The Impact of Robots on Labor Demand: Evidence from Job Vacancy Data in South Korea

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Abstract

The debate about the impact of robots on employment has been lively. In this paper, we examine the effect of robots on local labor demand in South Korea, one of the most technologically advanced countries in terms of robotics. Using the regional variation in robot exposure constructed from national industry-level robot adoption data and the initial distribution of industrial employment in cities, we find that robots did not reduce local labor demand. However, we estimate declines in labor demand in the manufacturing sector and routine jobs. An increase of one robot per 1,000 workers in terms of exposure to robots is correlated with a decline in the job vacancy growth rate of 2.9%p in the manufacturing sector and of 2.8%p in routine jobs. No significant relationship is found between robot exposure and labor demand in the service sector or non-routine jobs.

Keywords: Robots, Labor Demand, Job Vacancy, South Korea

JEL codes: J23, J63, E24

1. Introduction

How does the use of industrial robots, one of the leading automation technologies, affect labor demand? Nowadays, it is one of the most debated questions among policymakers and researchers. Theoretically, there are two opposing effects of robot adoption (Acemoglu and Restrepo, 2020). Firstly, robots substitute for tasks otherwise performed by workers. Thus, there is a negative displacement effect. The second is a positive productivity effect since robots can lower production costs and thus increase productivity. Then labor demand can increase following the productivity gains. There is a growing literature regarding the impact of robotization on the labor market (Acemoglu and Restrepo, 2020; Dauth et al., 2021; de Vries et al., 2020; Farber, 2020; Graetz and Michaels, 2018; Koch et al., 2019) and other socioeconomic outcomes (Anelli et al, 2021; Gihleb et al, 2020; Gunadi and Ryu, 2021).

In their seminal work, Graetz and Michaels (2018) found that robot adoption increased labor productivity using the variation across industries and countries. They suggest that increased robot use did not reduce total employment, but did reduce employment for low-skilled workers. Recently, Acemoglu and Restrepo (2020) and Dauth et al. (2021) exploit the geographical variation in the U.S. and German labor markets. Acemoglu and Restrepo (2020) found evidence of a negative effect of robots on employment and wages across local U.S. labor markets, and the effects were homogenous to different subgroups of workers. On the contrary, Dauth et al. (2021) found no significant effects of robot exposure on total employment, but show negative effects on employment in the manufacturing sector and positive effects on employment in the service sector, implying that displacement effects are offset by reallocation effects.

Our paper has focused on South Korea, one of the most technologically advanced countries in terms of robotics. Figure 1 shows robot density, defined as the number of installed industrial robots per 10,000 workers, in the manufacturing sector in different countries between 2007 and 2019. In 2019, the two countries with the highest robot densities were Singapore (918 robots per 10,000 workers) and South Korea (868 robots per 10,000 workers). Singapore replaced South Korea as the world leader in 2018.

<Figure 1. Robot Density>

In this paper, we examine the effect of robots on local labor demand in South Korea. Following Acemoglu and Restrepo (2020) and Dauth et al. (2021), we construct a Bartik-type local robot exposure measure using the baseline distribution of industrial employment in cities and the adoption of robots across industries over time. Robot adoption can be correlated with other domestic industry-specific trends. Therefore, we instrument our key variable of interest with the industry-level of robot adoption in Singapore, which has similar trends with Korea in terms of robot density. As an outcome variable, we use job vacancy data, a direct manifestation of labor demand for new workers.

Overall, we find no evidence of any negative effects of robots on local labor demand. We also examine whether an increase in robot exposure will have different effects on manufacturing versus service jobs and routine versus non-routine jobs. The displacement effects likely occur in the manufacturing sector and among routine jobs, since robots directly substitute the tasks that these groups do. As expected, our results show a decline in labor demand in the manufacturing sector and among routine jobs. An increase of one robot per 1,000 workers in exposure to robots is correlated with a decline in the job vacancy growth rate of 2.9%p in the manufacturing sector and of 2.8%p among routine jobs. Labor demand in the service sector or for non-routine jobs would increase when robots and labor are gross complements. We found no relationship between robots and labor demand for the service sector and non-routine jobs, suggesting that tasks in the service sector or among non-routine jobs are not complemented by industrial robots.

The remainder of this paper is structured as follows. Section 2 introduces the data we use and describes our empirical approach. Section 3 presents the main results. Section 4 concludes.

2. Data and Methods

2.1 Data and Descriptive Statistics

The unit of analysis is the city (city/borough/county).[1] We combine several data sources to create a city-level panel dataset and the period of the analysis is 2010–2019. The main source is data on job postings from WorkNet. Job vacancy data has been increasingly used to investigate changes in firms' labor demand (Hershbein and Kahn, 2018; Forsythe et al, 2020;

1 South Korea consists of 17 provinces, and these are further divided into 229 cities.

Javorcik et al 2020). WorkNet is one of South Korea's largest national job websites and is operated by the Korea Employment Information Service (KEIS). It is the second-largest online job site in Korea, and its market share in terms of the number of visitors is about 23%, as of March 2021. (The market share for the largest one is 24%). In general, job postings expire after 30 days. The same job posting can be re-registered if your original listing has expired. The job posting data include location, occupation (2-digit), industry (1-digit), type of contract, (self-reported) firm size, and educational requirements. The number and type of WorkNet job postings are closely correlated with the total number of job openings from the Occupation Labor Force Survey in Establishment (OLFSE), which is a survey of establishments that is conducted by the Ministry of Employment and Labor.[2] The correlation coefficient between job postings on WorkNet and the number of job postings from the OLFSE (seasonally adjusted) is 0.73 (p-value=0.00). Our main outcome variable is job vacancy growth between 2010 and 2019 at the city level. We also obtain industrial and occupational job vacancy growth data for each city. We classified the industries into manufacturing and service sectors and the occupations into routine and non-routine jobs, following the mapping of occupations used by de Vries et al (2021). Routine occupations may be sorted into routine-manual occupations, including production workers, agricultural workers, and routine-analytic occupations, which are administrative workers. Non-routine occupations can also be split into non-routine manual occupations, including support-services workers, drivers, and non-routine analytic occupations, including legislators, managers, engineers, health professionals, teaching professionals, other professionals, and sales workers.

The second source is data on the stock of industrial robots for country-industry pairs from the International Federation of Robotics (IFR). The data is collected from nearly all industrial robot suppliers worldwide, and it is supplemented with data provided by several national robot associations. A robot is defined as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile, for use in industrial automation applications" by the IFR. Using a shift-share approach, we construct our variable of interest, the change in robot exposure at the city level, c, as follows:

[2] The OLFSE does not cover establishments with fewer than five permanent employees, agriculture, forestry and fishing, households, and the public sector. The location information is only available at the province-level, not the city-level.

$$\Delta robot_c = \sum_{i=1}^{I} s_{ci,2005} \times \frac{\Delta robot_i}{emp_{i,2010}} \qquad (1)$$

where $s_{ci,2005}$ is the employment share of industry i in city c in 2005. $\Delta robot_i / emp_{i,2010}$ is the change in the total stock of robots from 2010 to 2019 in industry i, standardized by the industrial employment in 2010. Industry i is classified according to the 19 IFR industries following Acemoglu and Restrepo (2020).[3] For unclassified robots, we allocate them to each industry in the same proportion as in the classified data. The change in robot exposure in city c is calculated by combining the baseline employment share and the national industry-level robot exposure.

Figure 2 shows the regional distribution of the change in robot exposure between 2010 and 2019, expressed in terms of robots per thousand workers. Firstly, we can see that there is a substantial variation in the change in exposure across cities. The largest industry in 2005 for the top 10 robotized cities is the electronics or automotive industry. These two are the most robot-intensive sectors.[4]

<Figure 2. Regional Distribution of Exposure to Robots>

Our empirical analysis includes the share of workers in manufacturing and the female share of manufacturing workers, to control for other industry trends. We also use the shares of the male population, the population aged over 55, the college-educated population, and the population size as controls. The industry shares and demographic control variables are constructed from the Population and Housing Census. We use the export and import variables constructed from the Korea Trade Statistics Promotion Institute (KTSPI) to control the effects of trade on labor demand.

Table 1 shows the descriptive statistics of the outcome variables, the variable of interest, and control variables. The data are weighted by the population size in 2010. On average, job vacancies have declined slightly. There is great heterogeneity in the growth rate of job

[3] Our 19 IFR industries are the following. Outside manufacturing, there are agriculture, mining, utilities, construction, research, and services. In the manufacturing sector, the IFR industries includes food and beverages, textiles, wood and furniture, paper and printing, plastics and chemicals, minerals, basic metals, metal products, metal and machinery, electronics, automotive, other vehicles (for example, shipbuilding and aerospace), and other manufacturing.

[4] The automotive and electronic industry experienced an increase in robot exposure of 190 and 178 robots per 1,000 workers between 2010 and 2019 in South Korea. (Please refer to Column 1 in Table A1.) This significant increase is due to the huge projects aimed at manufacturing batteries for hybrid and electric cars, as well as the rise in the production of semiconductors and displays (International Federation of Robotics, 2018).

vacancies by industry and occupation. Job vacancies in both the manufacturing sector and routine jobs exhibit a steep decrease. Vacancies in each fell by 44% and 37% between 2010 and 2019, respectively.

On the other hand, the service sector and non-routine jobs saw vacancies increase by 29% and 18%. The average number of vacancies in 2010 is about 18,000, where the share of the manufacturing sector and routine jobs is 43% and 37%. Most regions saw an increase in robot exposure. The average city has experienced an increase in robot exposure by around 4.3 robots per 1,000 workers. The standard deviation of change in robot exposure again reveals considerable variation in robotization across cities. The distribution is right-skewed, with there being just a few cities that have very large robot exposure.

<Table 1. Summary Statistics>

2.2 Method

To empirically investigate how the change in robot exposure affects job vacancy growth, we estimate the following long-run first difference model

$$\Delta lny_c = \beta\Delta robot_c + X_c'\gamma + \delta_p + \epsilon_c \qquad (2)$$

where Δlny_c is the change in log number of job vacancies in city c and $\Delta robot_c$ is the change in robot exposure as defined in Equation (1). The vector X_c includes the industry shares, and the demographic and trade control variables measured in 2010. δ_p represents the province-fixed effects.

Although we control for regional characteristics in 2010 and province-fixed effects, and use the Baritk-style robot exposure measure, rather than actual robot exposure, our estimates from the simple OLS are likely to be biased if robot adoption in some industries can be endogenous to domestic industry-specific conditions. To alleviate the endogeneity concern, we apply an instrumental variable approach similar to Acemoglu and Restrepo (2020) and Dauth et al. (2021) who use exposure to robots from (other) European countries. Specifically, we instrument the Korean robot exposure ($\Delta robot_i$) using an analogous measure constructed from robot adoption across industries in Singapore $\left(\Delta robot_{i,SG}\right)$. The increase in robots in Singapore is probably less correlated with unobserved factors affecting the local labor market in Korea. We chose Singapore since it experienced a very similar trajectory in its robot stock to Korea, as shown in Figure 1.[5] Table A1 shows that the change in the stock of robots by industry and the industrial structure in terms of baseline employment share and robot stock are similar between the two countries. Moreover, manufacturing value-added as a share of GDP in Korea and Singapore was reported at 25% and 21% in 2020, according to World Bank.

Figure 3 depicts the first-stage relationship, together with the fitted regression line. Each point represents an observation of a city, with dark shading of an individual point implying greater weight, defined as the 2010 population size. The demographic and trade controls and province-fixed effects are partialled out. We observe a positive correlation between the Korean change in robot exposure and the change in robot exposure from Singapore, suggesting the instrument is a good predictor. Table 2 shows the first-stage results and again indicates that the change in robot exposure from Singapore is a relevant instrument. Column 1 shows a parsimonious specification with the province fixed effects as the only control variables. Column 2 adds the industry shares, Column 3 adds the demographic controls, and Column 4 adds trade controls. Across all the different specifications, the results show that our instrument is highly significantly correlated with the variable of interest. The first-stage F-statistics indicate we are free from the weak instrument problem.

<Figure 3. First-Stage Relationship, 2010-2019>

<Table 2. First-Stage Relationship, 2010-2019>

To be valid, the instrument should be uncorrelated with the unobservable confounders that affect local demand. Though it is not directly testable, we can provide suggestive evidence by checking whether there are significant pretrends. Specifically, we examine whether cities experiencing greater robot exposure in the 2010-2019 period would have had a similar job vacancy growth in the 2007-2010 period compared to those with less exposure. In Table 3, we regress the job vacancy growth between 2007 and 2010 on changes in robot exposure from Singapore between 2010 and 2019. The estimate in Column 1 indicates that there is no significant relationship between robot exposure and pre-period job vacancy growth. The

[5] Our instrumental variable is constructed as follows:
$\Delta robot_c = \sum_{i=1}^{I} s_{ci,2005} \times \frac{\Delta robot_{i,SG}}{emp_{i,2010}}$.

picture in Columns 2 through 5 is similar when we use the pre-period industrial or occupational job vacancy growth, supporting the validity of the IV estimates.[6]

<Table 3. Pre-Trend Check>

3. Results

In this section, we present our reduced-form and IV results for the impact of robots on labor demand and additionally investigate how exposure to robots has affected labor demand in different industries and occupations.

3.1 Descriptive Analysis

Before reporting our main results, we first show the descriptive correlation between job vacancy growth and the change in robot exposure, both between 2010 and 2019. Figure 4 presents a residual scatter plot for our specification from Equation (1) with the OLS fitted regression line. Standard errors are clustered at the level of 56 Living Zones (LZs).[7] The circle shading indicates the 2010 population size, as in Figure 3. The slope is slightly negative, but statistically not different from zero, and this correlation does not appear to be driven by outliers.

Figure 5 visually illustrates the differential effects of robots by industry. The significant adverse impact of robots is concentrated in the manufacturing industry (Panel A of Figure 5). This result is not surprising given that manufacturing industries are heavily robot intensive. The OLS estimate indicates that an increase of one robot per 1,000 workers in exposure to robots is correlated with a decline in the job vacancy growth of 2.6%p. We find that greater robot exposure contributes to an increase in job vacancy growth for the service sector. This relationship, however, is not statistically different from zero (Panel B of Figure 5). We separate the analysis by two occupational groups in Figure 6: routine and non-routine jobs. The increase in robot exposure is negatively associated with the job vacancy growth in routine jobs (Panel A of Figure 6). Since routine tasks are easily automated by industrial robots, it is natural that

[6] Goldsmith-Pinkham et al. (2021) show that the Bartik instrument is numerically equivalent to a generalized method of moments (GMM) estimator with the local industry shares as instruments. They suggest looking at pretrends in terms of the instruments with the largest Rotemberg weights. The electronic and automotive industries have the highest Rotemberg weights, which are 0.887 and 0.149, respectively. Table A2 verifies that there are no significant associations between the share of electronic or automotive industries and pre-period changes in labor demand.
[7] The LZs are geographical units referring to aggregated regions characterized by intense economic interactions.

the displacement created by robots is pronounced for routine jobs (Autor et al, 2003; Goos et al, 2014). The point estimate for routine jobs is −0.028 (p-value = 0.004), similar to that for the manufacturing sector.[8] One can see there is no evidence that an increase in robot exposure affects the job vacancy growth for non-routine jobs (Panel B of Figure 6). The estimated coefficient for non-routine jobs is small in magnitude, almost zero. These OLS estimates may be biased due to local unobservable factors, thus the next section presents the reduced-form and IV results using the instrument constructed from the industry-level Singapore robot data.

<Figure 4. Robot Exposure and Labor Demand>

<Figure 5. Robot Exposure and Labor Demand by Industry>

<Figure 6. Robot Exposure and Labor Demand by Occupation>

3.2 Reduced-Form and IV Results

Our main results are summarized in Table 4, with the reduced form results in Panel A and the IV results in Panel B. The regressions are weighted by a city's 2010 population size, and the standard errors are robust against heteroskedasticity and the within-LZ correlation. In the reduced-form specification, we regress the job vacancy growth rate on the change in robot exposure from Singapore. Each column includes a different set of controls, as in Table 3. Column 1 shows the basic specification controlling only for the province fixed effects and indicates that an increase in robot exposure has a significantly negative impact on labor demand. In Column 2, we include the share of workers in the manufacturing sector and the female share of manufacturing workers in 2010 as controls. These allow for differential trends by the baseline industrial composition of cities. The significance disappears after their inclusion. Qualitatively similar results are shown when we add demographic characteristics in 2010 (Column 3). In Column 4, we account for other contemporaneous changes that may be correlated with local labor demand and robot exposure: gross exports and imports proxied by

[8] Additionally, we further disaggregate routine labor demand into manual and analytic task-intensive occupations and estimate the negative impacts for both routine-manual and routine-analytic occupations. When we split up the non-routine labor demand into several manual and analytic task-intensive occupations, none of the estimates are significant.

their baseline shares of employment. These controls do not affect the estimates. The pattern of 2SLS estimates in Panel B is very close to the reduced-form counterparts. The effects are negative, but statistically insignificant across all specifications, except for Column 1 with a relatively parsimonious specification.

<Table 4. Robot Exposure and Labor Demand>

3.3 Effects by Industry and Occupation

We next study the effects of robots separately by industry. Specifically, we repeat the estimation of Table 4 for the manufacturing and service sector, respectively. We start with an analysis of the manufacturing sector. The reduced-form results are presented in Panel A and the IV results are in Panel B. Similar to the OLS estimates, the reduced form results in Panel A indicate that the effects of robot exposure are mainly concentrated on the manufacturing sector. The inclusion of control variables has a minor impact on our coefficient of interest. Panel B shows that the IV results are similar to the reduced form results. In all specifications, we find consistently negative and precise estimates for labor demand growth. Our preferred IV estimate with the full set of control variables in Column 4 is −0.029 (standard error= 0.011). To assess the economic magnitude of this, comparing a city at the median of the change in robot exposure (2.318) to a city with no change, the magnitude implies that the highly robot-exposed city experiences a 6.7%p (= 2.318×−0.029) lower labor demand growth. This amounts to about 15% of the average growth rate in manufacturing labor demand (which is -0.445, refer to Table 1). This is in line with the results in Dauth et al (2021), who also find the displacement effects of robots in the manufacturing sector in Germany.

In the next two panels, we investigate the impact on labor demand in the service sector, with Panel C in the reduced-form results and with Panel D in the IV results. Columns (1) and (2) of Panel C suggest the adverse impacts of robot exposure. However, accounting for demographic characteristics substantially reduces the effect of robots in absolute terms (−0.033 vs. −0.004) such that it becomes statistically insignificant (Column (3)). The next columns add trade controls, and the estimates remain small and statistically insignificant. The IV estimates in Panel D essentially mimic the reduced form estimates. The results suggest that displacement effects in manufacturing sectors do not lead to positive spillovers in labor demand on other local industries in service sectors.

<Table 5. Robot Exposure and Labor Demand by Industry>

In the following, we examine the heterogeneous impacts on labor demand by occupation, shown in Table 6. The effects across occupations paint a similar picture with the OLS estimates in Figure 6, with a pronounced negative effect for the routine occupations and a negligible impact on non-routine occupations. For routine occupations, the results are reported with a reduced form estimate in Panel A and an IV estimate in panel B. The reduced-form results in columns 1 to 4 in Panel A strongly support the interpretation of reduced labor demand for routine jobs in cities strongly exposed to robots. The IV estimates in four columns of Panel B mirror the reduced-form results. The estimates remain negative and significant as we enrich the specifications. The coefficient estimate in our preferred specification (column 4 in Panel B) is −0.028 (standard error= 0.011). Quantitatively, again comparing a city at the median of the change in robot exposure (2.318) to a city with no change, the magnitude corresponds to a 6.5&p (= 2.318×−0.028) decline in labor demand growth, which translates into about 18% of the average growth rate in routine labor demand (which is -0.370, refer to Table 1). This is corroborated with results in de Vries et al (2020), who find a reduction in routine employment from robot adoption using a country-industry level analysis.

Next, we present the reduced-form results in Panel C and the IV estimates in Panel D for non-routine occupations. Column 1 in Panel C shows us that non-routine labor demand decreased in cities that were exposed to robots. The inclusion of industry shares has a visible effect on our coefficient of interest, moving its magnitude from −0.033 to −0.018 and becoming not statistically different from zero. The following columns add demographic and trade controls, respectively, and the main results are unchanged. The coefficient estimates imply a little effect of robots on non-routine occupations. The pattern of the IV estimates in Panel C is very similar to the effects identified in the reduced form regressions in Panel D. These results suggest that the positive productivity effects from using robots have not resulted in an expansion of labor demand in nonautomated tasks. A possible explanation is that non-routine tasks are not directly complemented by industrial robots.[9]

<Table 6. Robot Exposure and Labor Demand by Occupation>

3.4 Robustness

Table 7 presents several robustness checks. To start with, Panel A of Table 7 shows that the effects of robots are qualitatively the same in the unweighted regression, though the magnitude of estimates is larger in general. We now estimate a coefficient of -0.043 for the manufacturing sector and -0.034 for routine jobs. Next, we again check whether our estimates might confound the effects of robots with the pre-trends. We include the growth rate in job vacancies between 2007 and 2010 as a covariate and repeat the IV estimation. If our estimates are driven by the correlation between persistent trends in our outcome and the change in robot exposure, the significance would disappear after including the pre-period outcome. The results in Panel B of Table 7 show that this is not the case. The estimates are very similar to our baseline results, suggesting the change in robot exposure is not correlated with the pre-trend in labor demand. We also consider the adjusted robot exposure in Acemoglu and Restrepo (2020) as the explanatory variable. We adjust for the overall expansion of each industry’s output when constructing the industry-level variation of robot use. With this measure of robot exposure, we obtain almost the same estimates.

4. Conclusion

The use of robots has increased considerably across countries, and at the same time, it has fueled the debate about the employment effects of rapid robot adoption. We examine the relationship between change in robot exposure and job vacancy growth between 2010 and 2019 in South Korea. We find little evidence that robot-exposed regions decrease labor demand, though the estimated effects of robots differ substantially across industries and occupations. We see a strong negative relationship between exposure to robots and labor demand changes

9 As a robustness check, we redo the analysis after excluding outliers and the results are unaffected, as shown in Table A2.

for the manufacturing sector and routine occupations, while we do not find any statistically significant effect on the labor demand for service sectors and non-routine occupations. This result seems plausible, given robots' specialization in manufacturing and their high degree of substitution for routine tasks. Our results suggest that advances in automation can be a big threat to workers who are most exposed to competition with new technologies. Training for the reskilling or upskilling of workers is needed to mitigate the displacement effects and to facilitate labor market reallocation. Note that our estimates only measure the robot effects on local demand, and do not account for positive spillovers resulting from a reduction in the cost of goods consumed in other cities due to robot adoption. To quantify the aggregate changes in labor demand, we would need to make further assumptions on cross-city spillovers.

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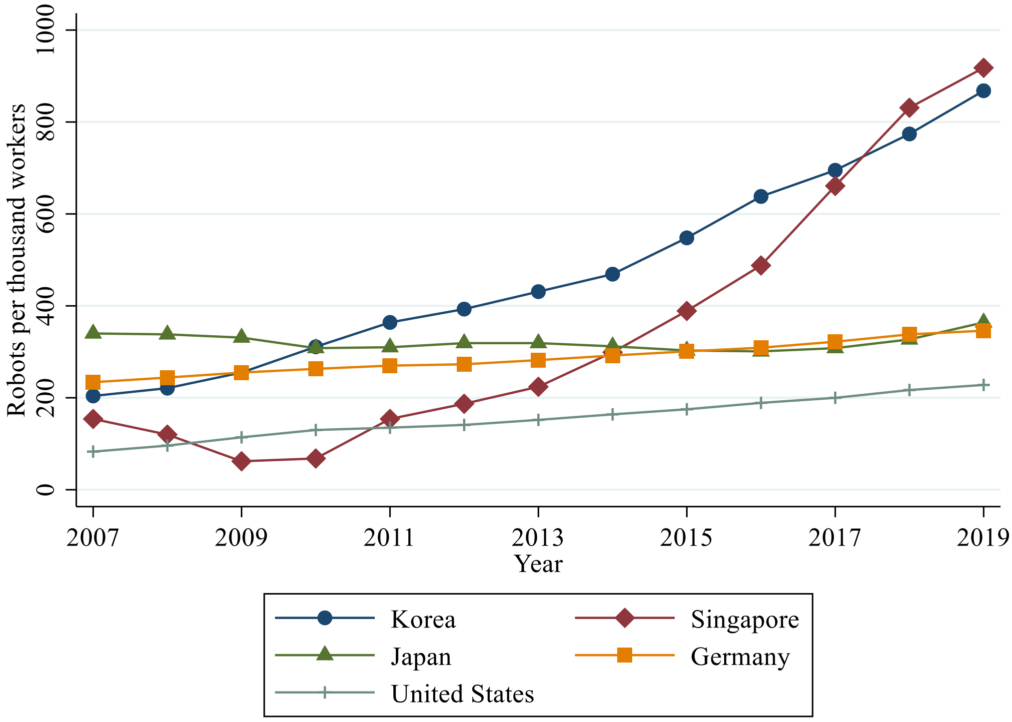
Figures

Figure 1. Number of Installed Industrial Robots per 10,000 Workers in the Manufacturing Sector, 2007-2019



Source: IFR

Figure 2. Geographic Distribution of the Change in Robot Exposure, 2010-2019

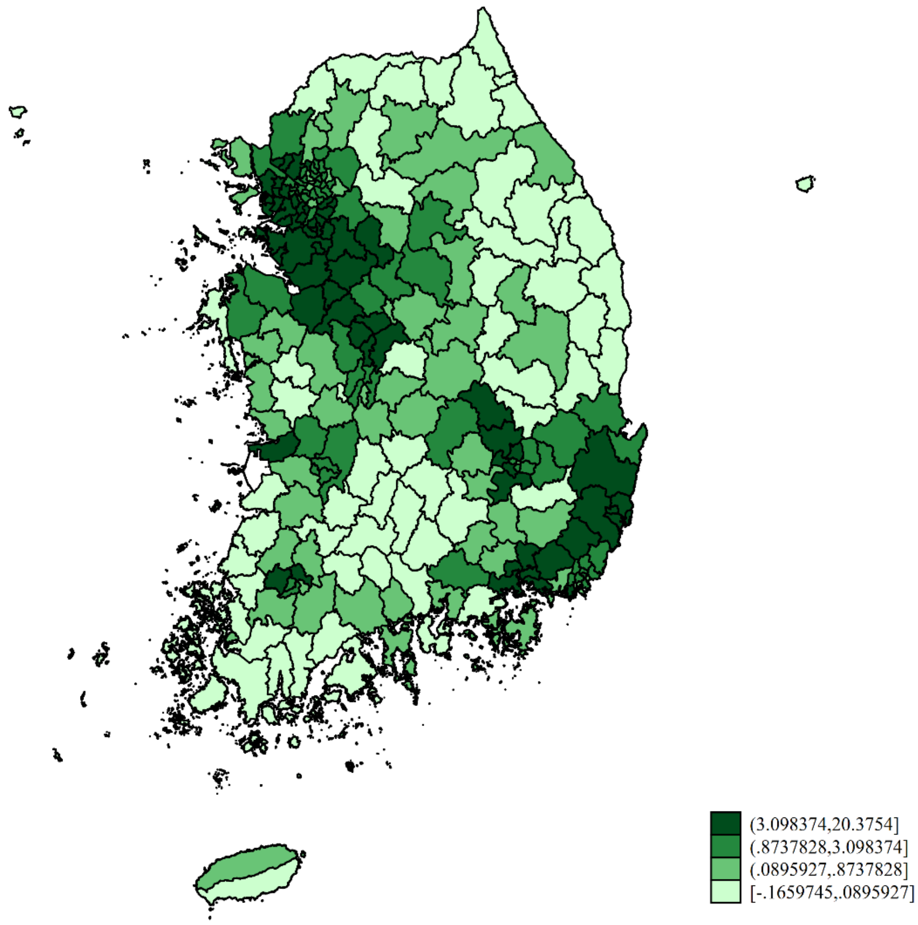
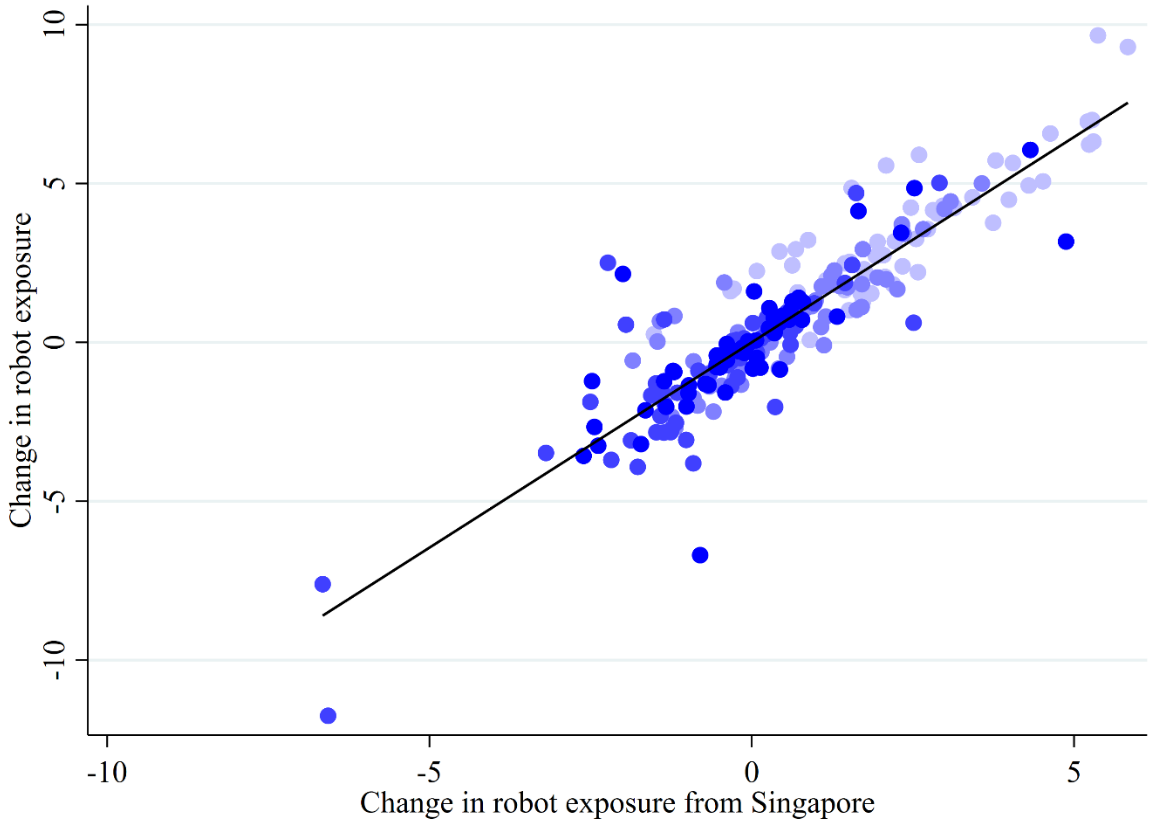
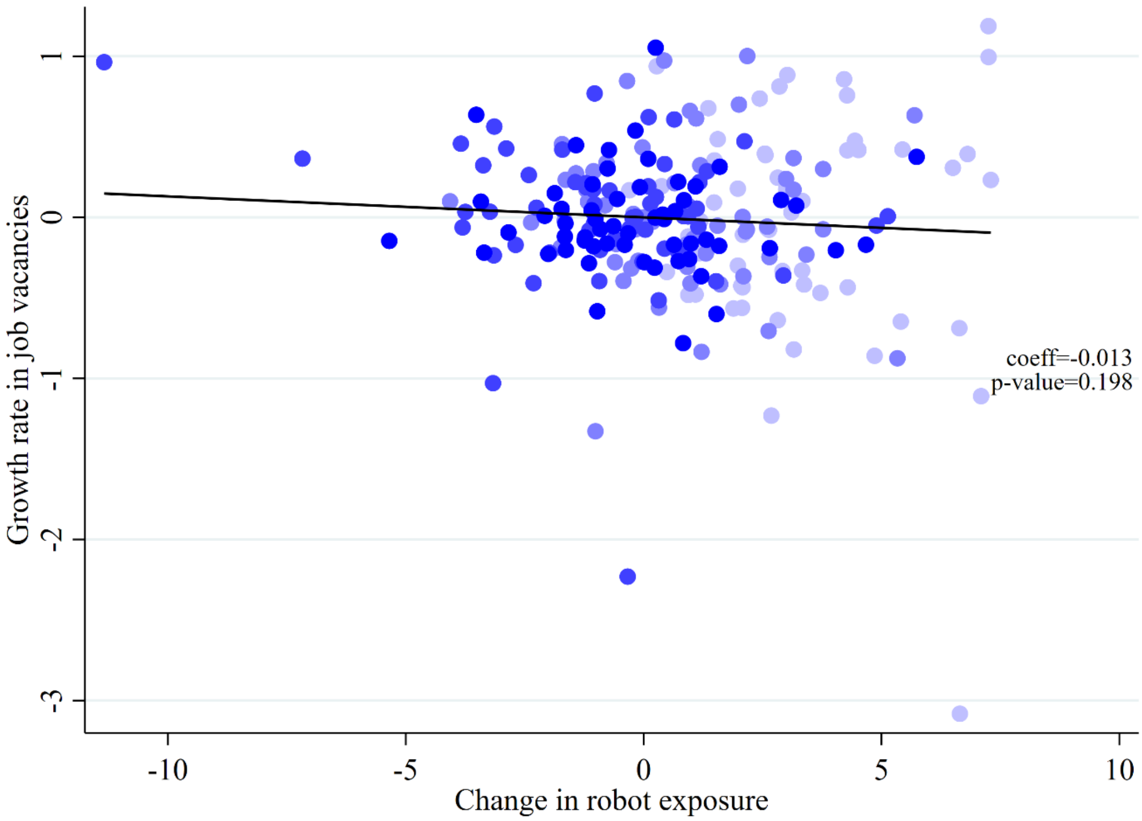


Figure 3. First-Stage Relationship, 2010-2019



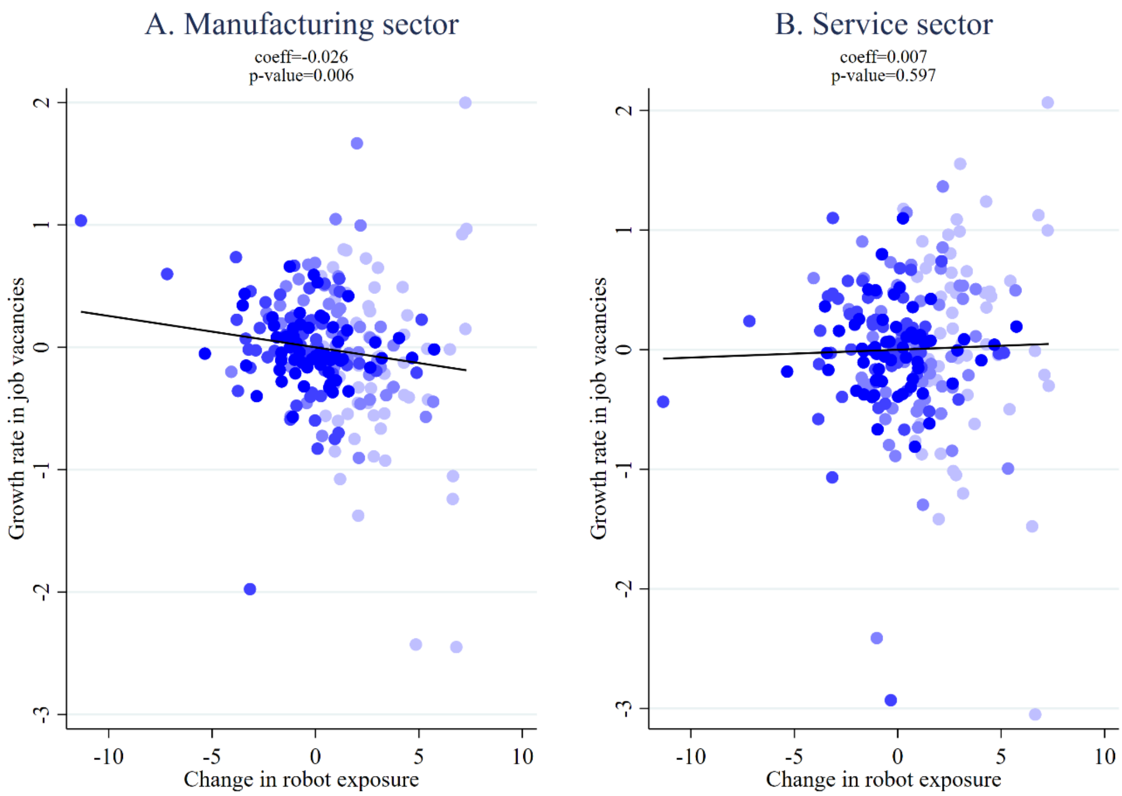
Note: The figure plots the relationship between the change in robot exposure from Singapore and the change in robot exposure between 2010 and 2019. The control variables from Column 4 of Table 2 are partialled out. The shading of an individual observation indicates the weight of each region defined as the population in 2010, with dark shading of an individual point implying greater weight.

Figure 4. Robot Exposure and Labor Demand, 2010-2019



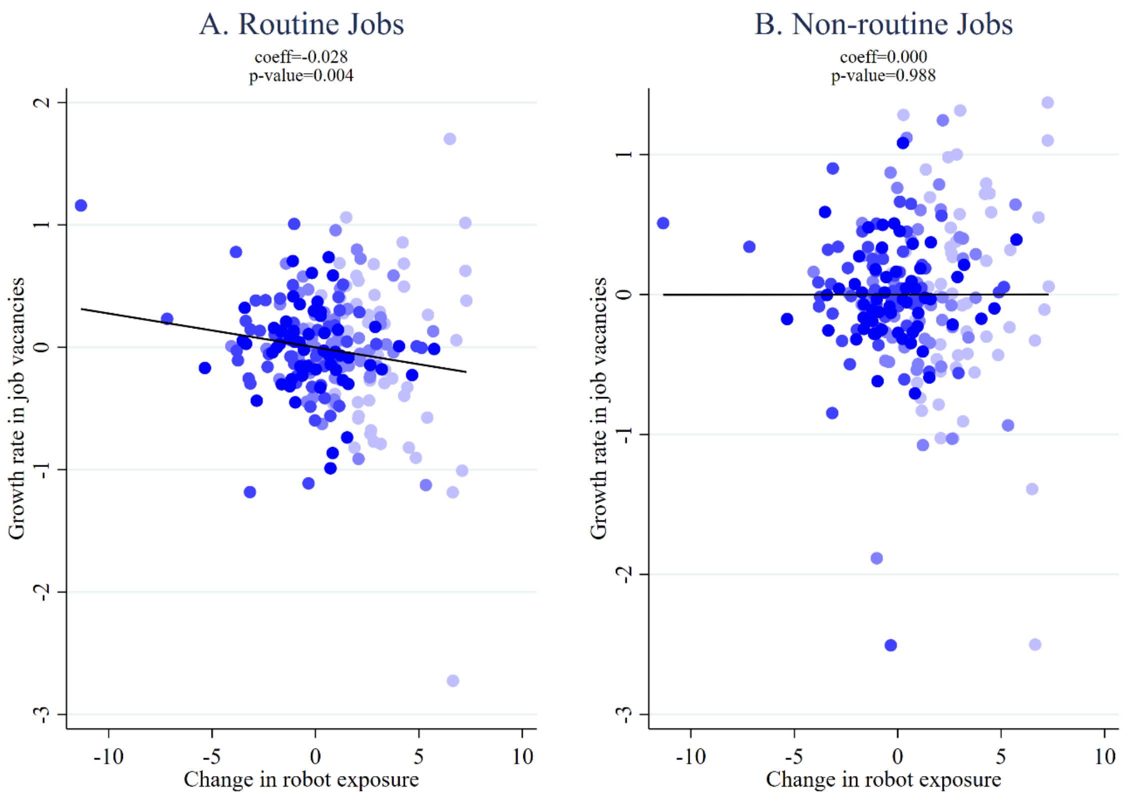
Note: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 4 are partialled out. The shading of an individual observation indicates the weight of each region defined as the population in 2010, with dark shading of an individual point implying greater weight.

Figure 5. Robot Exposure and Labor Demand, by Industry, 2010-2019



Note: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 5 are partialled out. The shading of an individual observation indicates the weight of each region defined as the population in 2010, with dark shading of an individual point implying greater weight.

Figure 6. Robot Exposure and Labor Demand, by Occupation, 2010-2019



Note: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 6 are partialled out. The shading of an individual observation indicates the weight of each region defined as the population in 2010, with dark shading of an individual point implying greater weight.

Tables

Table 1. Summary Statistics

	Mean	SD	p5	p95
Outcome variables				
Growth rate in job vacancies, 2010-2019	2.8	47.8	-59.6	99.1
Growth rate in vacancies, manufacturing, 2010-2019	-44.5	49.2	-123.9	38.9
Growth rate in vacancies, service, 2010-2019	29.5	61.3	-57.9	130.6
Growth rate in vacancies, routine, 2010-2019	-37.0	44.2	-99.7	36.3
Growth rate in vacancies, non-routine, 2010-2019	18.0	52.4	-54.5	115.5
Number of job vacancies, 2010	17,893	15,344	1,825	48,888
Number of job vacancies, manufacturing, 2010	7,728	10,845	295	32,268
Number of job vacancies, service, 2010	8,521	8,227	526	24,100
Number of job vacancies, routine, 2010	6,601	7,498	501	26,265
Number of job vacancies, non-routine, 2010	11,293	9,200	986	29,463
Variable of interest				
Change in robot exposure	4.3	4.7	0.1	16.2
Control variables				
Share of workers in manufacturing, 2010	18.0	8.9	7.0	32.7
Female share of manufacturing workers, 2010	31.7	7.2	18.0	43.8
Share of female population, 2010	50.8	1.4	48.0	53.0
Share of population aged over 55, 2010	16.5	4.5	10.7	25.4
Share of college-educated population, 2010	43.6	10.6	26.1	60.9
Population size, 2010	139,488	143,395	12,050	414,339
Exports (in $ 1,000), 2010	3,675,828	6,218,332	18,960	21,720,453
Imports (in $ 1,000), 2010	3,541,513	6,338,677	36,053	24,494,493

Notes: For variable descriptions, see Section 2.1. Except for population, we present the 2010 population-weighted average of each variable, except for population size.

Table 2. First-Stage Relationship, 2010-2019

Dependent Variable: Change in Robot Exposure, 2010-2019				
	(1)	(2)	(3)	(4)
Change in robot exposure from Singapore, 2010-2019	1.368***	1.315***	1.301***	1.272***
	(0.056)	(0.065)	(0.093)	(0.095)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
First stage F-statistics	593.80	411.91	196.29	180.36
Observations	229	229	229	229
R-squared	0.927	0.933	0.934	0.934

Notes: The dependent variable is the change in robot exposure between 2010 and 2019. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses. ***p< 0.01, **p< 0.05, *p< 0.1.

Table 3. Pre-Trend Check

Dependent Variable: Growth Rate in Job Vacancies, 2007-2010	All	Manufacturing	Service	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)
Change in robot exposure from Singapore, 2010-2019	0.006	0.013	-0.006	0.018	-0.004
	(0.011)	(0.013)	(0.019)	(0.012)	(0.015)
Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	227	229	229	229
R-squared	0.317	0.411	0.287	0.287	0.251

Notes: The dependent variable is the growth rate in job vacancies between 2007 and 2010. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.

Table 4. Robot Exposure and Labor Demand, 2010-2019

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019				
	(1)	(2)	(3)	(4)
	A. Reduced-form			
Change in the robot exposure from Singapore, 2010-2019	-0.037**	-0.019	-0.018	-0.019
	(0.016)	(0.014)	(0.020)	(0.022)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.363	0.413	0.435	0.436
	B. IV estimates			
Change in the robot exposure, 2010-2019	-0.027**	-0.014	-0.014	-0.015
	(0.011)	(0.010)	(0.014)	(0.016)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.369	0.414	0.435	0.435

Notes: The dependent variable is the growth rate in job vacancies between 2010 and 2019. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Panel A shows the reduced-form results, and Panel B shows the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.

Table 5. Robot Exposure and Labor Demand by Industry, 2010-2019

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019				
	(1)	(2)	(3)	(4)
	A. Reduced-form, manufacturing sector			
Change in the robot exposure from Singapore, 2010-2019	-0.050***	-0.047***	-0.031**	-0.037**
	(0.010)	(0.012)	(0.013)	(0.015)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.523	0.524	0.548	0.554
	B. IV estimates, manufacturing sector			
Change in the robot exposure, 2010-2019	-0.036***	-0.036***	-0.024***	-0.029***
	(0.007)	(0.008)	(0.009)	(0.011)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.521	0.521	0.549	0.555
	C. Reduced-form, service sector			
Change in the robot exposure from Singapore, 2010-2019	-0.046***	-0.033**	-0.004	-0.003
	(0.017)	(0.015)	(0.013)	(0.014)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.393	0.423	0.478	0.480
	D. IV estimates, service sector			
Change in the robot exposure, 2010-2019	-0.033***	-0.025**	-0.003	-0.002
	(0.012)	(0.011)	(0.010)	(0.010)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.384	0.416	0.478	0.479

Notes: The dependent variable is the growth rate in job vacancies between 2010 and 2019. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Panel A and C show the reduced-form results, and Panel B and D show the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.

Table 6. Robot Exposure and Labor Demand by Occupation, 2010-2019

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019				
	(1)	(2)	(3)	(4)
	A. Reduced-form, routine jobs			
Change in the robot exposure from Singapore, 2010-2019	-0.042***	-0.028**	-0.028*	-0.036**
	(0.010)	(0.012)	(0.014)	(0.016)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.355	0.392	0.398	0.407
	B. IV estimates, routine jobs			
Change in the robot exposure, 2010-2019	-0.031***	-0.021**	-0.021**	-0.028***
	(0.007)	(0.009)	(0.009)	(0.011)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.367	0.396	0.402	0.412
	C. Reduced-form, non-routine jobs			
Change in the robot exposure from Singapore, 2010-2019	-0.033**	-0.018	-0.004	-0.004
	(0.016)	(0.014)	(0.018)	(0.019)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.381	0.415	0.451	0.451
	D. IV estimates, non-routine jobs			
Change in the robot exposure, 2010-2019	-0.024**	-0.013	-0.003	-0.003
	(0.011)	(0.010)	(0.013)	(0.014)
Control variables				
Province fixed effect	√	√	√	√
Industry shares		√	√	√
Demographic controls			√	√
Trade controls				√
Observations	229	229	229	229
R-squared	0.380	0.414	0.450	0.450

Notes: The dependent variable is the growth rate in job vacancies between 2010 and 2019. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Panel A and C show the reduced-form results, and Panel B and D show the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.

Table 7. Robot Exposure and Labor Demand, 2010-2019 (Robustness Check)

A. Unweighted Regressions

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019	All	Manufacturing	Service	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)
	IV estimates				
Change in the robot exposure, 2010-2019	-0.031	-0.043**	0.000	-0.034**	-0.017
	(0.023)	(0.017)	(0.018)	(0.017)	(0.020)
Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	229	229	229	229
R-squared	0.438	0.401	0.527	0.405	0.484

B. Controlling for Pre-Trends

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019	All	Manufacturing	Service	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)
	IV estimates				
Change in the robot exposure, 2010-2019	-0.013	-0.030***	0.001	-0.027***	-0.001
	(0.015)	(0.010)	(0.010)	(0.009)	(0.014)
Growth rate in job vacancies, 2007-2010	-0.415***	0.152**	-0.533***	-0.261***	-0.418***
	(0.122)	(0.068)	(0.140)	(0.066)	(0.156)
Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	229	229	229	229
R-squared	0.503	0.563	0.547	0.443	0.507

C. Adjusted Robot Exposure

Dependent Variable: Growth Rate in Job Vacancies, 2010-2019	All	Manufacturing	Service	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)
	IV estimates				
Change in the robot exposure, 2010-2019	-0.016	-0.031***	-0.004	-0.029***	-0.004
	(0.016)	(0.011)	(0.011)	(0.010)	(0.015)

Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	229	229	229	229
R-squared	0.436	0.555	0.479	0.412	0.450

Notes: The dependent variable is the growth rate in job vacancies between 2010 and 2019. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in $1,000s) and the log of imports (in $1,000), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.

Appendix

Table A1. Comparison Between Korea and Singapore

	Change in the Stock of Robots (2010-2019)		The stock of Robots (2010)		Employment Share (2010)	
IFR industries	Korea	Singapore	Korea	Singapore	Korea	Singapore
Agriculture	0.07	0.09	0.02	0.00	5.06	1.74
Automotive	190.87	38.57	107.83	16.70	1.81	0.13
Construction	0.01	0.14	0.01	0.03	7.36	4.81
Electronics	178.80	175.57	66.27	15.15	3.97	4.63
Food and Beverages	4.37	6.54	1.46	2.01	1.51	1.24
Wood and Furniture	-0.07	-0.90	0.45	1.35	0.53	0.49
Other Manufacturing	33.41	58.50	3.11	1.98	0.45	0.60
Basic Metals	2.64	32.68	5.61	1.00	0.78	0.13
Metal and Machinery	15.19	2.93	1.14	0.71	1.76	2.96
Metal Products	-0.99	3.59	11.24	1.66	1.54	1.90
Minerals	0.51	0.19	0.51	0.00	0.59	0.29
Mining	-1.48	0.37	1.67	0.00	0.09	1.74
Paper and Printing	0.43	0.82	0.06	0.00	0.71	0.98
Plastics and Chemicals	13.77	-24.08	14.58	47.99	1.80	1.78
Research	0.10	0.34	0.18	0.13	4.20	5.21
Services	0.05	-0.01	0.00	0.03	64.11	65.60
Textiles	-0.10	0.00	0.12	0.00	1.94	0.19
Utilities	0.07	0.16	0.03	0.00	0.79	1.74
Other Vehicles	1.65	1.02	0.72	0.10	1.02	3.88
Correlation Coefficient	0.7601 (p-value= 0.0002)		0.4366 (p-value=0.0616)		0.9949 (p-value=0.000)	

Note: The robot variables are expressed in terms of robots per 1,000 workers.

Table A2. Pre-Trend Check for High Rotemberg Weight Industries

Dependent Variable: Growth Rate in Job Vacancies, 2007-2010	All	Manufacturing	Service	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)
Electronics share, 2005	0.027	1.610	-2.227	2.135	-1.494
	(1.842)	(2.247)	(2.939)	(2.192)	(2.011)
Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	227	229	229	229
R-squared	0.316	0.409	0.288	0.285	0.253
Automotive share, 2005	1.061	0.316	1.526	1.051	-1.091
	(1.731)	(2.638)	(2.493)	(2.701)	(2.320)
Control variables					
Province fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√
Observations	229	227	229	229	229
R-squared	0.316	0.408	0.287	0.283	0.252

Notes: The dependent variable is the growth rate in job vacancies between 2007 and 2010. The industry shares include the share of workers in manufacturing and the female share of manufacturing workers, measured in 2010. The demographic controls include the share of the male population, the population aged over 55, the college-educated population, and the log of population, measured in 2010. The trade controls include the log of exports (in \$1,000s) and log of imports (in \$1,000s), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors are clustered at the level of 56 living zones (LZs) in parentheses.***p< 0.01, **p< 0.05, *p< 0.1.