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, I 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, I find that robots did not reduce local labor demand. However, I estimate declines in labor demand in the manufacturing sector and routine jobs. An increase in one robot per 1000 workers in terms of exposure to robots is correlated with a decline in the job vacancy growth rate of 2.6%p in the manufacturing sector and of 2.5%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 Classification 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 policy-makers 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 (Autor and Dorn 2013). Then, labor demand can increase following the productivity gains. There is a growing literature regarding the impact of robotization on the labor

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market (Acemoglu and Restrepo 2020; Dauth et al. 2021; de Vries et al. 2020; Faber 2020; Graetz and Michaels 2018; Koch et al. 2021) and other socioeconomic outcomes (Anelli et al. 2021; Gihleb et al. 2022; 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 US and German labor markets. Acemoglu and Restrepo (2020) found evidence of a negative effect of robots on employment and wages across local US 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. This 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 1993 and 2021. In 2021, Korea was the country with the highest robot density, 1000 robots per 10,000 manufacturing workers.

In this paper, I examine the effect of robots on local labor demand in South Korea. Following Acemoglu and Restrepo (2020) and Dauth et al. (2021), I 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, I instrument the key variable of interest with the industry-level of robot adoption in
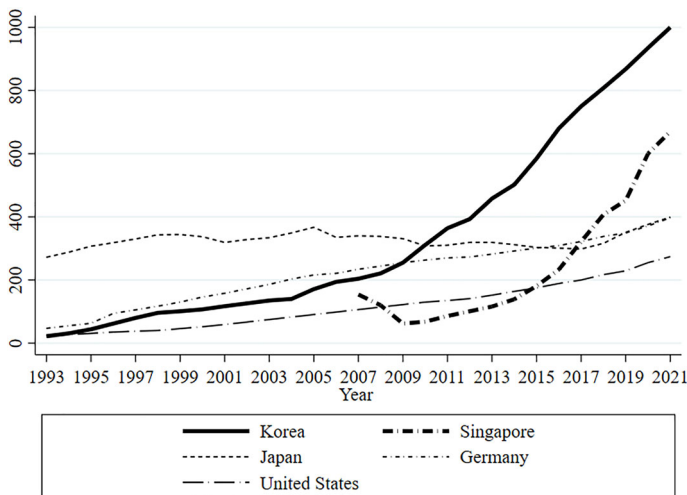

Fig. 1 Number of installed industrial robots per 10,000 workers in the manufacturing sector, 1993–2021. *Source*: IFR

Singapore, which has similar trends with Korea in terms of robot density. As an outcome variable, I use job vacancy data, a direct manifestation of labor demand for new workers.

Overall, I find no evidence of any negative effects of robots on local labor demand. I also examine whether an increase in robot exposure will have different effects on manufacturing versus service jobs and routine versus non-routine jobs. The negative effects likely occur in the manufacturing sector and among routine jobs, since robots directly substitute the tasks that these groups do. As expected, the results show a decline in labor demand in the manufacturing sector and among routine jobs. An increase in one robot per 1000 workers in exposure to robots is correlated with a decline in the job vacancy growth rate of 2.6%p in the manufacturing sector and of 2.5%p among routine jobs. Labor demand in the service sector or for non-routine jobs would increase when robots and labor are gross complements. I 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 I use and describes the empirical approach I use. Section 3 presents the main results. Section 5 concludes.

2 Data and methods

2.1 Data and descriptive statistics

The unit of analysis is the city (city/borough/county).[1] I 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 have been increasingly used to investigate changes in firms' labor demand (Hershbein and Kahn 2018; Forsythe et al. 2020; 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 are 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 $= 0.00$). Figure 7 illustrates the industry and occupational shares in WorkNet and OLFSE. Online vacancy postings in WorkNet

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[1] South Korea consists of 17 provinces, and these are further divided into 228 cities.

[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.

tend to overrepresent manufacturing jobs and blue-collar jobs, such as production and elementary occupations. Note that productivity effects for highly skilled workers may be underestimated in WorkNet data. The main outcome variable is job vacancy growth between 2010 and 2019 at the city-level. I also obtain industrial and occupational job vacancy growth data for each city. I 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. (2020).[3] 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 are 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, I construct the variable of interest, the change in robot exposure at the city-level, c, as follows:

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

where $s_{ci,2010}$ is the 2010 distribution of employment across industries and cities. $\Delta robot_i/emp_{i,2010}$ 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 18 IFR industries based on the classification of Acemoglu and Restrepo (2020).[4] For unclassified robots, I 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, I can see that there is a substantial variation in the change in exposure across cities. The largest

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[3] Their mapping of occupations into four different groups (routine-manual, routine-analytic, non-routine routine, and non-routine analytic) is based on Autor et al. (2003) and Goos et al. (2014).

[4] The 18 IFR industries are the following. Outside manufacturing, there are agriculture, mining, utilities, construction, research, and services. In the manufacturing sector, the IFR industries include food and beverages, textiles, 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 (including wood and furniture). Acemoglu and Restrepo (2020) use 19 IFR industries, and here, I aggregate "wood and furniture" and "other manufacturing."

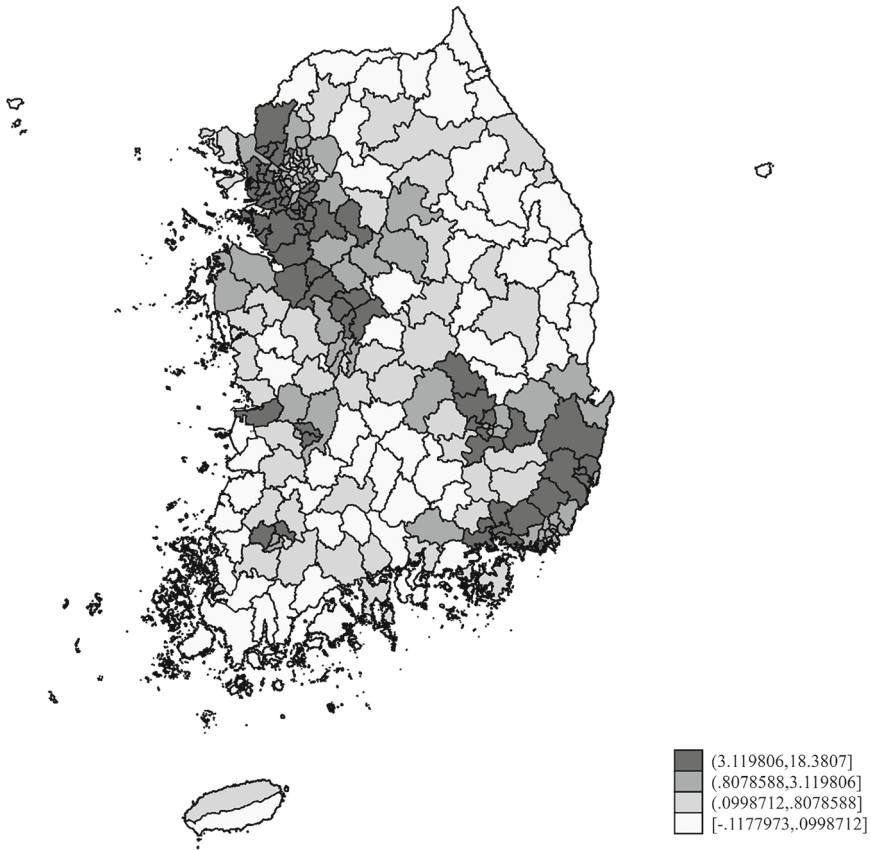|	
■	(3.119806,18.3807]
▨	(.8078588,3.119806]
▧	(.0998712,.8078588]
□	[-.1177973,.0998712]

Fig. 2 Geographic distribution of the change in robot exposure, 2010–2019

industry for the top 10 robotized cities is the electronics or automotive industry. These two are the most robot-intensive sectors.[5]

The empirical analysis includes the share of workers in manufacturing and the female share of manufacturing workers, to control for other industry trends. I 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. I 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 increased slightly. There is great heterogeneity in the

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[5] The automotive and electronic industry experienced an increase in robot exposure of 189.65 and 177.98 robots per 1000 workers between 2010 and 2019 in South Korea. (Please refer to Column 1 in Table 8.) 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.

Table 1 Summary statistics

	Mean	SD	p5	p95
Outcome variables				
Growth rate in job vacancies, 2010–2019	2.8	47.7	− 59.6	99.1
Growth rate in vacancies, manufacturing, 2010–2019	− 44.4	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	17,974	15,339	1825	48,888
Number of job vacancies, manufacturing, 2010	7789	10,871	295	32,268
Number of job vacancies, service, 2010	8535	8218	526	24,100
Number of job vacancies, routine, 2010	6640	7506	501	26,265
Number of job vacancies, non-routine, 2010	11,334	9189	986	29,463
Variable of interest				
Change in robot exposure	4.1	4.5	0.1	14.1
Control variables				
Share of workers in manufacturing, 2010	18.0	8.8	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	4.4	11.2	25.4
Share of college-educated population, 2010	43.6	10.6	26.1	60.9
Population size, 2010	287,064	177,616	36,905	661,163
Exports (in $ 1000), 2010	3,788,362	6,571,461	18,960	22,763,562
Imports (in $ 1000), 2010	3,642,738	6,561,904	36,053	24,494,493

For variable description, see Sect. 2.1. Except for population, I present the 2010 population-weighted average of each variable except for population size

growth rate of job 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 4.1 robots per 1000 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.

2.2 Method

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

$$\Delta lny_c = \beta \Delta robot_c + X_c'\gamma + \delta_p + \epsilon_c \tag{2}$$

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 Eq. (1). The vector X_c is control variables such as industry shares, the demographic and trade control variables measured in 2010.[6] δ_p represents the province-fixed effects.

Although I control for regional characteristics in 2010 and province-fixed effects, the 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, I 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, I instrument the Korean robot exposure ($\Delta robot_i$) using an analogous measure constructed from robot adoption across industries in Singapore $\left(\Delta robot_i^{SG}\right)$. I chose Singapore since it experienced a similar trajectory in its robot stock to Korea, compared to other countries, as illustrated in Fig. 1. Table 8 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. The instrument is constructed as follows:

$$\Delta robot_c^{IV} = \sum_{i=1}^{I} s_{ci,1995} \times \frac{\Delta robot_i^{SG}}{emp_{i,2010}^{SG}} \tag{3}$$

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[6] The 2010 control variables could potentially be endogenous since they are measured at a time when robotization may have already been underway. Therefore, I check the robustness of the results by including 1995 industry shares and demographic characteristics as control variables, since 1995 was before robotics technology advanced significantly, and find qualitatively similar results.

where $s_{ci,1995}$ is the 1995 distribution of employment across industries and cities. Here, I use the 1995 employment share to focus on historical differences in the industrial specialization of cities and to mitigate mechanical correlations. 1995 is the earliest year for which data are available, and robot density in Korea in 1995 was likely relatively close to zero compared to today's levels, as illustrated in Fig. 1. $\Delta robot_i^{SG}/emp_{i,2010}^{SG}$ is the change in the total stock of robots from 2010 to 2019 in industry i, standardized by the industrial employment in 2010. Data on the number of robots and number of the employed persons are obtained from IFR and Singapore department of statistics, respectively. The identifying assumption is the increase in robots in Singapore is uncorrelated with unobserved factors affecting the local labor market in Korea.[7] Robot adoption in Korea depends on changes in domestic supply and demand conditions, which may have direct effects on employment dynamics in the local Korean labor market. In contrast, the variation in robot adoption in Singapore only reflects the global technological progress in robot technology and the various supply and demand shocks in Singapore.

Figure 3 depicts the first-stage relationship, together with the fitted regression line. Each point represents an observation of a city, with the circle size of each point implying greater weight, defined as the 2010 population size. The demographic and trade controls and province-fixed effects are partialled out. I observe a positive correlation between the Korean change in robot exposure and the change in robot exposure from Singapore, suggesting that 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 the instrument is highly significantly correlated with the variable of interest. The first-stage F-statistics indicate that the results are free from the weak instrument problem.

To be valid, the instrument should be uncorrelated with the unobservable confounders that affect local demand. Though it is not directly testable, I can provide suggestive evidence by checking whether there are significant pre-trends. Specifically, I 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, I 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 picture in Columns 2 through 5 is similar when I use the pre-period industrial or occupational job vacancy growth, supporting the validity of the IV estimates.

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[7] The possible threat to the IV strategy is that there could be common shocks affecting the same industries in South Korea and Singapore, such as declining international demand or other technological changes, and these shocks could induce the same industries in two countries to adopt robots. In this case, the estimates may confound the impact of robots with these pre-existing industry characteristics. The result in Panel A of Table 9 shows that robot adoption in Singapore is not associated with industry characteristics in 2010, suggesting that these confounders are not responsible for the results.
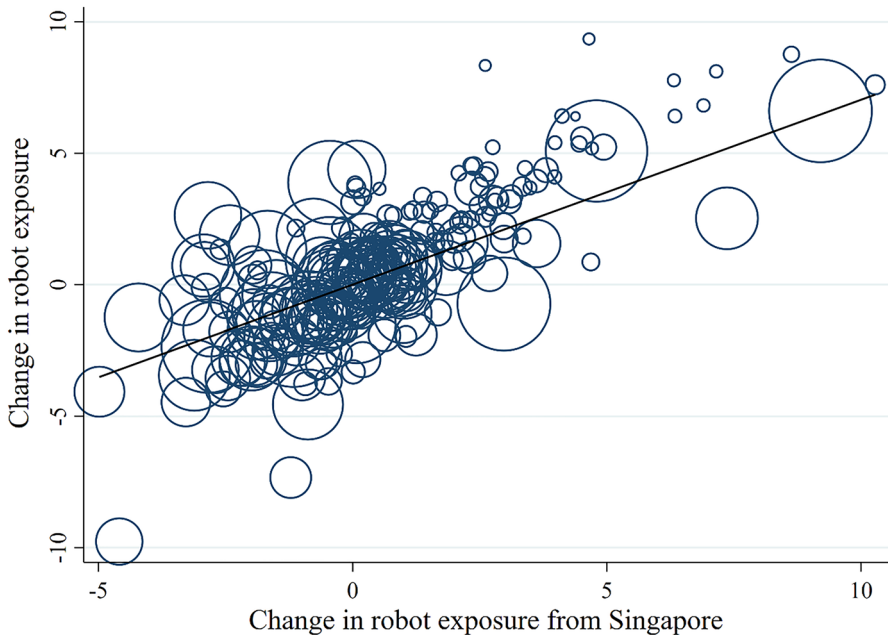
Fig. 3 First-stage relationship, 2010–2019. *Note*: The figure plots the relationship between the change in robot exposure from Singapore and the change in robot exposure between 2010 and 2019. The control variables from Column 4 of Table 2 are partialled out. The circle size of an individual observation indicates the weight of each region defined as the population in 2010

As I rely on the exogeneity of changes in the robot stock in Singapore to regional unobservables in Korea, I conducted the plausibility checks discussed in Borusyak et al. (2022) who treat the identification as based on exogeneity of the shocks, that is, the industry-level changes in the robot stocks in Singapore in this paper. Borusyak et al. (2022) recommend implementing industry-level and region-level balance tests. Initially, in Panel A of Table 9, I report the results of the industry-level balance tests. The balance variables are the log average wage in 2010, log profit in 2010, log R&D investment in 2010, and the share of production workers in 2010. There are no statistically significant associations between these variables and industry-level robot adoption in Singapore. Similarly, as demonstrated in Panel B of Table 9, I again find no statistically significant correlations between the region characteristics and the instrument, except for the share of the college-educated population and the log of the population. Borusyak et al. (2022) say: "Alternatively, one may argue that the observed imbalances are unlikely to invalidate the research design. … To gauge this potential for omitted variable bias, one can include such variables as controls in the SSIV specification and check the sensitivity of the coefficient" (pp. 207–208). I report the results of this exercise in Sect. 3.4.

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	0.956***	0.863***	0.707***	0.704***
	(0.084)	(0.084)	(0.066)	(0.069)
Control variables				
Province-fixed effect	✓	✓	✓	✓
Industry shares		✓	✓	✓
Demographic controls			✓	✓
Trade controls				✓
First-stage F-statistics	129.58	104.91	114.15	103.54
Observations	228	228	228	228
R-squared	0.787	0.834	0.864	0.866

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 female 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 export (in $ 1000) and log of imports (in $ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

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	0.003	0.010	−0.004	−0.002	0.003
	(0.006)	(0.006)	(0.014)	(0.009)	(0.008)
Control variables					
Province-fixed effect	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Trade controls	✓	✓	✓	✓	✓
Observations	228	226	228	228	228
R-squared	0.309	0.413	0.266	0.298	0.241

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 female 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 export (in $ 1000) and log of imports (in $ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$
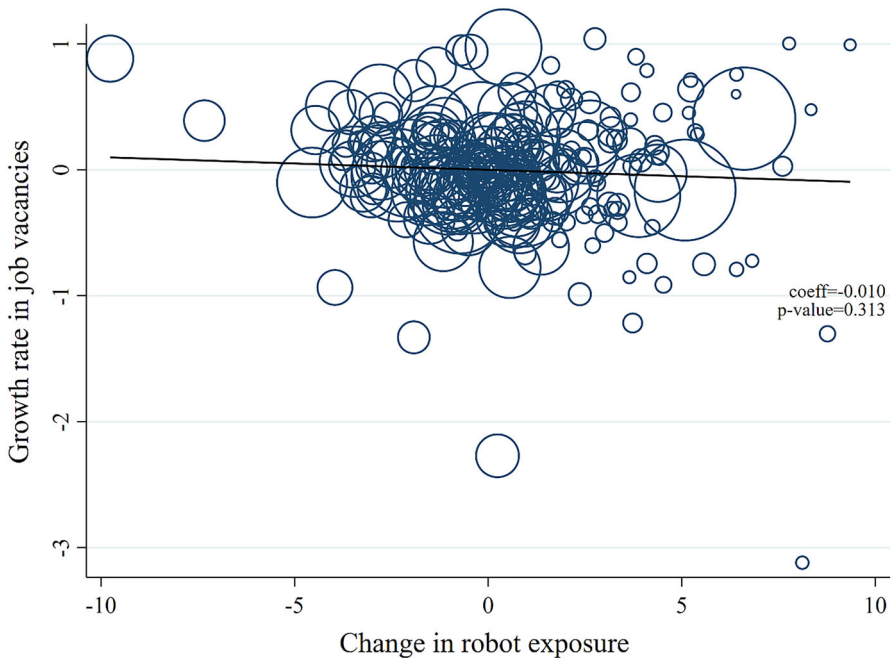
Fig. 4 Robot exposure and labor demand, 2010–2019. *Note*: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 4 are partialled out. The circle size of an individual observation indicates the weight of each region defined as the population in 2010

3 Results

In this section, I present the 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 the main results, I 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 the specification from Eq. (1) with the OLS fitted regression line. Standard errors are clustered at the level of 55 living zones (LZs).[8] The circle shading indicates the 2010 population size, as shown in Fig. 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

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[8] The LZs are geographical units referring to aggregated regions characterized by intense economic interactions.
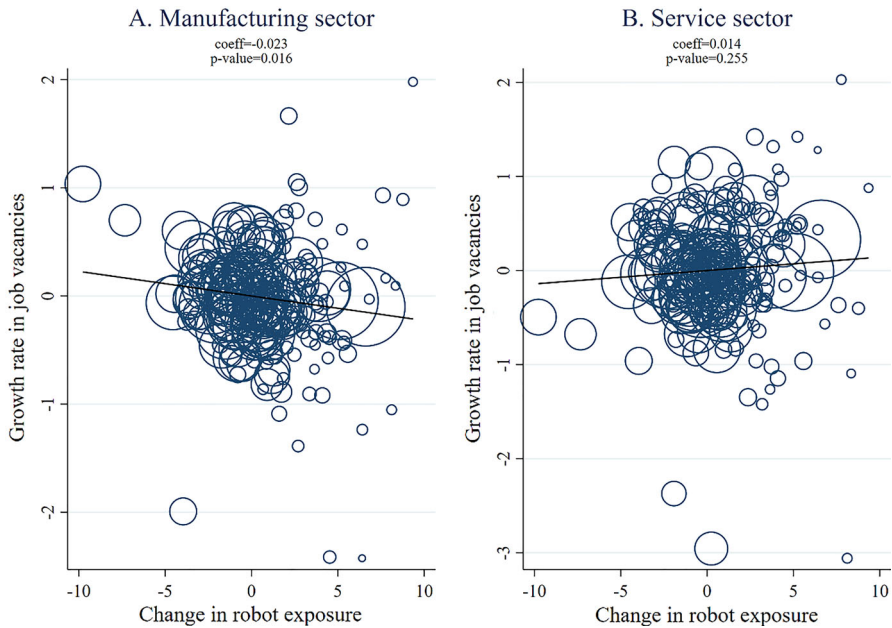
Fig. 5 Robot exposure and labor demand, by industry, 2010–2019. *Note*: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 5 are partialled out. The circle size of an individual observation indicates the weight of each region defined as the population in 2010

of Fig. 5). This result is not surprising given that manufacturing industries are heavily robot intensive. The OLS estimate indicates that an increase in one robot per 1000 workers in exposure to robots is correlated with a decline in the job vacancy growth of 2.3%p. I 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 Fig. 5). I separate the analysis by two occupational groups in Fig. 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 Fig. 6). Since routine tasks are easily automated by industrial robots, it is natural that the declines in labor demand resulting from robot adoption are pronounced for routine jobs (Autor et al. 2003; Goos et al. 2014). The point estimate for routine jobs is − 0.023 (*p* value = 0.020), similar to that for the manufacturing sector.[9] 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 Fig. 6). The estimated coefficient for non-routine jobs is small in magnitude. 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.

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[9] Additionally, I 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
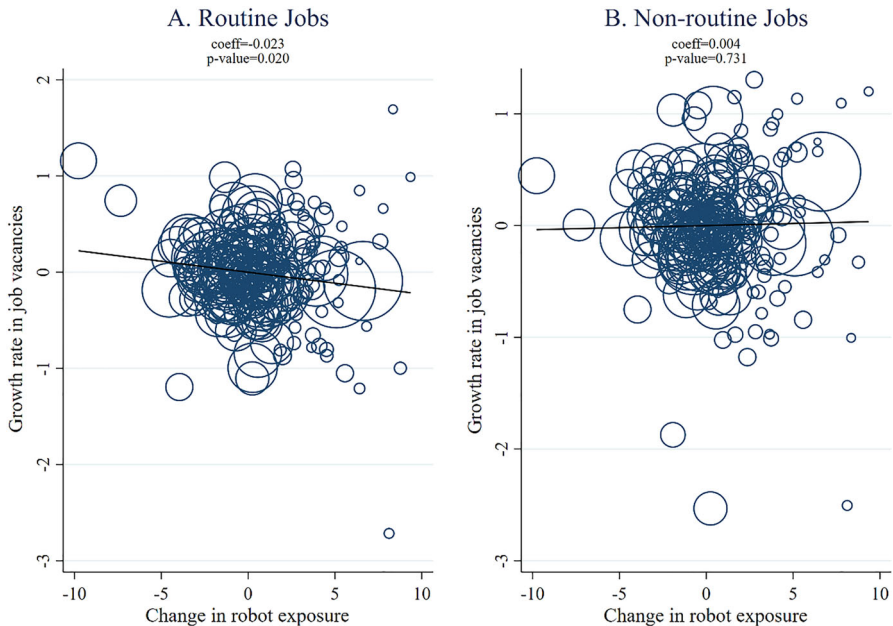
Fig. 6 Robot exposure and labor demand, by occupation, 2010–2019. *Note*: The figure plots the relationship between the change in robot exposure and the growth rate of online vacancies between 2010 and 2019. The control variables from Column 4 of Table 6 are partialled out. The circle size of an individual observation indicates the weight of each region defined as the population in 2010

3.2 Reduced-form and IV results

The 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, I regress the job vacancy growth rate on the change in robot exposure from Singapore. Each column includes a different set of controls, as shown in Table 2. Column 1 shows the basic specification controlling only for the province-fixed effects. In Column 2, I 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 results indicate that an increase in robot exposure has a negative effect on labor demand, but this relationship is not statistically different from zero. Qualitatively similar results are shown when I add demographic characteristics in 2010 (Column 3). In Column 4, I account for other contemporaneous changes that may be correlated with local labor demand and robot exposure: gross exports and imports. With the inclusion of trade controls, the estimate becomes positive but still insignificant. The pattern of 2SLS estimates in Panel B is very close to the reduced-form counterparts.

Footnote 9 continued
I split up the non-routine labor demand into several manual and analytic task-intensive occupations, none of the estimates are significant.

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	− 0.018	− 0.006	− 0.001	0.004
	(0.019)	(0.016)	(0.012)	(0.016)
R-squared	0.334	0.405	0.431	0.452
	B. IV estimates			
Change in the robot exposure, 2010–2019	− 0.019	− 0.008	− 0.002	0.006
	(0.018)	(0.017)	(0.015)	(0.021)
R-squared	0.368	0.413	0.432	0.447
Control variables				
Province-fixed effect	✓	✓	✓	✓
Industry shares		✓	✓	✓
Demographic controls			✓	✓
Trade controls				✓
Observations	228	228	228	228

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 female 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 export (in \$ 1000) and log of imports (in \$ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Panel A reports reduced-form results, and Panel B reports the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

The estimates are not statistically insignificant from zero across all specifications. Since the shift-share instrument was correlated with the share of the college-educated population and the log of the population as in Panel B of Table 9, it is necessary to check whether the main coefficient is sensitive to the inclusion of these two and other controls. Comparing Columns 1 and 4 in Table 4 find that the results are qualitatively similar with or without controls.

3.3 Effects by industry and occupation

I next study the effects of robots separately by industry. Specifically, I repeat the estimation of Table 4 for the manufacturing and service sector, respectively. I 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. Panel B shows that the IV results are similar

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	− 0.038***	− 0.034***	− 0.019***	− 0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
R-squared	0.508	0.514	0.545	0.545
	B. IV estimates, manufacturing sector			
Change in the robot exposure, 2010–2019	− 0.040***	− 0.040***	− 0.026***	− 0.026***
	(0.006)	(0.006)	(0.007)	(0.008)
R-squared	0.519	0.519	0.549	0.549
	C. Reduced-form, service sector			
Change in the robot exposure from Singapore, 2010–2019	− 0.026	− 0.017	0.002	0.006
	(0.020)	(0.015)	(0.008)	(0.011)
R-squared	0.371	0.411	0.477	0.484
	D. IV estimates, service sector			
Change in the robot exposure, 2010–2019	− 0.027	− 0.020	0.003	0.009
	(0.018)	(0.015)	(0.011)	(0.015)
R-squared	0.382	0.413	0.478	0.486
Control variables				
Province-fixed effect	✓	✓	✓	✓
Industry shares		✓	✓	✓
Demographic controls			✓	✓
Trade controls				✓
Observations	228	228	228	228

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 female 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 export (in $ 1000) and log of imports (in $ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Panels A and C report reduced-form results, and Panels B and D report the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

to the reduced-form results. In all specifications, I find consistently negative and precise estimates for labor demand growth. The preferred IV estimate with the full set of control variables in Column 4 is − 0.026 (standard error = 0.008). To assess the economic magnitude of this, comparing a city at the median of the change in robot exposure (2.108) to a city with no change, the magnitude implies that the highly robot-exposed city experiences a 5.5%p (= 2.108 × − 0.026) lower labor demand growth. This amounts to about 12.3% of the average growth rate in manufacturing labor demand (which is −0.444, 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, I 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, albeit insignificant. The next two columns add demographic and trade controls, and the estimates become positive, but remain statistically insignificant. The IV estimates in Panel D essentially mimic the reduced-form estimates. The results suggest that the reduction of job vacancies in the manufacturing sector does not lead to positive spillovers in labor demand on other local industries in service sectors.

In the following, I 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 Fig. 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 1–4 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 I enrich the specifications. The coefficient estimate in the preferred specification (Column 4 in Panel B) is − 0.025 (standard error = 0.011). Quantitatively, again comparing a city at the median of the change in robot exposure (2.108) to a city with no change, the magnitude corresponds to a 5.3%p (= 2.108 x − 0.025) decline in labor demand growth, which translates into about 14.2% 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, I present the reduced-form results in Panel C and the IV estimates in Panel D for non-routine occupations. No significant relationship can be found between robot adoption and non-routine labor demand. 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.

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	− 0.030***	− 0.020***	− 0.018**	− 0.018**
	(0.008)	(0.007)	(0.008)	(0.009)
R-squared	0.334	0.386	0.394	0.395
B. IV estimates, routine jobs				
Change in the robot exposure, 2010–2019	− 0.031***	− 0.023***	− 0.026***	− 0.025**
	(0.006)	(0.006)	(0.009)	(0.011)
R-squared	0.368	0.395	0.400	0.400
C. Reduced-form, non-routine jobs				
Change in the robot exposure from Singapore, 2010–2019	− 0.015	− 0.004	0.008	0.014
	(0.020)	(0.016)	(0.011)	(0.016)
R-squared	0.359	0.409	0.452	0.470
D. IV estimates, non-routine jobs				
Change in the robot exposure, 2010–2019	− 0.015	− 0.005	0.011	0.019
	(0.019)	(0.017)	(0.015)	(0.022)
R-squared	0.379	0.413	0.448	0.461
Control variables				
Province-fixed effect	✓	✓	✓	✓
Industry shares		✓	✓	✓
Demographic controls			✓	✓
Trade controls				✓
Observations	228	228	228	228

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 female 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 export (in $ 1000) and log of imports (in $ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Panels A and C report reduced-form results, and Panels B and D report the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

3.4 Robustness

Table 7 presents several robustness checks. To start with, I check whether the main estimates might confound the effects of robots with the pre-trends. I include the growth rate in job vacancies between 2007 and 2010 as a covariate and repeat the IV estimation. If the estimates are driven by the correlation between persistent trends in the outcome and the change in robot exposure, the significance would disappear after including the pre-period outcome. The results in Panel A of Table 7 show that this is not the case. The estimates are very similar to the baseline results, suggesting that the change in robot exposure is not correlated with the pre-trend in labor demand. I also consider the adjusted robot exposure in Acemoglu and Restrepo (2020) as the explanatory variable. I 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, I obtain very similar estimates (Panel B of Table 7). I also check the robustness of the results by excluding observations with outlier values with respect to the robot measure. Specifically, I exclude observations where the change in the change in robot exposure is less than the bottom 5% or more than the top 5%. The results remain unaffected, as shown in Panel C of Table 7. In Panel D of Table 7, I have reported standard errors using the procedure from Adão et al. (2019) and find that the results are qualitatively identical. They suggest a clustering procedure that clusters according to the similarity of industry structures, instead of clustering by geographical proximity, as regression residuals in shift-share settings are likely to be correlated across regions with similar industry structures.

4 Conclusion

The use of robots has increased considerably across countries, and at the same time, it has fuelled the debate about the employment effects of rapid robot adoption. I examine the relationship between change in robot exposure and job vacancy growth between 2010 and 2019 in South Korea. I find little evidence that robot-exposed regions decrease labor demand, though the estimated effects of robots differ substantially across industries and occupations. I see a strong negative relationship between exposure to robots and labor demand changes for the manufacturing sector and routine occupations, while I 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. The 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 the estimates I obtain 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, I would need to make further assumptions on cross-city spillovers. In addition, since this paper focuses on labor demand rather than actual job matches, it would be interesting to explore whether a decline in

Table 7 Robot exposure and labor demand, 2010–2019 (robustness check)

A. Controlling for pre-trends

Dependent variable: growth rate in job vacancies, 2010–2019	All	Manufacturing	Service	Routine	Non-routine
	(1)	(2)	(3)	(4)	(5)
	Reduced-form				
Change in the robot exposure, 2010–2019	0.005	− 0.019***	0.008	− 0.017*	0.015
	(0.016)	(0.006)	(0.012)	(0.009)	(0.017)
Growth rate in job vacancies, 2007–2010	− 0.410***	0.157**	− 0.540***	− 0.245***	− 0.417**
	(0.125)	(0.066)	(0.144)	(0.064)	(0.163)
Observations	228	228	228	228	228
R-squared	0.518	0.554	0.554	0.423	0.527

B. 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	0.008	− 0.028***	0.009	− 0.026**	0.022
	(0.023)	(0.009)	(0.016)	(0.012)	(0.024)
Observations	228	228	228	228	228
R-squared	0.446	0.549	0.486	0.400	0.460

C. Excluding outliers

Dependent variable: growth rate in job vacancies, 2010–2019	All	Manufacturing	Service	Routine	Non-routine
	(1)	(2)	(3)	(4)	(5)
	IV estimates				

Table 7 (continued)

A. Controlling for pre-trends

Dependent variable: growth rate in job vacancies, 2010–2019	All	Manufacturing	Service	Routine	Non-routine
	(1)	(2)	(3)	(4)	(5)
Change in the robot exposure, 2010–2019	− 0.038	− 0.209***	0.024	− 0.087*	− 0.001
	(0.064)	(0.080)	(0.074)	(0.047)	(0.074)
Observations	206	206	206	206	206
R-squared	0.488	0.476	0.507	0.395	0.492

D. Adão et al. (2019) standard errors

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	0.006	− 0.026***	0.009	− 0.025***	0.019
	(0.011)	(0.009)	(0.008)	(0.009)	(0.011)
Observations	228	228	228	228	228
R-squared	0.447	0.549	0.486	0.400	0.461
Control variables					
Province-fixed effect	√	√	√	√	√
Industry shares	√	√	√	√	√
Demographic controls	√	√	√	√	√
Trade controls	√	√	√	√	√

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 female 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 export (in $ 1000) and log of imports (in $ 1000), measured in 2010. All estimates are from regressions weighted by population in 2010. Panel A reports reduced-form results, and Panel B, C and D reports the 2SLS results where we instrument the change in Korean robot exposure using the change in robot exposure from Singapore. Standard errors clustered at the level of 55 living zones (LZs) in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

labor demand for manufacturing and routine jobs could affect unemployment rates, worker out-migration, or posted wages in further research.

Declarations

Conflict of interest The author did not receive support from any organization for the submitted work and has no competing interests to declare that are relevant to the content of this article.

Appendix

See Tables 8 and 9 and Fig. 7.

Table 8 Comparison between Korea and Singapore

IFR industries	Change in the stock of robots (2010–2019)		The stock of robots (2010)		Employment share (2010)	
	Korea	Singapore	Korea	Singapore	Korea	Singapore
Agriculture	0.07	0.09	0.02	0.00	5.06	1.74
Automotive	189.65	38.57	107.14	16.70	1.81	0.13
Construction	0.01	0.14	0.01	0.03	7.34	4.81
Electronics	177.98	175.57	65.97	15.15	3.97	4.63
Food and beverages	4.34	6.54	1.46	2.01	1.51	1.24
Wood, furniture, and other	15.28	31.76	1.67	1.70	0.97	1.08
Basic metals	2.63	32.68	5.59	1.00	0.78	0.13
Metal and machinery	15.13	2.93	1.14	0.71	1.76	2.96
Metal products	− 0.99	3.59	11.19	1.66	1.54	1.90
Minerals	0.51	0.19	0.51	0.00	0.59	0.29
Mining	− 1.48	0.37	1.66	0.00	0.09	1.74
Paper and printing	0.16	0.82	0.02	0.00	1.87	0.98
Plastics and chemicals	13.69	− 24.08	14.51	47.99	1.80	1.78
Research	0.10	0.34	0.18	0.13	4.18	5.21
Services	0.05	− 0.01	0.00	0.03	62.99	65.60
Textiles	− 0.10	0.00	0.12	0.00	1.94	0.19
Utilities	0.07	0.16	0.03	0.00	0.78	1.74
Other vehicles	1.64	1.02	0.71	0.10	1.02	3.88
Correlation coefficient	0.7649 (p value = 0.0002)		0.4338 (p value = 0.0721)		0.9946 (p value = 0.000)	

The robot variables are expressed in terms of robots per thousand workers

Table 9 Shock balance test

Dependent variable: change in the stock of robots in Singapore, 2010–2019

A. Industry-level	
Log average wage, 2010	0.085
	(0.077)
Log profit, 2010	0.302
	(0.300)
Log R&D investment, 2010	0.594
	(0.387)
Share of production workers, 2010	0.008
	(0.053)
Observations	18
R-squared	0.312
B. Region-level	
Dependent variable: change in the robot exposure from Singapore, 2010–2019	
Share of manufacturing workers, 2010	1.550
	(1.677)
Share of the female population, 2010	− 1.691
	(5.099)
Share of the population aged over 55, 2010	4.759
	(3.717)
Share of the college-educated population, 2010	− 2.945***
	(0.707)
Log of population, 2010	0.920***
	(0.197)
Log export (in $ 1000)	− 0.012
	(0.075)
Log import (in $ 1000)	0.130
	(0.124)
Observations	228
R-squared	0.492

Panel A of this table reports coefficients from regressions of the industry-level characteristics measured in 2010 on the change in the robot stocks in Singapore between 2010 and 2019. Standard errors are reported in parentheses, and results are weighted by the number of employed persons in 2010. Panel B reports coefficients from regressions of region-level characteristics measured in 2010 on the change in the robot exposure from Singapore between 2010 and 2019. Standard errors clustered at the level of 56 living zones (LZs) in parentheses, and results are weighted by population in 2010. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$

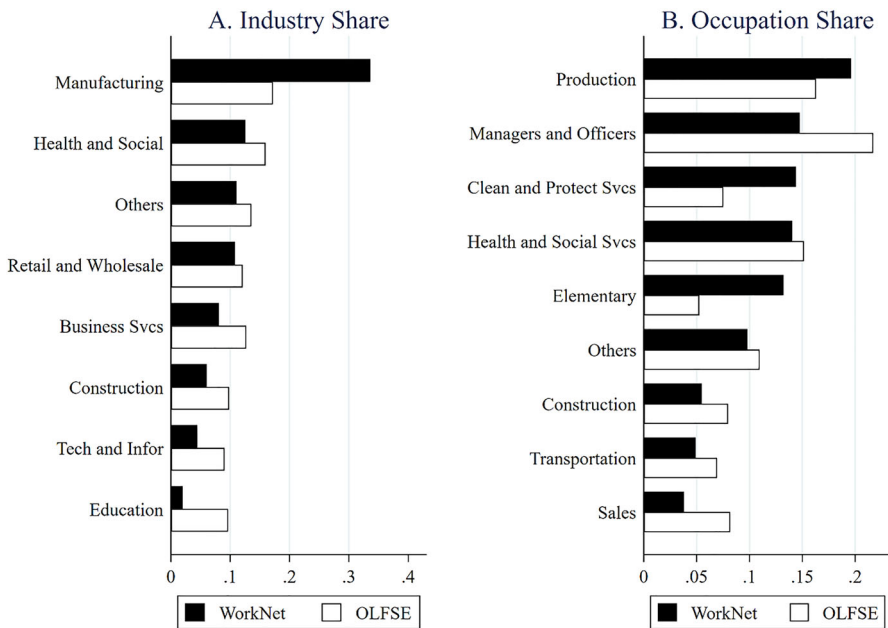**Fig. 7** Industry and occupation shares in WorkNet and OLSFE, 2019. *Note*: Panel A plots the share of vacancies by broad industry in 2019 WorkNet data and in OLSFE data. Panel B plots the share of vacancies by broad occupation in 2019 WorkNet data and in OLSFE data

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