Task allocation: Automation often involves the delegation of repetitive and mundane tasks to machines or software. This can free up employees to focus on more meaningful and complex aspects of their work, leading to increased job satisfaction. When individuals are relieved of tedious tasks, they may have more opportunities for creativity, problem-solving, and engaging in tasks that require human judgment and skills.

2) Skill utilization: Automation can require workers to acquire new skills or adapt existing ones to work alongside machines. This process of upskilling or re-skilling can contribute to job satisfaction by providing opportunities for personal and professional growth. When employees are equipped with the necessary skills to effectively collaborate with automated systems, they can feel more confident and satisfied in their roles.

3) Job security and displacement: Automation can raise concerns about job security, particularly if certain tasks or job roles become redundant. Employees may experience lower job satisfaction when they perceive automation as a threat to their livelihoods. However, job displacement can also lead to new opportunities as individuals transition to tasks that are less easily automated, potentially leading to increased job satisfaction in the long run.

4) Workload and control: The introduction of automation can affect the workload and level of control employees have over their work. While automation can increase productivity and efficiency, it may also lead to increased expectations and work intensity. If employees feel overwhelmed or have limited control over their work processes due to automation, it can negatively impact job satisfaction. Striking the right balance between automation and human involvement is crucial to maintaining job satisfaction.

5) Psychological and social factors: Job satisfaction is influenced by various psychological and social factors. Some employees may find satisfaction in working alongside automation, feeling empowered by the technology and the ability to accomplish tasks more efficiently. On the other hand, individuals who derive satisfaction from social interactions and human connections in the

workplace may experience a decline in job satisfaction if automation reduces interpersonal interactions.

South Korea provides unique features to investigate the relationship between automation and job satisfaction. First, South Korea has one of the highest robot densities in the world, indicating a significant presence and adoption of robotics in various industries. According to the International Federation of Robotics (IFR) data from 2020, South Korea had a robot density of 855 industrial robots per 10,000 employees, making it one of the leading countries in terms of robotic automation. The high robot density in South Korea reflects the country's focus on advanced manufacturing, including industries such as automotive, electronics, and semiconductors. South Korean firms have heavily invested in robotics and automation technologies to enhance productivity, improve quality, and maintain a competitive edge in global markets. The South Korean government has played a crucial role in promoting robotics and automation. It has implemented policies and initiatives to support research and development in robotics, foster industry-academia collaboration, and encourage the adoption of automation technologies in various sectors. These efforts have contributed to the significant robot density in South Korea.

Second, South Korean workers have been known to face high levels of stress due to various factors in the work environment.

1) Long working hours: South Korea has had a culture of long working hours, with employees often facing extensive overtime and a lack of work-life balance. This prolonged working time can lead to physical and mental fatigue, contributing to increased stress levels among workers.

2) Competitive work environment: South Korea has a highly competitive job market, and workers often face pressure to excel and meet high performance standards. The competitive nature of the workplace can create a stressful atmosphere, where individuals may feel compelled to work longer hours and strive for perfection.

3) Hierarchical work culture: South Korea has a hierarchical work culture, where respect for authority and seniority is deeply ingrained. This can create additional stress for workers, particularly when they need to navigate complex power dynamics and adhere to strict workplace hierarchies.

4) Job insecurity: Concerns about job security can contribute to stress among South Korean workers, especially in industries affected by economic fluctuations or restructuring. Fear of layoffs and the need to maintain employment stability can significantly impact mental well-being and increase stress levels.

5) High expectations and performance pressure: South Korean society places a strong

emphasis on academic achievements and success in the workplace. The pressure to meet societal and family expectations, perform well, and secure promotions can lead to heightened stress levels among workers.

6) Limited social support: South Korean workers may experience limited social support systems within the workplace due to the competitive and demanding nature of the work environment. This lack of support networks can further exacerbate stress levels and impact overall well-being.

The net effect of automation on job satisfaction will be the sum of all. While testing each channel will be necessary to shed light on the mechanism, our analysis draws on the empirical studies that focus on estimating the reduced-form effects on subjective well-being and mental health. For example, Schwabe and Castellacci (2020) studies the extent to which automation affects workers' job satisfaction. Using Working Life Barometer survey of Norway for the period 2016–2019, automation induced 40% of the workers that are currently in employment to fear that their work might be replaced by a smart machine in the future causing negative effects on workers' job satisfaction at present. O'Brien et al. (2022) present evidences that increases in automation over the period 1993–2007 in the US led to substantive increases in all-cause mortality. In particular, they find evidence that automation is associated with increases in drug overdose deaths, suicide, homicide, and cardiovascular mortality, although patterns differ by demographic characteristics. Nazareno and Schiff (2021) considers five hypothetical channels through which automation may impact workers' wellbeing: influencing worker freedom, sense of meaning, cognitive load, external monitoring, and insecurity. Based on a 2002–2018 dataset from the General Social Survey, they reveal that workers facing automation risk appear to experience less stress, but also worse health, and minimal or negative impacts on job satisfaction. In addition, these impacts are more concentrated on workers facing the highest levels of automation risk.

For Korea, existing works focus on physical health. Kim(2023) examines the effect of robots on workplace injuries and workers' health in South Korea. She finds that increase in robot exposure reduces workplace injuries, and attributes this to the reallocation of workers towards less physically intensive tasks. Gunadi and Ryu(2020) find evidences that higher penetration of industrial robots in the local economy is positively related to the health of the low skilled population. Overall. there are growing studies to understand the various impacts of automation on individual life, more attempts still require to reveal the unknown facts. Our study adopts a similar approach to these studies as we use the local-level exposure to robotization. However, our study is distinct in the sense that we examine individual-level outcomes using panel data, whereas they construct and analyze the city/county-level data.

Ⅲ. Empirical Strategy and Data

1. Empirical Strategy

Our empirical strategy follows Giuntella, Yi, and Wang (2022), which associates city-level robot penetration and examine how it affects individual outcomes. The specification can be expressed as follows:

where is robotization risk of region (city and county) j at time t, and measures individual's various subjective well-being. is a vector of various individual-level covariates, such as gender, education, and industry.

Robotization exposure is calculated following the previous literature, using the International Federation of Robotics (IFR)'s data. These data are based on yearly surveys of robot suppliers and contain information for 70 countries from 1993 to 2019 covering more than 90 percent of the industrial robot market. The IFR data provide the operational stock of industrial robots", which are defined as automatically controlled, reprogrammable, and multipurpose [machines]" (IFR, 2014).

Like most studies using the IFR data, we follow Acemoglu and Restrepo (2020) to construct . We exploit variations in the pre-existing distribution of industrial employment across cities and counties and changes in the amount of robots across industries, measured at the nation level, to create a measure of robots penetration:

where is the share of industry s in the baseline year. We first construct robot density of each industry, , which denotes the number of robots in industry s in year t divided by the number of workers in industry s in the baseline year. We selected 2004 and 2012 as baseline years and will conduct analysis for two periods, 2004-2012 and 2012-2019. Then we use the differences in the industrial composition among regions to create the robot exposure that varies by region. We use the employment share of industry s in the region j using the 2000 the Survey of Establishmtnt which provides employment information for all enterprises in Korea.

Because there can be unobserved factors that affect both robotization and labor market outcomes, such as various industry promotion policies or product demand shocks. If a positive demand shock occurs in a specific industry, that industry can simultaneously increase robot adoption and employment in order to produce more goods. In such cases, the ordinary least squares (OLS) estimates for the aforementioned model tend to be overestimated. Therefore, economists commonly construct Bartik-type instrument variable by using another country's robot adoptions, indicated as s' in the definition below. In this paper, we chose Singapore, Germany, Taiwan as they also an export-oriented country that are aggressive in installing robots for improving export competitiveness. In the robustness section, we present the estimated results using the number of robot adoptions from alternative countries, such as developed countries in Europe or China, to investigate the sensitivity of the estimates to the countries used as instrumental variables.

Using the instrumented robot exposure indicator, we conduct the long-difference analysis and an panel analysis using annual data. Our panel data analysis uses a common specification as below:

where various individual characteristics, , and region and time fixed effects are included.

Like many other existing studies, we employ the standard specification for long difference to express the equation of the changes in robot penetration and outcome variables. Doing so, we control for unobserved city-level factors.

We have three observations years: 2004, 2012, and 2019. Thus we use two intervals for the long-distance analysis. We conduct a long-difference analysis for each interval and a panel analysis for both. Long-difference analysis has some advantages when assessing the effect of technology on labor market outcomes as it takes time for individuals and firms to adjust according to what new technology requires. Sometimes they choose to exit the current industry and enter new one, which is captured not by high-frequency panel data analysis but by long-difference analysis.

2. KLIPS Data

This study examines the Korean Labor and Income Panel Study (KLIPS). The KLIPS is a longitudinal survey of urban households in Korea modeled after a set of successful panel studies, including the Panel Study of Income Dynamics (PSID) of the United States and the Socio-Economic Panel Study (SEOP) of Germany. Starting in 1998, the KLIPS has surveyed a nationally representative sample of 5,000 urban households and their members aged 15 years or older. We utilize the data from the 2001 and 2005–2010 when the survey collected the informaton about the respondents' health perception and behaviors.

The KLIPS collects detailed information on individuals, including their employment, hours worked, earnings, education, and other demographic and household characteristics. In addition to a survey on labor market activities and income, a supplemental survey on respondents' health behaviors was conducted in 2001. In 2005, a set of questions on health-related behaviors was added to the regular survey questionnaire.

For the dependent variable, this paper uses several questions regarding job satisfaction. In addition to overall job satisfaction, KLIPS asks job satisfaction with respect to compensation, employment stability, job content, work environment, work hours, career development, communication and interprsonal relationship, fair human resource management, and employee welfare.

Ⅳ. Estimation Results

1. Panel Data Analysis

We first present the general pattern in Table 2. The table reports only the coefficient for robot exposure and omit those for other covariates and fixed effects due to limited space. Column 1 of each Panel reports the results for overall job satisfaction and Columns 2 to 9 job satisfaction in specific areas. Panel A and B report the results from the pooled OLS and instrument variable analysis for the period 2004-2012. Panel C and D report the pooled OLS and IV results for 2012-2019. Panel A and B show somewhat different results. For example, Column 1 of Panel A indicates that robotization led to an increase in overall job satisfaction, whereas Column 1 of panel B suggests that they are not statistically associated. As the IV analysis controls for unobserved characteristics thus is considered to be more credible, our discussion will be based on the IV results.

Panel B suggests that individuals in regions with greater robot exposure between 2004 and 2012 experienced in a reduction in most areas of job satisfaction: employment stability, job content, work environment, work hours, career development, human resource management, and employee welfare. Panel D shows that such patterns persist after 2012. It is noted that overall job satisfaction also decreased, along with satisfaction in work environment, work hours, career development, communication and relationship, human resource management, and employee welfare.

Table 3 explores whether the effects are different for female with the IV analysis results. From the magnitude of the coefficients in Column 1, it can be said that women had a greater job satisfaction decrease in both periods, though the coefficient for overall job satisfaction in 2012-19 is not statistically significant. It is likely to be associated with greater fear of losing their jobs, as shown in Column 3. Women with greater exposure to robotization also have more discontent related compensation and work hours. Although we find a greater decrease in women's job satisfaction, the effects appear to have diminished after 2012, as shown in Panel B.

<Table 2> Robotization and Job Satisfaction: OLS and IV

Panel A. Pooled OLS with Fixed Effects, 2004-2012

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	0.153*	0.251**	-0.119	-0.146	-0.199**
	(0.084)	(0.108)	(0.098)	(0.089)	(0.094)
Obs.	57307	57360	57357	57358	57365
R-Square	0.154	0.103	0.140	0.144	0.164

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.180*	-0.363***	0.062	-0.482***	-0.764***
	(0.101)	(0.093)	(0.085)	(0.100)	(0.120)
Obs.	57361	57365	57333	38457	38598
R-Square	0.148	0.147	0.104	0.112	0.150

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

Panel B. Instrument Variable Analysis Result, 2004-2012

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	-0.010	0.005	-0.044**	-0.048***	-0.086***
	(0.016)	(0.020)	(0.018)	(0.017)	(0.017)
Obs.	57307	57360	57357	57358	57365
R-Square	0.154	0.102	0.140	0.144	0.164

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.099***	-0.076***	0.008	-0.100***	-0.216***
	(0.019)	(0.018)	(0.016)	(0.019)	(0.022)
Obs.	57361	57365	57333	38457	38598
R-Square	0.148	0.147	0.104	0.112	0.151

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

<Table 2> Robotization and Job Satisfaction: OLS and IV (continued)

Panel C. Pooled OLS with Fixed Effects, 2012-2019

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	-0.019	0.053	-0.004	-0.003	-0.095***
	(0.029)	(0.036)	(0.033)	(0.031)	(0.031)
Obs.	66700	66690	66696	66689	66689
R-Square	0.123	0.082	0.109	0.121	0.130

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.071**	-0.122***	-0.031	-0.091***	-0.088**
	(0.034)	(0.032)	(0.030)	(0.033)	(0.044)
Obs.	66690	66690	66688	47201	47200
R-Square	0.113	0.112	0.082	0.112	0.155

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

Panel D. Instrument Variable Analysis Result, 2012-2019

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	-0.024*	0.018	-0.022	-0.014	-0.085***
	(0.013)	(0.017)	(0.015)	(0.014)	(0.014)
Obs.	66700	66690	66696	66689	66689
R-Square	0.123	0.082	0.109	0.121	0.130

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.076***	-0.094***	-0.024*	-0.060***	-0.051**
	(0.015)	(0.014)	(0.013)	(0.015)	(0.020)
Obs.	66690	66690	66688	47201	47200
R-Square	0.113	0.112	0.082	0.112	0.155

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

<Table 3> Robotization and Job Satisfaction: Female

Panel A. Instrument Variable Analysis Result, 2004-2012

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	−0.059**	−0.102***	−0.073**	−0.090***	−0.115***
	(0.025)	(0.032)	(0.029)	(0.026)	(0.028)
Obs.	23089	23108	23106	23112	23113
R-Square	0.170	0.105	0.133	0.186	0.183

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	−0.173***	−0.115***	−0.040	−0.122***	−0.271***
	(0.029)	(0.028)	(0.025)	(0.030)	(0.035)
Obs.	23112	23114	23097	15385	15447
R-Square	0.181	0.174	0.117	0.111	0.138

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

Panel B. Instrument Variable Analysis Result, 2012-2019

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	−0.031	−0.024	−0.042*	−0.037*	−0.103***
	(0.020)	(0.026)	(0.023)	(0.021)	(0.021)
Obs.	27745	27742	27742	27741	27741
R-Square	0.129	0.081	0.097	0.139	0.136

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	−0.101***	−0.112***	−0.036*	−0.095***	−0.105***
	(0.023)	(0.022)	(0.021)	(0.023)	(0.031)
Obs.	27741	27742	27741	19948	19947
R-Square	0.130	0.123	0.088	0.102	0.129

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

We explore further heterogeneity by limiting the scope of analysis to those who were 40 years old or less in the baseline years, 2004 and 2012. The existing literature suggests that automation may have different effects on different ages. For example, Lee and Kim(2023) examine the Workplace Panel Survey(WPS) to show that automation may provide new opportunities for young unskilled workers. But because labor unions have incentives to protect

<Table 4> Robotization and Job Satisfaction: Under 40 in the baseline years

Panel A. Instrument Variable Analysis Result, 2004-2012

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	-0.008	-0.015	-0.074***	-0.071***	-0.102***
	(0.024)	(0.031)	(0.028)	(0.025)	(0.027)
Obs.	22819	22842	22838	22839	22844
R-Square	0.143	0.087	0.120	0.122	0.145

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.148***	-0.059**	0.018	-0.093***	-0.188***
	(0.030)	(0.028)	(0.026)	(0.028)	(0.032)
Obs.	22840	22843	22831	18181	18243
R-Square	0.149	0.127	0.085	0.095	0.136

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

Panel B. Instrument Variable Analysis Result, 2012-2019

DV:	Overall Job Satisfaction	Compensation	Employment stability	Job content	Work environment
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	-0.062***	0.001	-0.025	-0.059**	-0.107***
	(0.022)	(0.028)	(0.026)	(0.023)	(0.024)
Obs.	20847	20841	20843	20842	20841
R-Square	0.116	0.081	0.107	0.096	0.106

DV:	Work Hours	Career Development	Communication & relationship	Fair HR	Employee Welfare
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	-0.121***	-0.111***	-0.050**	-0.072***	-0.045
	(0.027)	(0.025)	(0.023)	(0.024)	(0.032)
Obs.	20842	20842	20842	17583	17584
R-Square	0.106	0.099	0.077	0.096	0.146

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

incumbent workers, they may neutralize such effects of automation by negotiating with the employers. If this is the case, job satisfaction would have fallen among young workers, while old workers are better off as their work environment improves. Otherwise, if old workers are not protected from automation, their job satisfaction would have fallen.

However, Table 4 shows that there is no much difference between the old and the young. Compared to Panel B and D of Table 2, we find the significance and magnitude of the coefficients are more or less similar. Our hypothesis rejects the hypothesis that robotization would have caused a increase, or a much smaller decrease, to the young workers as they have more abilities and skills to work with machines. They share the anxiety regarding automation.

2. Long Difference

In this subsection, we present the results from the long-difference analysis. The general pattern is reported in Table 5. The table reports only the coefficient for robot exposure and omit those for other covatiates and year fixed effect in multiple-period analysis. In each panel, the first three columns report the results from the ordinary least square analysis and the last three columns for the instrument variable analysis using Singapore. Panel A shows the results for all. Column 1 suggests that individuals in cities with higher exposure to robotization experienced an increase in overall job satisfaction. Columns 2 and 3 report the results for each interval and show that it was driven by robotization during 2004-2012. However, the IV results in Columns 4 to 6 show no significant effect on job satisfaction. It implies that there would have existed unobserved factors that affected both job satisfaction and robotization. Panel B limits the sample to males, but it still finds no significant coefficients.

In Panel C, we further limit the sample to male under 40 years old as of the baseline year. This is to capture potentially different responses to automation by age or tenure. While most coefficients appear to be not statistically significant, we find a negative coefficient in Column 18, indicating that young male workers in regions with more robotization exposure would have experienced more reduction in job satisfaction.

Panel D reports the results for male production workers that include machine operators (occupation code starting with 8) and manual workers (occupation code starting with 9). However, we do not find any significant effects. Robotization effect would not have varied by occupation.

<Table 5> Overall Job Satisfaction and Robotization

A. All

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV		
Time	All	2004-12	2012-19	All	2004-12	2012-19
△ Robot exposure	0.488***	2.058*	-0.023	0.267	0.441	-0.104
	(0.166)	(1.234)	(0.184)	(0.162)	(0.307)	(0.194)
Obs.	7223	2970	4253	7223	2970	4253
R-Square	0.029	0.057	0.052	0.028	0.057	0.052

B. Male

	(7)	(8)	(9)	(10)	(11)	(12)
	OLS			IV		
Time	All	2004-12	2012-19	All	2004-12	2012-19
△ Robot exposure	0.179	0.879	-0.256	0.030	0.261	-0.314
	(0.215)	(1.576)	(0.240)	(0.210)	(0.391)	(0.255)
Obs.	4599	1921	2678	4599	1921	2678
R-Square	0.036	0.078	0.067	0.036	0.078	0.068

C. Male, under 40 years old

	(13)	(14)	(15)	(16)	(17)	(18)
	OLS			IV		
Time	All	2004-12	2012-19	All	2004-12	2012-19
△ Robot exposure	-0.013	-0.368	-0.405	-0.200	0.017	-0.664*
	(0.355)	(2.433)	(0.408)	(0.323)	(0.593)	(0.401)
Obs.	1976	899	1077	1976	899	1077
R-Square	0.081	0.165	0.138	0.081	0.165	0.140

D. Male, production workers

	(19)	(20)	(21)	(22)	(23)	(24)
	OLS			IV		
Time	All	2004-12	2012-19	All	2004-12	2012-19
△ Robot exposure	0.123	0.324	-0.134	0.249	0.675	-0.105
	(0.404)	(3.047)	(0.455)	(0.377)	(0.719)	(0.460)
Obs.	1376	581	795	1376	581	795
R-Square	0.127	0.190	0.181	0.127	0.191	0.181

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

Since we found no meaningful patterns on overall job satisfaction, we examine the effect of automation on specific job satisfaction measures and report the results in Table 6. All results are obtained from the instrument variable analysis for 2012-2018.

The results for all sample in Columns 1-5 and 21-24 show that individuals in regions with greater robot exposure experienced in a reduction in job satisfaction with respect to employment stability and communication and interpersonal relationship. Subsample analysis in the following columns also confirm that such concerns are stronger among male, young/production workers. Based on the previous literature, it appears that older workers who are near their retirement feel less anxiety for possible job displacement, while young workers have much longer horizon and have enough reason for having concerns about their employment stability. It is also interesting that young and production workers have more discontent with communication and relationship in regions with more robot exposure. Robotization would have brought less human interactions and it was probably much larger at production lines.

Table 6 also demonstrates that robotization is not associated with more satisfaction regarding job content, work environment, and work hours. While cost-saving motivation can be one of the most important drivers of automation and robot adoption, firm mangers say that work environment improvement is another important goal. However, it is not supported by empirical evidence.

While the long-difference analysis yields more attenuated coefficients, which is commonly seen in the empirical studies of robotization, they also reproduce what the panel analysis demonstrates – robotization appears to have made people feel worse. It is likely because people had more concerns about their employment stability first and found that adapting to a new environment was never easy.

Table 6. Specific Job Satisfaction and Robotization, 2009-2018

	Compensation	Employment stability	Job content	Work environment	Work hours
	(1)	(2)	(3)	(4)	(5)
△ Robot exposure	−0.040	−0.466**	0.220	−0.025	0.172
	(0.227)	(0.230)	(0.210)	(0.218)	(0.222)
Obs.	4254	4254	4254	4254	4254
R-Square	0.039	0.047	0.045	0.051	0.051
Male	(6)	(7)	(8)	(9)	(10)
△ Robot exposure	−0.167	−0.603**	0.139	−0.141	−0.319
	(0.281)	(0.297)	(0.276)	(0.293)	(0.289)
Obs.	2679	2679	2679	2679	2679
R-Square	0.052	0.071	0.066	0.075	0.068
Male, under 40	(11)	(12)	(13)	(14)	(15)
△ Robot exposure	−0.106	−0.823*	−0.274	−0.564	−0.655
	(0.455)	(0.448)	(0.443)	(0.450)	(0.454)
Obs.	1078	1078	1078	1078	1078
R-Square	0.125	0.166	0.143	0.147	0.157
Male, prod workers	(16)	(17)	(18)	(19)	(20)
△ Robot exposure	−0.106	−0.823*	−0.274	−0.564	−0.655
	(0.455)	(0.448)	(0.443)	(0.450)	(0.454)
Obs.	1078	1078	1078	1078	1078
R-Square	0.125	0.166	0.143	0.147	0.157

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

<Table 6> Specific Job Satisfaction and Robotization, 2009-2018 (continued)

All	Career Development	Communication & relationship	Fair HR	Employee Welfare
	(21)	(22)	(23)	(24)
△ Robot exposure	-0.213	-0.439**	0.178	0.049
	(0.214)	(0.204)	(0.226)	(0.274)
Obs.	4254	4254	2467	2468
R-Square	0.058	0.045	0.069	0.064
Male	(25)	(26)	(27)	(28)
△ Robot exposure	-0.167	-0.603**	0.139	-0.141
	(0.281)	(0.297)	(0.276)	(0.293)
Obs.	2679	2679	2679	2679
R-Square	0.052	0.071	0.066	0.075
Male, under 40	(29)	(30)	(31)	(32)
△ Robot exposure	-0.106	-0.823*	-0.274	-0.564
	(0.455)	(0.448)	(0.443)	(0.450)
Obs.	1078	1078	1078	1078
R-Square	0.125	0.166	0.143	0.147
Male, prod workers	(33)	(34)	(35)	(36)
△ Robot exposure	-0.106	-0.823*	-0.274	-0.564
	(0.455)	(0.448)	(0.443)	(0.450)
Obs.	1078	1078	1078	1078
R-Square	0.125	0.166	0.143	0.147

*, **, *** indicate significance at 10%, 5%, and 1%, respectively.
Robust standard errors are in the parentheses.

V. Conclusion

We examined the effect of robotization on job satisfaction. By employeing the conventional method of constructing Bartik-type regional robot exposure and combining with KLIPS, we find that robotization is associated with a reduction in job satisfaction. While the panel analysis shows somewhat greater negative effects, the long-difference analysis suggests that the negative effects might be attenuated over the long run. However, it shows that robotizaton since 2012 made young workers feel less satisfaction, particularly about worsening employment stability and workplace communication.

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