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Abstract

This paper uses a quasi-differences-in-differences approach to identify impacts of robotisation and exposure to robots owned by foreign competitors on labour market outcomes of Czech workers. Utilising employee-level data allows for identification of differential impacts on workers of different skill levels. We find that while robot adoption substantially increases demand for college-educated labour, demand for employees with an elementary and/or high school diploma decreases slightly. Exposure to robots owned by foreign competitors also seems to drive up the demand for college graduates and to suppress the demand for workers with lower qualifications.

Keywords: Automation, Differences-in-differences
JEL Codes: F61, J29

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1 Introduction

A growing literature explores the consequences of the adoption of robotic technologies.[1] At first glance, displacing workers with industrial robots should unambiguously lead to lower labour demand and thus to depressed wages. Indeed, this seems to be the dominant result in the extant literature. However, the increased productivity arising from robotisation can also lead to more investment and productivity, which can drive labour demand up (Acemoglu and Restrepo, 2019).

In this paper, we exploit time variation in workers' exposure to robots owned by domestic firms and by foreign competitors to study the effects of robots on wages and employment. Our quasi-differences-in-differences approach is based on employer-employee decade-long panel data on all workers in a sample of Czech firms, which allows us to analyse the heterogenous impacts by worker type. In this respect, the present paper extends recent findings from studies that, due to data limitations, used only firm-level data (e.g. Acemoglu et al., 2020), occupation-level data (e.g. Adachi, 2021) or industry-level data (e.g. Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020b).

Previous studies of the introduction of labour-substituting technology have identified a number of surprising results. On the one hand, survey evidence from Japan shows that firms expect to substitute a part of their workforce with robots (Morikawa, 2017), which is in line with the economic intuition that the robots' comparative advantage in the production process will outcompete human labour. This finding was later corroborated by evidence from 17 countries gathered by Graetz and Michaels (2018), who find that robotisation displaces low-skilled labour but at the same time leads to improvements in productivity accompanied by increases in wages for higher-skilled workers. A similar picture emerges from detailed Chinese labour market data analysed by Giuntella and Wang (2019), who find that increased exposure to robots is linked to substantial job losses for low-skilled workers and depressed wages. Furthermore, and more worryingly, this analysis has linked

[1] The terms "robots" and "robotic technologies" are taken to mean autonomous, reprogrammable, multipurpose automation technology, cf. ISO 8373:2012. See Wōrk et al. (1984) for a discussion of the term "automation", which is rather tautologically defined by ISO 11065:1992 as "the implementation of processes by automatic means."

the introduction of robots to increased social unrest.

To an extent, US employment data analysed by Autor et al. (2015) buttress the view that in areas with higher exposure to robots, employment in routine jobs declines. At the same time, however, the American labour data reveal further nuances beyond the simple picture of capital-labour substitution. Unlike the results based on world-wide data used by Graetz and Michaels (2018), Autor et al. (2015, p. 644) show that the losses in routine jobs seem to be "offset by increasing employment in abstract or manual task-intensive occupations." This finding indicates that robotisation not only increases labour productivity of workers employed in firms that purchased robots but also has spillover effects on other firms within a region exposed to robots.

Another important aspect of robotisation noted by Autor (2015) is its impact not just on low-skilled jobs, but also on relatively high-skilled occupations. These higher-skill jobs are shown to be changing in their job description due to the automation of some of the tasks involved even though the jobs themselves remain. Case studies documented by Agrawal et al. (2019) lend further credence to this view that technology impacts the high-skilled segment of the labour market by supplanting human labour in specific tasks, rather than supplanting the entire occupation, e.g. that artificial intelligence may outperform judges in making bail decisions by more accurately predicting bail violations.

These insights are integrated in a theoretical framework by Acemoglu and Restrepo (2019, 2020a) , who present a model in which labour can be replaced by capital (automation), but the automation displaces tasks rather than occupations. At the same time, the introduction of automation increases value added, which creates new tasks within the firm, which in turn drives up demand for labour. Atack et al. (2019) use this model to interpret the effects of the introduction of steam engines in the nineteenth century and argue that the massive increase in output due to automation countervailed the destructive effects on jobs lost due to displacement of tasks previously performed by humans.

The present paper focuses on the exposure of individual workers to domestic robots as well as to robots installed by the foreign competitors of the workers' Czech-based employers. In this way, we are able to test the Acemoglu and Restrepo (2020a) mechanism, which predicts displacement of human labour in automatisable tasks by capital. In addition, this setup allows us to test whether the competitive advantage of foreign robot-adopters creates pressure on domestic firms to supplant human labour by robotic technologies. This spillover effect of robots has been considered in a pioneering study by Adachi (2021), who associated declines in the prices of different types of Japanese robots with downward movements in the wages of American workers employed in occupations exposed to them. In the Czech context, identifying the effect of exposure to foreign-owned robots is potentially even more salient than in the US context considered by Adachi (2021), because (unlike the US), the Czech Republic can be treated as small open economy in a meaningful way. Therefore, foreign robot installations are more plausibly exogenous with respect to the Czech market. Thus, in addition to unpacking the heterogeneity of impact on workers, this study helps to address the thus far poorly explored question of spillover effects of foreign-owned robots on domestic markets in a manner similar to the FDI literature (Smarzynska Javorcik, 2004).

By resolving the impacts of robots at the level of individual workers, this study adds to the relatively few research projects that have attempted to reach this level of granularity. The China Family Panel Studies dataset has been utilised by Giuntella and Wang (2019) to estimate differential impacts of robotic technologies, using county-level exposure to robots. Thus, the exposure variable does not vary by the individuals' employers, but rather by their place of residence. Even with this relatively coarse measure of exposure, however, Giuntella and Wang (2019) estimate sizeable negative impacts on wages and hours worked. A different approach is taken by Yashiro et al. (2020), who study the impacts of occupation-specific *risk* of automation (Frey and Osborne, 2017) on different cohorts of Finnish workers. Their analysis shows that exposure to automation has a more pronounced effect on the risk of leaving employment for workers approaching the retirement age.

The closest parallels to this paper are Dauth et al. (2017, 2018), who use a German employer-employee spell data set (Integrated Employment Biographies, IEB) to identify the effects of exposure to robots on occupational mobility and wages. While their results on wages are somewhat specification-sensitive (cf. Dauth et al., 2017, Table 6), their main conclusion is that robot exposure leads to depressed wages for medium-skilled workers engaged in routine tasks, while higher-skilled workers may benefit from robot exposure. The effects on mobility are clearer: robot exposure appears to lower rates of entry for new workers and decreases length of employment for current workers. In this paper, we shall see if the German results are replicable in the Czech context.

2 Data and methodology

Following the previous literature, our information on robot installations comes from the data collected by the International Federation of Robotics (IFR). This dataset is a panel containing shipments of new robots, as well as robot stock in a given year across 99 countries and territories. Within each country or territory, the stocks and shipments of robots are disaggregated by industry. The industrial categories used for the present analysis are reported in Table 1.

Following the ISO 8373:2012 definition, the IFR considers an industrial "robot" to be "[a]n 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" (Müller and Kutzbach, 2020). The IFR interprets this definition noting that robots are "designed so that the programmed motions [...] can be changed without physical alteration [..., and are] capable of being adapted to a different application with physical alteration" (Müller and Kutzbach, 2020, p. 23). This sets robotic technologies apart from other automation solutions, which are dedicated to performing specific manipulations and cannot be re-programmed to perform other ones.

For the Czech Republic, we observe robot stocks for the 2009–2019 but we limit the sample to 2011–2019 due to missing observations in the first two years. Robots in the Czech economy are predominantly concentrated in the manufacturing industry, where about 147 robots are installed per 10,000 employees. More specifically, within the manufacturing industry, robots are concentrated in the automotive industry, where 607 robots are installed per 10,000 employees. In all other remaining industries, we observe about 66 robots per 10,000 employees.

Since IFR data provide only information on robots delivered and installed within a country and industry, we need to construct a measure of exposure of Czech industries to robot installations abroad. To that end, we appeal to the following intuition: Czech exporters are more exposed to foreign robots if the markets to which they ship their goods also buy

Table 1: List of industries reported in the IFR data used in this analysis

Code	Description
01-03	Agriculture, hunting, forestry and fishing
05-09	Mining and quarrying
10-12	Food products, beverages and tobacco
13-15	Textiles, wearing apparel, leather and related products
16	Wood and products of wood and cork, except furniture
19-20	Paper and paper products
21	Pharmaceutical products
22	Rubber and plastics products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products, except machinery and equipment
26	Computer, electronic and optical products
27	Electrical equipment
28	Other machinery and equipment
29	Motor vehicles, trailers and semi-trailers
30	Other transport equipment
31-32	Furniture, other manufacturing
35-36	Utilities

from robotised exporters elsewhere. Thus, if the Czech-based automotive manufacturers export their products to the United Kingdom (as they do), but the United Kingdom also imports automobiles from other countries (as it does), Czech automotive exporters will be deemed as exposed to foreign robots if their competitors are robotised. To operationalise this idea formally, define the exposure variable E_i as:

$$E_i = \sum_j \frac{x_{ij} W_{ij}}{\sum_{j''} x_{ij''}}, \tag{1}$$

where

$$W_{ij} = \sum_{i' \neq i} \frac{x_{i'j} r_{i'}}{\sum_{i'' \neq i} x_{i''j}}, \tag{2}$$

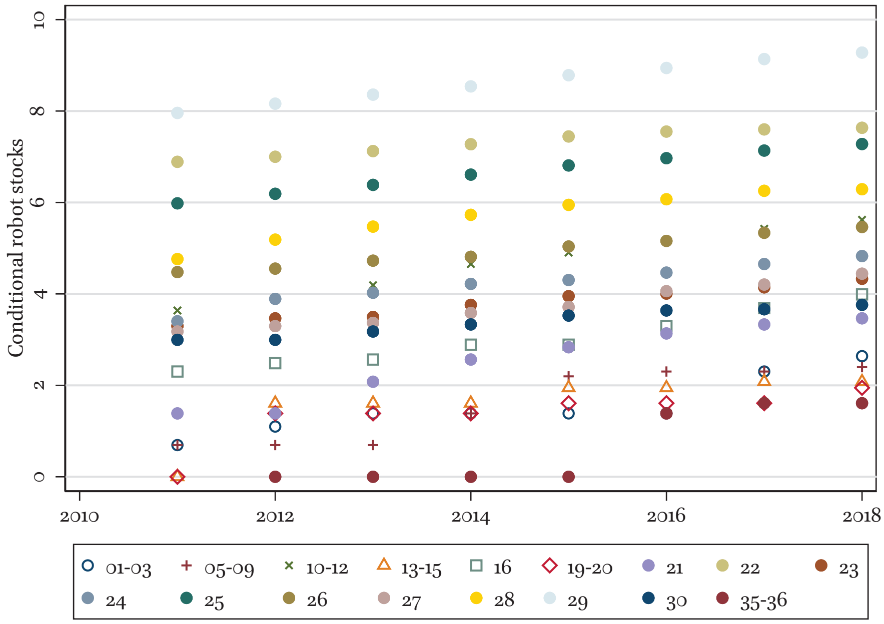
and x_{ij} are the exports from exporting industry i to importing country j, $r_{i'}$ are robot stocks installed in competing exporting industries i'.[2] Thus, the weighting factor W_{ij} measures how intensely importer j relies on products made by robotised industries abroad. If robotised exporter i' accounts for a large portion of importer j's total imports (the denominator in (2)), then W_{ij} is large. However, even if the exporter uses a large robot stock ($r_{i'}$), W_{ij} need not be large if importer j does not import large amounts of output from i'. Consequently, exporter i is exposed to robots from overseas if two conditions are met: (a) she exports to a market j that purchases competing goods from robotised exporters i', i.e. W_{ij} is large, and (b) she exports a large proportion of her output to j, i.e. $x_{ij}/\sum_{j''} x_{ij''}$ is large.

In order to compute E_i, we utilise product-level international trade data from BACI (Gaulier and Zignago, 2010), which are created by reconciling exporter and importer records kept by the United Nations Statistics Division. BACI data were then associated with industries using a product-industry concordance constructed by Pierce and Schott (2009). Using this concordance, we are able to match about 99% of the value of traded goods reported in the BACI dataset with the corresponding industries. To overcome a missing data problem at the end of the dataset, we employ linear extrapolation using the last observed growth rate and applying it to the last observed level of exposure.

Figures 1 and 2 show the time trend of both the robot stock and the exposure of Czech-based firms to robot installations overseas. The values displayed are residuals from an OLS model where robot stock (R) is projected on E and industry fixed effects. Similarly, exposure to foreign robots (E) is projected on R and industry fixed effects in order to disentangle the global trend in robotisation from its Czech-specific variation. Broadly speaking, both E and R are growing over time, and the automotive industry is both the most robotised, but also the most exposed to robotised competition abroad. Among the least robotised and least exposed is mining and quarrying, where the precise manipulation achievable by robotic technologies may be less useful.

[2]Note that x_{ij}, $r_{i'}$, W_{ij}, and E_i are all time-varying, but we suppress time indices to avoid clutter.

Figure 1: Robot stocks (log-scale) in the Czech Republic conditional on industry fixed effects and exposure to foreign robots. Industry codes are reported in Table 1.



Data on labour market outcomes were taken from the Average Earnings Information System (ISPV). ISPV contains data on earnings and hours worked of employees in the Czech Republic. Moreover, the ISPV reports characteristics of individual workers such as level of qualification, age, gender, and the type of occupation. Alongside worker characteristics, employer-specific variables in the ISPV report company size, sector classification, place of operation etc. The ISPV uses data from a regular statistical survey called the Quarterly Survey of Average Earnings, which represents the EU-wide harmonized Structure of Earnings Survey (SES).

These data are not proper employer-employee data, since they do not contain a worker-specific identifier. Therefore, it is impossible to track an employee in different employment spells working for different employers, thus precluding the type of occupational mobility analysis carried out by Dauth et al. (2017, 2018). However, using data on occupation, gender, and age, it is possible to match observations within one firm that plausibly belong to a single employee. In this way, employee-employer IDs were constructed, which can be used to create fixed effects for our analysis. Summary statistics are reported in Table 2.

Figure 2: Exposure to foreign robots (log-scale) in the Czech Republic conditional on industry fixed effects and the domestic stock of robots. Industry codes are reported in Table 1.

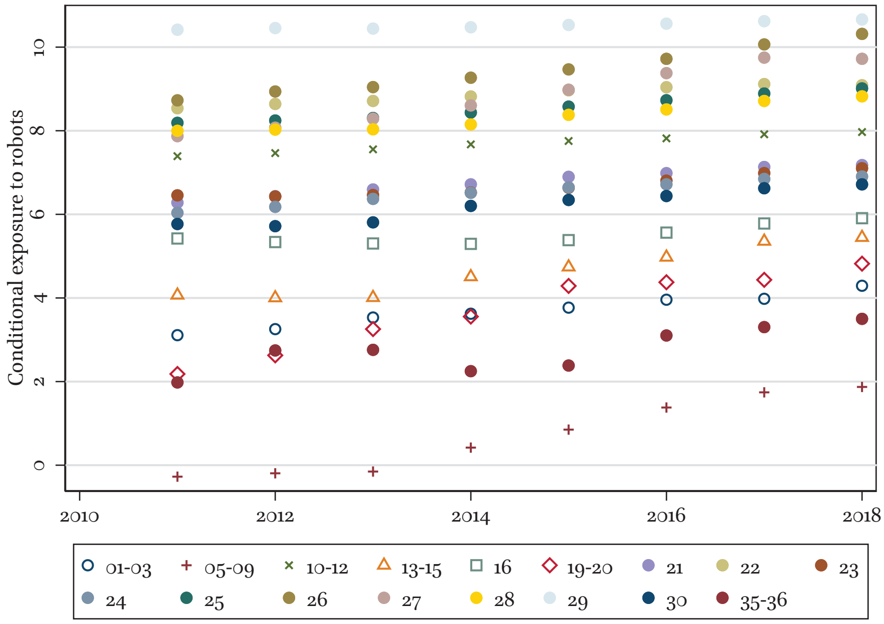


Table 2: Summary statistics: Earnings = cumulative earnings of a worker (thousands of CZK); Hours total = total hours worked for a single employer within a year (thousands of hours); Hours/month = average monthly hours worked for an employer within a year; E = Exposure to foreign-owned robots defined in (1) (thousands of weighted robots); R = robot stock (thousands). Each panel represents a different category of workers: ISCO9 = workers employed in "elementary occupations" as defined by International Standard Classification of Occupations; Elementary/High school = employees with elementary and/or high school diplomas; College = employees with college degrees.

	All sectors				Manufacturing			
ISCO9	N	Mean	Min	Max	N	Mean	Min	Max
Earnings	358,399	132.64	47.19	365.06	169,019	152.63	55.64	365.06
Hours total	358,399	82.60	0.26	1444.32	169,019	43.23	0.33	603.59
Hours/month	358,399	138.14	55.42	189.79	169,019	132.73	55.42	189.79

E	259,147	12.18	0.00	42.69	218,993	14.40	0.01	42.69
R	259,147	1.84	0.00	10.71	218,993	2.17	0.00	10.71
Elementary/High school								
Earnings	1,987,370	125.24	47.19	480.97	947,268	145.71	48.47	480.97
Hours total	1,987,370	85.48	0.26	1512.14	947,268	56.10	0.33	1104.68
Hours/month	1,987,370	130.23	0.00	236.17	947,268	127.21	3.33	236.17
E	1,425,154	12.07	0.76	42.69	1,204,740	14.27	0.01	42.69
R	1,425,154	1.84	0.00	10.71	1,204,740	2.17	0.00	10.71
College								
Earnings	2,692,183	338.96	52.74	2634.60	1,238,760	360.93	52.74	1906.43
Hours total	2,692,183	641.80	0.50	5807.61	1,238,760	571.71	0.57	4539.69
Hours/month	2,692,183	138.17	3.61	191.98	1,238,760	137.30	3.61	191.98
E	1,425,154	12.07	0.00	42.69	1,204,740	14.27	0.01	42.69
R	1,425,154	1.84	0.00	10.71	1,204,740	2.17	0.00	10.71

In order to estimate the impact of exposure to robots (domestic and foreign), the following OLS model is used:

$$\mathbb{E}[y_{it}|\mathbf{\Theta}] = \alpha_i + \alpha_t + \beta_1 E_{it} + +\beta_2 R_{it} + \mathbf{X}_{it}\gamma, \tag{3}$$

where y_{it} is the outcome variable (earnings, hours worked) observed for individual i in year t; $\mathbf{\Theta}$ is the conditioning set, which consists of individual-specific fixed effects (α_i), time fixed effects (α_t), exposure to foreign-owned robots (E_{it}), domestic robot stock (R_{it}), and additional controls ($\mathbf{X}_{it}$). The control matrix $\mathbf{X}_{it}$ contains age, tenure, and firm size. Due to the high correlations between E_{it} and R_{it}, adding an interaction term resulted in significant collinearity problems and thus the interaction is omitted.

Model (3) is a quasi-differences-in-differences model, which eliminates time-invariant worker characteristics and also the economy-wide trend. Parameters β_1 and β_2 thus measure the difference in outcome *as the same employee* becomes marginally more exposed to robots. By controlling for the tenure effects, we also eliminate potential confounding effects of accumulation of experience on the job, thus disarming a potential objection of trend heterogeneity across different workers. Since the robot exposure variables E_{it} and R_{it} are defined at the industry-level only, standard errors are clustered by employers' industry classifications listed in Table 1.

Contrary to the typical approach employed in the literature, we do not conduct a Bartik-type instrumental-variables identification (Bartik, 1991). The rationale for relying on the simpler quasi-differences-in-differences model rests on the common experience in the robot-related literature that OLS and IV estimates tend to be very close to each other, see e.g. Dauth et al. (2017, esp. Table 1 and 3) or Graetz and Michaels (2018, Tables 1–4). This would indicate that the endogeneity problems with robot exposure variables are minor.

3 Results

Starting with employees in elementary occupations, we present a long-difference version of model (3), in which we only use the years 2010 and 2020 in Table 3. We observe a relatively imprecise zero for the impact of foreign-owned robots but considerable impacts of domestic ones: a single robot displaces about 3 hours worked by ISCO-9 workers, and each worker's monthly hours decline by about 0.3 per 100 robots installed. The increases in log-earnings[3] are consistent with findings of wage increases in Dauth et al. (2017) and and Acemoglu et al. (2020) and may thus indicate positive pass-through elasticity from output per worker to wages.

Table 4 shows analogous results to Table 3 but for workers with only an elementary and/or high school diploma. Due to the substantial overlap between the ISCO-9 sample and workers without a college degree, the estimates largely coincide.

Moving to the full sample, Table 5 shows negative impacts of the exposure to foreign robots on log-earnings, as well as the total hours worked by workers without a college degree. This is similar to the findings of Adachi (2021), who documented downward movements in American wages associated with declines in prices of robots in Japan. In both instances domestic employees face increased competition: in the case of the US, it is the possibility of being displaced by robots imported from Japan; in the Czech case it is the competition

[3]It is acknowledged that a Poisson model would have been preferable in this context (Santos Silva and Tenreyro, 2006; Blackburn, 2007) but this plan proved infeasible due to problems with convergence.

Table 3: Quasi-differences in differences estimates (3) for the subsample of workers classified to be in elementary occupations (ISCO-9) on long differences (2010 and 2020 only). Standard errors clustered by industry in parentheses. Scale indicates normalisation of the regressors R and E to match the variance of the dependent variable (1e4 = increase in robot exposure by 10,000).

	Log-earnings		Hours - total		Hours/month	
Scale:	1e4		1		1e2	
	Manuf.	All	Manuf.	All	Manuf.	All
E	-0.016	-0.009	0.683	1.237	-0.007	-0.021
	(0.011)	(0.018)	(0.623)	(0.886)	(0.01)	(0.014)
R	0.339***	0.329***	-3.22***	-2.811***	-0.27***	-0.281***
	(0.012)	(0.012)	(0.700)	(0.856)	(0.01)	(0.012)
R-sq	0.8754	0.8752	0.0840	0.0926	0.7464	0.7364
Obs	157274	175093	157274	175093	157274	175093
Indiv.	81395	90361	81395	90361	81395	90361

from foreign firms operating in the same sector. These findings match those found by Graetz and Michaels (2018), which identified lower-skilled workers as the most vulnerable to robot exposure. On the assumption that these types of workers are carrying out tasks that can be performed by robots, their displacement from the production process is also predicted by the Acemoglu and Restrepo (2019) mechanism.

Table 6 reports the long-difference estimates for college-educated workers exposed to domestic robots. In parallel to the previous results, college graduates also receive a wage boost, which, curiously, is noticeably smaller than that received by lower-skilled workers. On the other hand, Czech robot adopters utilise significantly more hours worked by the college-educated workforce (even though individual workers in those firms work shorter hours). These results point to a large composition effect, in which the robot adopters hire more college-educated employees, whose skills are, presumably, better complements to the robotic technologies. It is worth noting, however, that the decline in total hours worked by workers without college degrees is not nearly as pronounced as the increase in the total

Table 4: Quasi-differences in differences estimates (3) for the subsample of workers with only elementary/high school diploma on long differences (2010 and 2020 only). Standard errors clustered by industry in parentheses. Scale indicates normalisation of the regressors R and E to match the variance of the dependent variable (1e4 = increase in robot exposure by 10,000).

	Log-earnings		Hours - total		Hours/month	
Scale:	1e4		1		1e2	
	Manuf.	All	Manuf.	All	Manuf.	All
E	-0.016	-0.009	0.682	1.237	-0.007	-0.022
	(0.011)	(0.018)	(0.623)	(0.886)	(0.012)	(0.014)
R	0.329***	0.334***	-3.224***	-2.811***	-0.27***	-0.281***
	(0.012)	(0.015)	(0.700)	(0.856)	(0.011)	(0.012)
R-sq	0.8754	0.8725	0.0840	0.0926	0.7464	0.7364
Obs	157274	175093	157274	175093	157274	175093
Indiv.	81395	90361	81395	90361	81395	90361

hours worked by college graduates. This implies that adoption of robots mostly creates *additional* labour demand, while displacing a comparably smaller portion of lower-skilled labour.

Using the full time series on the subsample of college graduates (Table 7) shows a mirror effect to the results presented in Table 5: firms more intensely exposed to foreign-owned robots appear to hire more college-educated workers and also increase their wages. These estimates are, admittedly, noisy and thus they should be approached with more caution than their more precise analogues in Table 5. Taken at face value, increased labour demand and higher wages for college-educated workers in response to higher exposure to foreign-owned robots (while holding the stock of own robots constant) might indicate that the increased competitive pressure from abroad increases the demand for a high-skilled labour force to maximise any competitive advantage created by the (fixed) stock of robots installed domestically.

Table 5: Quasi-differences in differences estimates (3) for the subsample of workers with only elementary/high school diploma on full sample (2010–2020). Standard errors clustered by industry in parentheses. Scale indicates normalisation of the regressors R and E to match the variance of the dependent variable (1e4 = increase in robot exposure by 10,000).

	Log-earnings		Hours - total		Hours/month	
Scale:	1e4		1		1e2	
	Manuf.	All	Manuf.	All	Manuf.	All
E	-0.041***	-0.028**	-1.023***	-0.803*	0.002	-0.004
	(0.007)	(0.013)	(0174)	(0.444)	(0.006)	(0.007)
R	0.258***	0.269***	-1.974	-1.723***	-0.191***	-0.197***
	(0.008)	(0.013)	(0.226)	(0.475)	(0.007)	(0.008)
R-sq	0.7895	0.7859	0.0882	0.0727	0.9596	0.9616
Obs	881298	978727	881298	978727	881298	978727
Indiv.	81398	90364	81398	90364	81398	90364

Table 6: Quasi-differences in differences estimates (3) for the subsample of workers with a college degree on long differences (2010 and 2020 only). Standard errors clustered by industry in parentheses. Scale indicates normalisation of the regressors R and E to match the variance of the dependent variable (1e4 = increase in robot exposure by 10,000).

	Log-earnings		Hours - total		Hours/month	
Scale:	1e4		1		1e2	
	Manuf.	All	Manuf.	All	Manuf.	All
E	0.056	0.055	3.608	-0.836	-0.003	-0.020
	(0.034)	(0.035)	(3.767)	(5.069)	(0.015)	(0.017)
R	0.149***	0.147***	131.422***	128.392***	-0.129***	-0.140***
	(0.034)	(0.036)	(4.399)	(5.243)	(0.012)	(0.015)
R-sq	0.5078	0.4854	0.4859	0.4642	0.6671	0.6366
Obs	205495	233487	205495	233487	205495	233487
Indiv.	106247	121296	106247	121296	106247	121296

Table 7: Quasi-differences in differences estimates (3) for the subsample of workers with a college degree on the full sample (2010–2020). Standard errors clustered by industry in parentheses. Scale indicates normalisation of the regressors R and E to match the variance of the dependent variable (1e4 = increase in robot exposure by 10,000).

	Log-earnings		Hours - total		Hours/month	
Scale:	1e4		1		1e2	
	Manuf.	All	Manuf.	All	Manuf.	All
E	0.032*	0.041**	5.713*	4.158	-0.003	-0.003
	(0.016)	(0.017)	(3.179)	(3.002)	(0.005)	(0.005)
R	0.078***	0.085***	93.659***	92.257***	-0.062***	-0.068***
	(0.018)	(0.019)	(3.554)	(3.611)	(0.005)	(0.006)
R-sq	0.3094	0.2806	0.4224	0.4109	0.9878	0.9879
Obs	1147620	1304063	1147620	1304063	1147620	1304063
Indiv.	106253	121302	106253	121302	106253	121302

4 Concluding remarks

In this paper, a quasi-differences-in-differences approach has been used to identify impacts of robotisation and exposure to robots owned by foreign competitors on labour market outcomes of Czech workers. Estimates on employee-level data suggest a mechanism that operates along the lines put forward by Acemoglu and Restrepo (2019) and Adachi (2021), namely that workers whose job description involves tasks that can be taken over by robotic technologies (workers with elementary occupations or occupations that do not require a college degree) face depressed demand for their labour. Conversely, we found evidence of increased demand for labour of college graduates, implying a degree of complementarity between robotic technologies and college-educated labour. Another remarkable finding is that all groups of workers studied here show increases in wages in response to adoption of robots, which points to a positive pass-through elasticity from output per worker to wages. Stated differently, as robot adopters become more productive, their workers' marginal product increases, which is reflected in rising wages.

Evidence for spillover effects of foreign robots on domestic workers is somewhat more specification-sensitive than the evidence for the effects of domestically-held robot stocks. However, this evidence is consistent with that for domestic robot stocks: college graduates benefit from the increased exposure to robots in terms of both wages and demand for their labour, while workers with lower qualifications face adverse effects of foreign robots.

This analysis adds to the relatively limited discussion on the impact heterogeneity of exposure to robots on different types of workers. More refined data identifying specific tasks carried out by individual employees might be useful in matching employees with exposure specific types of robots, which could be a productive line for future research.

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Abstrakt

Pomocí kvázi-rozdílů v rozdílech identifikujeme dopady robotizace v domácích a zahraničních firmách na český trh práce. Data na úrovni jednotlivých zaměstnanců umožňují identifikaci heterogenity dopadů podle úrovní kvalifikace zaměstnanců. Ukazujeme, že zatímco zavedení robotů v českých firmách výrazně zvyšuje podávku po vysokoškolsky vzdělané pracovní síle, poptávka po zaměstnancích se střední, případně pouze základní školou mírně klesá. Při robotizaci u zahraničních konkurentů také pozorujeme zvýšenou poptávku po zaměstnancích s vysokou školou a pokles poptávky po zaměstnancích s nižšími kvalifikacemi.

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