Robots and Work

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Abstract

This paper examines the effects of robot adoption on employment and skills in US manufacturing plants (2010-2022). Using a difference-in-differences method, we find approximately 150% increase in job postings and 15% increase in employment in plants that adopt robots compared to non-adopters matched by industry and labor market. Requirements for design, maintenance and other technical skills increase for those who work with robots. Non-adopters lose employment reflecting negative spillover effect from adopters. These findings suggest increased competitiveness of robot adopters that raise output not only in the robotized stage of production but have positive spillover effects in the rest of the plant and in other plants within the same firm. Industry-level employment effects are negligible due to counterbalancing gains and losses. Our plant, firm, and industry level analyses suggest that productivity and human-robot complementarity effects dominate displacement, with job losses limited to outcompeted non-adopters.

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Robots, capable of performing both manual and cognitive tasks autonomously, have been integrated in various industries (Figure 1). The increasing adoption of robots has generated concern about the loss of jobs and skills (Frey and Osborne, 2017; Susskind, 2020). This paper addresses these concerns by studying the introduction of robots in US manufacturing plants during the period 2010-2022. Specifically, it investigates several key effects of robots: (a) the displacement of tasks performed by low-skill workers; (b) the creation or enhancement of tasks for both high-skill and low-skill workers due to complementarities with robots; (c) employment gains in robot adopters resulting from increased competitiveness due to productivity and quality improvements; (d) loss of employment in plants that do not adopt robots due to reduced competitiveness and production; and (e) changes in skill requirements for employees in different occupations.

--- Insert Figure 1 here ---

Early research from the 2010s used industry-level data to identify the effects of robots from variations in robot penetration in different industries and regions or countries over time (e.g., Graetz and Michaels, 2018; Borjas and Freeman, 2019; Acemoglu and Restrepo, 2020). These studies found negative employment effects that could not be attributed to either robot adopters or outcompeted non-adopters. Recent studies have estimated the effect of robot adoption at the firm-level, comparing employment before and after the introduction of robots relative to comparable firms that did not adopt robots. They find largely gains in employment, including for low-skill workers and losses by non-adopting firms (Koch et al., 2021; Dixon et al., 2021; Acemoglu et al., 2023; Hirvonen et al., 2022; Aghion et al., 2022).

In this paper, we investigate the effects of robots in the plants where they are installed. Generally, most plants belong to multi-plant firms. Adoption of robots rarely occurs in all plants in a firm. In our analytical sample of US manufacturing plants, which omits very small firms, only a tenth of plants that adopt robots are in single plant firms. Hence, firm-level studies combine the effects of adoption in some plants with any spillover effects from adoption to non-adoption in the same firm. This likely underestimates the direct effects of robot adoption on employment, although the severity of underestimation is likely less than in industry-level studies.

To conduct plant-level analyses, we use job postings from 2010-2022 (from Burning Glass Technologies). Adoption is identified based on the date of first job postings requiring robot-related skills. We use a difference-in-differences estimation method developed by Callaway and Sant'Anna (2021) to estimate changes in labor demand for plants that adopt robots in different periods compared to those that do not. Adopters and non-adopters are propensity-matched by industry, local labor market, and size. This method is the closest to random assignment to treatment and control groups to assess causality. Job postings do not necessarily reflect employment; to verify that results for postings hold for employment, we use plant employment data for a subset of the plants and sample period (from the Occupational Safety and Health Administration).

In addition to plant-level analyses, since robots are usually installed only in some units of the production process, resulting in different adoption intensities, we assess the effects of the intensity of the use of robots on demand for employees. We also compare skill requirements for jobs that require robotic skills with those that do not.

This paper contributes to the literature on the effects of technology on work by examining the multifaceted effects of robots on employment and skills. Our multilevel analyses at the unit, plant, firm, and industry levels are unique in the literature and allow us to identify key mechanisms through which robots affect work. We identify the effects of robot adoption on adopting plants as well as on non-adopting plants within the same firm and in non-adopting firms. Importantly, this approach permits the identification of spillover effects from robots within a plant, within a firm, and across firms. Furthermore, our analysis identifies occupations and skills directly from job postings rather than inferring them from educational levels. Our analyses concentrate on manufacturing plants, excluding warehouses, distribution centers, headquarters, and other establishments that do not affect production efficiency and product quality through robots.

Our findings suggest that robots enhance employment and some skills in adopting plants and firms. They do so because robots may displace some production workers but require others to do programming, installation, maintenance, repair, supervision, and other activities that are carried out by humans. Robots also enhance competitiveness through productivity and quality improvement, resulting in greater output that increases demand for employees in the non-robotic parts of a plant and in some upstream and downstream plants that belong to the same firm. We do find that robots displace employment in firms that do not adopt robots, but the industry-level effect is close to nil.

Literature review

Concerns and anxiety about the impact of technology on labor have a long history (Mokyr, et al., 2015, Acemoglu and Johnson, 2023). The recent increase in the adoption of industrial robots has raised concerns about jobs and skills displacement (De Vries et al., 2020; Dixon et al., 2021; Salunkhe et al., 2023).

The literature identifies three primary effects of robots on labor demand: substitution, complementarity, and productivity (Acemoglu and Restrepo, 2019). (a) Robots can substitute for workers whose main tasks are repetitive, require precision and consistency, must be sustained without interruption, or are hazardous. Substitution is often considered the dominant effect, the main source of anxiety about reduced employment (Frey and Osborne, 2017; Chiacchio et al., 2018; Blanas et al., 2019; Susskind, 2020). (b) However, workers must design the robotized workplace and install, program, maintain, and supervise the robots (Battisti and Gravina, 2021; Wallace, 2021). This entails complementarity between workers with different types of skills and robots. This suggests a shift in workers' roles rather than complete substitution. (c) Firms that invest in new technologies produce more valuable output than their competitors (Bresnahan et al., 2002). Robots outperform humans in speed, accuracy, consistency, and waste reduction (DeStefano and Timmis, 2023) and improve workplace safety Gihleb, 2022; Bloss, 2016). Koch et al. (2021) find that industrial robots lead to substantial output gains. These gains can lead to increased production and sales of robot adopters, often at the expense of competitors in the same industry (Aghion et al., 2023).

What is the net effect of these three factors on demand for labor and employment? The evidence is mixed regarding the effect of robots on employment and scant on the impact on skills. Early studies on the impact of robots on employment relied on industry-level data, identifying the effects of robots through variations in robot penetration across industries and regions (Graetz and Michaels, 2018; Borjas and Freeman, 2019; Acemoglu and Restrepo, 2020). These studies often found negative overall impacts, with Acemoglu and Restrepo (2020) estimating that one robot reduced employment by six workers in US commuting zones between 1993 and 2007.

However, industry-level analyses could not distinguish between job displacement in robot-adopting plants and job losses in non-adopters due to increased competition (Aghion and Howitt, 1990; Bresnahan et al., 2002).

The availability of firm-level data enabled researchers to compare employment changes in robot-adopting and non-adopting firms matched by industry and local labor market. Firm-level studies generally found positive employment effects in adopters. For instance, Koch et al. (2021) observed increased output and employment in Spanish firms that adopted, whereas non-adopters experienced job losses. Similar findings were reported in other countries (Dixon et al., 2021; Acemoglu et al., 2023; Hirvonen et al., 2022; Aghion et al., 2022, Bonfiglioli et al., 2024). Bessen et al. (2023) found wage increases and no effect on employment in firms with more than 500 employees compared to not-yet adopter firms.

Firm-level analyses may mask heterogeneity across plants within firms, as robot adoption often occurs in only a minority of plants. Our data indicate that only a small proportion of plants in multi-plant firms adopt robots, and they do so at different times. Research has begun to focus on plant-level effect of robots on productivity and employment. However, this research is constrained by the lack of plant-level data about the introduction of robots, which forces researchers to use various proxies for robot adoption (Leigh et al., 2020; Raj and Seamans, 2018; Aghion et al., 2022; Gihleb, 2022; Brynjolfsson et al., 2023; and Deng et al., 2023). Moreover, these studies do not have information about changes in skill requirements or occupational composition to evaluate possible heterogeneous effects of robot adoption. (We expand on this point later in the paper.)

In sum, the literature has evolved from broad industry-level analyses to more precise firm- and plant-level studies. Growing evidence suggest that during the 2010s firms that adopted robots did not lose employment but likely have gained it. We still do not know whether this reflects all skill levels and occupations within a firm. Furthermore, we do not know if changes occur in the robotized or non-robotized parts of a firm. Therefore, conclusions about the complex interactions among the substitution, complementarity, and productivity effects and their combined net effect await further research.

This paper aims to fill these lacunae. We estimate the effects of introduction of robots on labor and skill demand in much of the US manufacturing sector between 2010 and 2022 using several datasets, principally the content of job postings by occupation at the plant, firm, and industry levels. This permits us to provide new insights into the multifaceted effects of robotics on work in manufacturing.

Theoretical framework

Building on the literature review, we develop a theoretical framework that leads to the statement of key testable hypotheses. Consider a technology in which three inputs participate in production: capital (equipment and tools), high-skill workers (engineers), and lower-skill workers (technicians and operators). Each input carries out specific tasks necessary for producing a single output of given quality. These tasks complement each other. The introduction of robots alters the relationships among these inputs. Robots can perform tasks previously carried out by lower-skill workers, but they require new tasks to be performed by high-skill workers (planning, programming, experimentation) and lower-skill workers (installation, maintenance, repair, monitoring). This technological change does not alter the fundamental production process but replaces direct labor with capital (robots) in some or all production tasks. Specific technical tasks such as programming and maintenance of robots become crucial. These tasks require both high-skill and lower-skill workers to possess new capabilities. These relationships are illustrated in Figure 2, which draws on Figure 2 in Acemoglu and Restrepo (2022).

--- Insert Figure 2 here ---

The balance between complementarity and displacement effects depends on the nature of the production process, where robots are introduced, and characteristics of specific robots. Specifically, some robots require more planning, experimentation, maintenance, repair, or monitoring than others. Such differences result in different degrees of complementarity and substitution with positive or negative net effects on the demand for labor in general and specific skills and occupations in particular. Hence in these grounds, it is possible that introduction of robots in a plant in different stages such as welding, painting, or assembly may lead to positive or negative changes in overall demand for labor, associated with changes in the same direction or in mixed directions for occupations with different skills.

The literature reviewed earlier indicates that robots increase productivity, product quality, and workplace safety, improving adopters' competitiveness in their market, leading to greater production and sales, often at the expense of competitors. This expansion of production driven by the robotized stage of production in a plant drives increased activity in other parts of the process. For example, if robots can weld more rapidly and reliably a certain part that makes the product more desirable to buyers, the demand for the plant's product will grow. Figure 3 illustrates schematically a production process with four stages of which the third is robotized.

--- Insert Figure 3 here ---

To accommodate this growth, upstream and downstream stages of the production process receding and succeeding the welding stage will need to produce more. This increase will also necessitate increased support employees in logistics, accounting, HR and so on. To the extent that some of these stages are housed in the same plant, their demand for all types of labor will increase (although not necessarily in the same proportions). The magnitude of spillover effect from the robotized stage to demand for labor at the plant level is likely to depend on the relative magnitude of the non-robotized stages. The spillover effect will be small if the robotized stage constitutes a large segment of a plant's workforce; this may be the case, for example, if the other stages are executed in other plants. Such plants may belong to the same firm as the plant that introduced robots, in which case the spillover effect will be captured within the same firm, or belong to other firms, in which case the spillover demand will affect other firms.[1] We do not observe fully robotized, or lights-out, plants in our data.[2] Our data show that only fifteen percent of jobs within an average robotic plant are directly related to robots, suggesting a positive net employment effect at the plant level.

Based on this theoretical framework, we propose several hypotheses. The first is based on the interplay of substitution, complementarity, and productivity effects. There is substitution of blue-collar workers performing routine or replaceable tasks, along with complementarity, as robot adoption indirectly creates new tasks for workers, including those in occupations that no longer carry out tasks performed by robots (Acemoglu et al., 2023). Additionally, the productivity effect suggests that robot adoption enhances efficiency and output quality,

[1] Acemoglu and Restrepo (2022) refer to a "ripple effect" on worker groups that are not directly affected by automation but are impacted by it through the impact of adopters on labor and product markets. Our spillover effect is similar to the ripple effect.

[2] Based on press reports, we identify three nearly lights out plants: Tesla Gigafactory in Nevada, FANUC in Michigan, and Kiva Systems in Massachusetts. These plants post 56 percent, 38 percent, and 16 percent robotic job advertisements, respectively, above the average of 15 percent of such job postings in an average robotic plant.

allowing adopting plants to expand their production and gain market share, which can lead to increased employment.

Hypothesis 1. *Robot adoption increases employment in adopting plants.*

However, the effect of robot adoption differs across all occupations or production stages within a plant. The productivity effect of the robotized stage results in spillover demand for labor in the non-robotized stages.

Hypothesis 2. *Robot adoption increases demand for labor in the non-robotized stages of production and support activities to accommodate the positive productivity effect of robots.*

The increased production in a robotized plant has positive spillover effects throughout the value chain to which the plant belongs. In multi-plant firms in which some plants adopt robots, non-robotized plants that belong to the same value chain as the robotized plants will enjoy positive spillover effects. However, with the exception of fully vertically integrated firms, plants that belong to the same firm generally have outside customers, so the spillover effect in the firm will be limited.

Hypothesis 3. *Robot adoption in one or more plants in multi-plant firms will have positive effects on demand for labor in non-robotized plants in these firms.*

Adopting plants gain competitive advantage and increase their market share at the expense of non-adopters (Aghion et al., 2023). This leads to employment displacement in non-adopting plants. The extent of this displacement may vary depending on several factors, including the competitiveness of the market and the speed of robot diffusion. The displacement will occur in firms in which plants did not adopt robots.[3]

Hypothesis 4. *Robot adoption in adopting firms displaces employment in non-adopting firms.*

By examining these hypotheses, we aim to provide a comprehensive understanding of how robot adoption affects employment and skill dynamics in manufacturing plants.

[3] We assume that in general plants that make the same product within the same firm will be treated similarly, that is, will be robotized together, although this may depend on factors such as the degree of autonomy of plants, availability of skills required to implement robots, and so on.

Data

We use online job postings for 2010-2022 collected by Burning Glass Technologies (BGT) as our primary data source. We focus on the manufacturing sector (NAICS codes 31-33). Each job posting contains information on the date the job vacancy was advertised, its job title, Standard Occupational Classification (SOC) code, firm name, job location, offered wage, required years of education, required years of experience, and required skills.[4] Not all postings include information about all fields; for example, wages are not specified in a large majority of postings. A growing literature has used BGT data to study firms' labor demand for skills (e.g., Deming and Kahn, 2018; Hershbein and Kahn, 2018; Deming and Noray, 2020; Leigh et al., 2020; Acemoglu et al. 2022, Ben-Ner et al., 2023).

Identification of robotic job postings and robotic technology. We use the common method of identifying technology adoption from job postings by identifying terms related to technology (Atalay et al., 2018; Dillender and Forsythe, 2019; Alekseeva et al., 2020; Atalay et al., 2020; Goldfarb et al., 2020; Leigh et al., 2020; Acemoglu et al., 2022; and Ben-Ner et al., 2023). This approach assumes that the adoption of technology requires specialized human capital. For example, Atalay et al. (2018) use 'CAD' or 'CNC' as included in jobs advertised in newspapers over several decades to identify the introduction and adoption of information and communication technologies (ICTs), Dillender and Forsythe (2019) use terms like 'spreadsheet software' to identify computerization, and Acemoglu et al. (2022) use 'machine learning' or 'computer vision' to identify AI. We identify the use of robots through terms like 'robotics' (the full list is in Online Appendix B).

Identification of robot adoption. We classify plants as robotic if they meet the following criteria. (a) A plant has posted at least ten robotic production jobs between the year in which it introduced robots and the last year of the sample period (2022). This ensures that we capture plants with sufficient human capital to meaningfully integrate robotics into their production process, and exclude those that only explored the possibility of introducing robots but did not pursue their adoption. Tables B1 and B2 in Online Appendix B1 show that results for job postings and employment are robust to changes in this criterion.

[4] BGT scrapes more than 40,000 online job boards and company websites. BGT removes duplicate postings and uses machine-learning algorithms to distill the full text of job advertisements into short phrases that summarize the skills that employers demand.

(b) A plant has to post robotic jobs in at least one of the last two years of the sample period. Table B3 in Online Appendix B indicates that the effects of robots remain significant and positive if we alter this criterion.

(c) The timing of robot adoption is the year a plant first posts at least one production job opening requiring robotic skills. We perform two robustness checks on our approach to identify the timing of adoption. First, we move the adoption timing one year earlier and later than the adoption year we identified through the first robotic job posting. Results are available in Online Appendix Table A1 and Figure A1. Second, we increase the minimum threshold for identifying the timing of adoption from one robotic job posting to five and ten. The increase may postpone the year of adoption for plants that post very few robotic job postings in the beginning, which could indicate that they have not deployed robots in this period. Table A2 shows the results. The two analyses show strong positive effects of robot adoption on all occupations.

It is possible for robots to be introduced in a plant without posting jobs for workers with robot skills. For instance, the adopting plant might rely on an external company, such as a robot integrator, to handle the planning, installation, maintenance, and reprogramming of robots. Alternatively, the plant may upskill its current workforce by retraining employees to manage robot-related tasks (Kelley, 1990; Fernández, 2001). In multi-plant firms, skilled workers could also be transferred from other plants to the adopting plant. These scenarios could lead to robot adopters being misclassified as non-adopters. Our job posting strategy to identify adopters captures the labor dynamics of the external market but does not account for internal dynamics such as these. Misclassification of robotic plants as non-adopters attenuates the estimated effect of robot adoption and thus works against our hypotheses.

Table A3 in Online Appendix shows strong correlation between our measure of robot adoption from job postings and robot adoption data (stock and new installations) from the International Federation of Robotics (IFR). Figure A2 in the same appendix explores this relationship in further detail, including at the 3-digit level NAICS. This evidence suggests that our measure of robot adoption captures well changes in the use of robots at the industry level.

As noted earlier, identification of a technology based on terms used in job postings is used in multiple research papers. There are other measures, IFR at the 3-digit NAICS level being the most commonly used in the literature. The use of this measure has substantial limitations because it is available only at the industry-level, and imputations have to be applied to use it at the commuting zone or firm- and plant-levels (an issue with the firm-level is that most firms have multiple plants in different locations). The US Census Bureau offers plant-level data through the Survey of Manufacturing Technology (SMT) and the Annual Survey of Manufacturers (ASM). The SMT, conducted in the late 1980s, collected plant-level data on robotics in five high-tech industries representing less than 50% of total manufacturing employment. Studies such as Dinlersoz and Wolf (2024) and Dunne and Wolf (2005) have used the SMT data to analyze the effects of robotics. In 2018, ASM surveyed approximately 50,000 manufacturing establishments, asking about the stock of industrial robots, the number of robots purchased, and capital expenditures on robotics. This dataset is experimental and may not meet some of the Census's statistical quality standards. It covers the period from 2018 to 2021, which is much shorter than ours. Findings derived from this dataset remain unpublished (Brynjolfsson et al., 2023).[5]

The analyses summarized in this subsection suggest that our measure of robot adoption and its timing provide a robust basis for the estimation of the effects of robots on work. Job postings offer unique insights into the tasks and skill requirements of jobs, enabling a direct analysis of the intensive margin, that is, changes in the skill content of jobs. As noted by Leigh et al. (2020), a worker operating a welding machine to manually weld sheet metal may have very different skills, qualifications and employment prospects than a worker who programs a robot to perform the same task. However, both workers would be classified under the same SOC code. Job postings highlight detailed shifts, such as an increased focus on programming or monitoring automation systems. See Online Appendix B for more details.

Analytical sample. We construct an analytical sample of manufacturing establishments, to which we refer as plants, excluding headquarters, R&D centers, and other non-manufacturing facilities. We exclude numerous very small plants, and those that entered our sample already as robotic. The selection of our analytical sample follows established criteria commonly used in BGT data research (Deming and Kahn, 2018). Additionally, these criteria ensure that the analyzed plants have production processes suitable for robotization, enhancing relevance and accuracy. Online Appendix B describes the sample selection in detail. Our analytical sample consists of 28,394 plants in 8,575 firms; these posted 5,976,817 jobs, which represent 31 percent of all manufacturing job postings in 2010-2022 in the BGT dataset.

[5] In the next section we report results in which we control for firm level capital expenditure and find that it absorbs little of the effect of robots on labor demand.

Job postings and employment. Differences in the number of job postings for the same occupation in different plants that have similar characteristics are likely to reflect differences in changes in employment across plants. Yet job postings cannot be converted into changes in employment because of separations, multiple jobs advertised in some postings, and more.[6] We do not have access to the Annual Survey of Manufacturers' plant-level longitudinal data, but obtained employment information for a sample of plants that reported to the US Occupational Safety and Health Administration (OSHA) for the period 2016-2022, which we matched with the job postings data. For industry-level data we use public datasets.[7]

Classification of job postings by role and skill level. We classified the workforce in a plant into production-related occupations and support. Production jobs are directly involved with the production process. Professional production jobs typically require at least a four-year technical education and include engineers, programmers, managers and others; we refer to this group as high-skill workers. Other jobs are in production on the shop floor and include operators, welders, assemblers, and so on, referred to as low-skill workers. We extracted from this group jobs we call "direct," such as assemblers, welders, and painters that are most likely to be replaced by robots. A third group of production workers consists of technicians, the middle skill. The rest of the workforce in the plant, from warehouse to accounting, purchasing, HR, finance, to general management, are in support jobs. In our analytical sample, 57% of postings are in production occupations and 43% in support. For details, see Online Appendix Table A4.

We defer discussion of skill measures and related variables including descriptive statistics to the section that discusses skill change.

Descriptive statistics. Table 1 displays the number of firms, plants, and job postings, along with the average number of postings per plant per year. These figures are provided separately for plants that did not adopt robots during 2010-2022 (referred to as never-adopter plants) and for those that did (adopter plants). For adopter plants, postings are further differentiated into those

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[6] In the skill analysis, we find evidence that robotic job postings require greater technical skills. If some plants resort to retraining incumbent workers to transition into new roles with these skills instead of hiring externally (Kelley, 1990; Fernández, 2001), our estimates are conservative and may underestimate the total impact of robot adoption on labor demand. See Table 8 for more details. In the OSHA dataset for which we have both job postings and employment, we estimate the relationship between job postings and the change in employment at the plant level, presented in Online Appendix Section C. Moreover, Online Appendix Section D discusses the relationship between job postings and the Quarterly Workforce Indicator (QWI). Both analyses show that job postings correspond to a significant increase in employment.

[7] KLEMS, IPUMS-CPS, the Occupational Employment and Wage Statistics (OES), the Statistics of US Businesses (SUSB), and the Quarterly Workforce Indicators (QWI).

advertised before adoption (by not-yet adopter plants) and those advertised after adoption. Panel A focuses on our analytical sample of plants, while Panel B addresses a narrower subset of plants for which plant-level employment data is available from OSHA. We restrict the sample by ensuring data availability in both BGT and OSHA, removing outliers, and excluding plants that adopted robots before 2017, resulting in 93 firms and 118 plants.

--- Insert Table 1 here ---

Panel A reveals that within our analytical sample, adopter plants—-which constitute 3.8% of all plants——advertise significantly more job postings on average than never adopter plants. Specifically, while never adopter plants post an average of 29 job advertisements per year, adopter plants post 65 jobs during the pre-adoption period. Following robot adoption, the difference is even more pronounced. The ratio of production to support workers is highest post robot adoption followed by pre-adoption and lowest for never adopters. A similar pattern is reflected in Panel B for OSHA for both job postings and employment (occupational breakdown is not available for this sample).

Figure 4 shows the average number of job postings per plant and the share of robotic job postings in a robotic plant. The shares of high-skill and low-skill robotic job postings are relatively stable over time, hovering around 15 and 10 percent of the total job postings in each skill level occupational group. Medium-skill (technician) jobs experienced a slight decline during 2011-2014 and a steady increase thereafter, approaching 30 percent of technician job postings in an average robotic plant in 2022. Panel B shows that non-robotic plants within adopting firms hire more jobs on average than non-robotic plants in non-adopting firms. Both types of plant experience a steady increase in the proportion of low-skill jobs.

--- Insert Figure 4 here ---

Table 2 shows the distribution of the number of plants owned by firms with at least one plant adopting robots within our sample period. Most plants and the vast majority of job postings are in firms that own multiple plants, but the more plants a firm owns, the smaller the proportion of plants that adopt robots. In firms with more than 100 plants only 4.88 percent of plants adopted robots. Analyzing adoption of robots at the firm-level masks substantial heterogeneity.

--- Insert Table 2 here ---

The industry distribution of plants is presented in Table A8. The largest concentration of robotic plants is in the transportation equipment manufacturing, which covers one-quarter of all robotic plants in the manufacturing sector, followed by computer and electronic product manufacturing and machinery manufacturing. The three industries combined cover one-half of robot adoption in manufacturing.

Empirical analysis

Our principal analyses of the impact of robot adoption on labor demand are based on the difference-in-differences estimation method developed by Callaway and Sant'Anna (2021). Plants that adopt robots are matched with non-adopting plants based on industry, local labor market, and size. This approach allows us to estimate the number of job postings and required skills while accounting for potential confounding factors.

We test our hypotheses in the context of job postings and employment. Additionally, we explore the relationship between job postings and realized employment and conduct various robustness checks. Finally, we study the impact of robot adoption on the demand for skills in both robotic and non-robotic jobs.

Effects of robots on labor demand

In this section we explore first the effects of robot adoption on job postings at the plant-level, distinguishing between production occupations at three skill levels and support occupations. Next, we examine the effect of robot adoption on employment at the plant level. Finally, we estimate the effect of robot adoption at the firm and industry levels and evaluate the effects on non-adopter plants.

Job postings at the plant level

Table 3 details the average treatment effects (ATT) on the yearly job postings per plant. It compares plants that have adopted robotic technology with those that adopt robots in later years (between $t + 1$ and 2022). We refer to them as not-yet adopters. We refer to plants that do not adopt robotics during the sample period as never adopters. The two groups of plants differ in size, as observed in Table 1, and most likely in their capabilities to introduce new technology (as found by Koch et al., 2021). It is possible that some not-yet adopters in t have plans to adopt in future years and others adopt based on later decisions. It is also possible that some never-adopters in our sample plan to adopt later than 2022 and will adopt at some point. We have no information or instruments to handle these possibilities.

--- Insert Table 3 here ---

We find significant increases in job postings within the five-year window following robot adoption when comparing adopters with not-yet adopters and adopters with never-adopters. For all job postings, the estimated ATT is 64 in comparison with not-yet adopters and 98 in comparison with never-adopters. This implies that an average adopter plant that had 64.71 postings before robot adoption will post 64.37 more jobs on average in the five years after adoption than a similar plant that did not yet adopt robots but will do so in the future. The comparison with never-adopters is even striking, where the average adopter will post 98.36 more jobs than the control group. Both differences are statistically highly significant. This means that if the control group of never-adopters did not change their level of job postings in the relevant time frame, adopters increased the rate of job postings by 2.5 (i.e., (98.36+64.71)/64.71). This reflects the predicted number of annual job postings for a plant that posted 64.71 jobs before robot adoption as compared to a plant that never adopts robots. The ratio is smaller, about 2, for the comparison with future adopters. These findings provide support for Hypothesis 1.

Consider next changes in demand for specific job categories. The ATT for all production workers is 39.16 for the not-yet adopter comparison and 62.03 for the never-adopter comparison, whereas for support jobs the parallel figures are 25.21 and 36.33. The ATT for production jobs relative to pre-adoption postings is much larger than for support jobs. The greatest increase in demand has been for high- and medium-skill workers, although there was an increase for low-skill and even direct workers.[8]

The estimates in Table 3 are time treatment effects averaged over five years post adoption (Callaway and Sant'Anna, 2021). Figure 5 displays annual treatment effects. It shows a gradual rise in demand for every occupational category from the adoption year t_0 to t_4. Note that growth starts only after robot adoption, suggesting that the parallel trends assumption (that adopters and non-adopters do not have different job posting growth rate pre-adoption) is satisfied. The long-term effects of adoption tend to moderate (the curve becomes less steep) after five years

[8] Heterogeneous impacts by skill level were found during the pandemic (Cortes and Forsythe, 2023).

or so, as indicated in Figure A3. The results are less precise because the number of plants with more than seven years is small.

--- Insert Figure 5 here ---

These results demonstrate that integrating robots into the workplace positively affects labor demand across all occupations and skill levels. This increase can be driven by output expansion and complementarity between workers and robots. Output may increase if robots enhance the cost efficiency or the quality of the product of the robotized stage such as stage 3 in Figure 3. This will result in an increase in demand for the plant's output. The increase in plant demand necessitates an increase in production in non-robotized stages such as 1, 2 and 4 in Figure 3. These stages must increase employment of workers on the floor, primarily low and medium skill and of high-skill workers who are likely to serve multiple production stages. The robotized stage will require fewer workers who work on the product but will require workers to install, supervise, maintain and repair the robots. This complementarity effect for low- and medium-skill workers may be smaller than the displacement effect of direct workers in the robotized stage but the output effect that increases demand in other stages is larger leading to a net increase in demand for all workers in Table 3. The expansion of plant production requires an increase in support functions, though the increase is smaller in proportion to pre-adoption levels as compared to the increase in production workers.[9]

Our data do not allow us to separate the output, substitution, and complementarity effects of the introduction of robots because we do not observe plant output or postings in different stages of the production process. Studies show that the estimates for output elasticities of labor for production and support workers are similar (Dunne and Roberts, 1993; Roberts and Skoufias, 1997).[10] Demand for support workers is not affected directly by robots but responds to the volume of activities in a plant. The similarity in elasticities suggests that the demand for workers in the two groups of occupations (production and support) should be similar to produce a given increase in output. If the proportional increase in demand for production workers is

[9] For example, the General Electric plant in Norwich, NY, advertised 169 job openings between 2014 and 2022. Of these, five were specifically for robotic welding positions under the SOC code 51-4122, beginning with the first one in 2017. This initial posting sought a welder skilled enough to set up a welding robot. The trend continued with a total of 33 additional welder jobs announced from 2017 onwards. Pre-adoption, 20% of non-robotic welding job postings required troubleshooting skills. Post-adoption, this demand increased to more than half of the non-robotic postings. This example supports our results regarding the growth of job postings in direct occupation and reveals how the adoption of robots drives the need for complementary skills and increases overall productivity.

[10] The estimates from the two studies are similar to other studies that estimate overall output elasticities of labor demand, e.g., 0.75 by Hamermesh (1976) in the US and 0.78 by Görg et al. (2023) in OECD countries.

lower than that for support workers then the net effect of robots on production workers is negative because of substitution and displacement by robots. Conversely, if the increase is greater, the complementarity effect outweighs the substitution effect. While we cannot confirm directly the existence of a substitution effect, it likely exists for direct workers in the robotized stage, as studies have shown that robots increase turnover among low-skill workers (Deng et al., 2023). As noted earlier, Table 3 shows that the ratio of ATT to the number of pre-adoption number of postings is larger for production that support workers.

Spillover effects from robot adaption within robotized plants and firms

Within-plant spillover effects. We expect that in a plant with more non-robotized stages the spillover effect will be larger than that where the production process includes fewer non-robotized stages with regard to the need to increase their employment to accommodate the increased production caused by the robotized stage. We measure the robotization of the production process using two proxies: the share of robotic job postings in total production postings and the share of unique robotic occupations (SOC) postings in total unique production occupations postings. We divide the 1,085 adopting plants into two groups based on the median of each of the two robotization proxies. The analysis presented in Table A5 in the Online Appendix indicates that plants in both groups of robotic plants experience significant increases in job postings across all occupations. However, plants with low share of robotized production exhibit higher ATTs than plants with a higher share of robotized production. This supports Hypothesis 2.

Between-plants spillover effects. We turn next to examine the spillover effects from robot adopter plants to non-adopter plants within the same multi-plant firm. Are non-adopting plants in these firms like plants in firms that did not adopt robots in any of their plants or more like their robot-adopting sibling plants? Table 4 presents results from an analysis similar to that in the last column of Table 3 (where never-adopter plants are the control group) but removing non-adopting plants within adopting firms in Panel A and removing adopting plants in Panel B. In panel B, the unit of analysis is plant cohorts; we assign the non-robotic plants an adoption year for each adoption cohort and duplicate them for as many as the number of adoption cohorts in the adopting firm.

--- Insert Table 4 here ---

Table 4 shows that both robotic and non-robotic plants increase their job postings relative to plants in non-adopting firms. The growth in adopting plants is substantially larger than in non-adopting plants in the same adopting firm (ATT for all postings of 112.02 relative to pre-adoption postings of 72.18 for robotic and ATT of 8.23 and pre-adoption postings of 39.21 for non-robotic plants). This suggests a spillover effect across plants in adopting firms that may occur because some plants in the same firm are part of the same production process, similar to the stages in the same plant depicted in Figure 3. It is likely that some multi-plant firms are partially vertically integrated so increased production in the robot-adopting plant required greater production–hence more jobs and job postings–in upstream and downstream plants.[11] For robustness, we reproduced the analysis for large firms (with more than 20 plants) and obtained similar conclusions (see Table A6 in the Online Appendix). These results support Hypothesis 3.

Capital expansion

A plant may introduce robots along with other capital expansion (e.g., in expectation of higher output demand in the future). The expansion may include hiring new workers and investing in new capital, including robots. As robot adoption and capital expansion happen simultaneously, the estimation from an (unconditional) difference-in-differences design combines the effect of the two events. To separate the robot adoption effect, we incorporate firm capital expansion—proxied by real capital expenditures normalized by real total assets from COMPUSTAT. Table A7 shows the ATTs are significantly positive, although slightly smaller. This shows that robot adoption has a separate effect beyond general plant expansion. The capital expansion measure is at the firm level, which may raise a concern that the expansion may not be distributed equally across plants. As a robustness check, we restrict the sample to adopting firms with three or fewer plants to ensure that the expansion happens in robotic plants. We still find a significantly positive effect within this subsample.

Employment effects

To check that the increased number of job postings at plants adopting robots results in higher employment, we replicate our difference-in-differences analysis on a sample of plants with

[11] Such spillover effects may occur also across firms but we cannot detect them with our data and analysis; nevertheless, the cross-firm effects are likely to be much diffused across multiple firms and therefore of very small magnitude at the individual plant level.

available employment data from OSHA during 2016-2022. We construct a stacked sample similar to Bessen et al. (2023), in which adopting plants are matched with the comparison group by cohort. With a shorter sample period and some plants not reporting annually, we compare average employment in two pre-adoption years with average employment in three post-adoption years.[12] We estimate the average treatment effects on the treated using a two-way doubly-robust difference-in-differences design proposed by Sant'Anna and Zhao (2020), controlling for size, industry, the logarithm of wage in a commuting zone, and adoption cohort. We conduct the analysis at the plant- and at the firm-level. Employment is in logs.[13]

The first column of Table 5 shows that plants adopting robots experience a 15% higher employment growth than non-adopters annually. The second column indicates that at the firm-level the effect is positive but not significant. These findings suggest that the growth in job posting following robot adoption is reflected in increase in employment at the plant-level. Figure A4 in the Online Appendix shows event-time ATT for the log of full-time employment[14], closely resembling Figure 5. This provides further support for Hypothesis 1.

--- Insert Table 5 here ---

Impact of robot-adopter plants on employment in never-adopting plants. Next, we explore whether the employment growth seen in robot-adopting plants occurs at the expense of plants owned by firms that have not adopted this technology. We cannot estimate the effect of robot adoption on non-adopters using difference-in-differences analysis because there is no control group for the non-treated plants. Instead, we estimate the impact of the penetration (density) of robots at the industry level on log of employment in non-adopting plants. As it is common in the literature on robot and other technology adoption in the US, we implement an instrumental variables two-stage least squares (IV 2SLS) approach from IFR data on European countries to reduce possible endogeneity with the following specification:

$$Y_{kt} = \beta_0 + \beta_1 R_{it-p} + \gamma_1 Q_{it} + \sigma_k + \tau_t + \varepsilon_{ijt} \quad (1)$$

[12] For example, the 2017 adopters are matched with non-adopters that posted online job advertisements between 2016 and 2019. A non-adopter may be repeated in more than one cohort if it has non-missing observations in at least one pre-adoption and one postadoption years. Hence, our observations are plant cohorts.

[13] Job postings represent changes (additions) in employment. The log of employment is comparable to job postings as it also measures changes in, as opposed to level of, employment. Online Appendix C shows that one job posting yields a 0.11 percent increase in employment and the relationship changes by plant size.

[14] We use three methods, no imputation, and the median or the last observation carried forward to impute missing values in years when plants do not report to OSHA.

where Y represents log of employment of plant k and year t. R is robot penetration rates, measured as the number of US robots in operation per one thousand workers in industry i at time $t - p$, where $p = \{0,1,2\}$. The coefficient of interest is β_1, the effect of a one-unit increase in robot stock per one thousand workers on employment in a given industry and year. We control for the industry output, $Q_{i,t}$, plant fixed effects (σ_k), and year fixed effects (τ_t). Table 6 presents the second-stage estimates of the 2SLS IV model.

--- Insert Table 6 here ---

Table 6 indicates that in industries where robot usage per one thousand workers increases by one unit in year t, employment in non-adopters does not respond in that year but decreases by 0.4 percent one year later and by 0.5 percent in two years. This suggests that over time, the introduction of robots in an industry may lead to a gradual decline in employment at plants owned by firms that do not adopt this technology. The findings support the negative spillover effect on non-adopters in Hypothesis 4. As a robustness test, Table A9 in the Online Appendix replicates Acemoglu and Restrepo's (2020) regression of the adjusted penetration of robots from IFR on the change in the log of postings. It corroborates the labor trade-off from non-adopters to adopters. This supports Hypothesis 4.

Industry level effects on employment. We aggregate data from our analytical sample to the industry level and use IV 2SLS regression to estimate the relationship between robot stock and employment. The specification is similar to Equation 1 but at the industry-level. Table A10 in the Online Appendix shows the second stage coefficients of industry-level robot penetration at three lengths of exposure on the log of full-time employment. At the industry level, we do not observe a consistent change in the level of employment within two years of a change in robot penetration rates.

In sum, our findings in this section suggest that examining hiring and employment effects of robots at more granular levels reveals more nuanced results. The expansion in hiring activities is located in robotic plants, suggesting concentration of production activities within this type of plant. The small number of robotic relative to non-robotic plants, however, dilutes the effect at more aggregated levels. Moreover, studying the effect at the firm level may give a false impression that an adopting firm expands at the same rate.

Robot adoption effect on skills

We focus on technical and general skills related to work in manufacturing. There are numerous technical and general skills; we select a subset of skills that were identified in the literature to be of relevance to work in manufacturing (Deming and Noray, 2020; Ben-Ner et al., 2023). We measure skills in similar ways as this literature. For each plant, we calculate the average count per posting in each occupational group of the terms that describe a given technical or general skill.

For technical skills, we analyze design, production, repair and maintenance, quality control, machine learning, and automation (excluding robotics). These skills span the entire production process. For example, we measure design by counting terms such as 'system design', 'product design', and 'engineering design and installation'. For general skills, we analyze reasoning, character, and social skills. For example, reasoning is measured by counting terms such as 'problem solving', 'research', and 'creativity'. Online Appendix Table A11 lists the terms we use to identify the skills analyzed below.

Table 7 shows descriptive statistics of these technical and general skills comparing, as in Table 1, never-adopter plants with adopter plants. For adopter plants, we distinguish preadoption and post-adoption skills. Post-adoption postings seem to require more production, repair and maintenance, machine learning, automation, reasoning, and character skills than pre-adoption postings. About fifteen percent of total post-adoption jobs are robotic postings, as indicated in Panel A of Figure 4. Adopter plants in pre-adoption demand more design, automation, and reasoning skills than never-adopters, but less repair and maintenance and quality control. As averages, these differences do not account for occupational distribution and other factors, which we analyze next.

--- Insert Table 7 here ---

Some plants do not post jobs every year in every occupation of interest. As a result, there are missing observations that cannot be analyzed with the difference-in-differences we used earlier, where zero postings are meaningful as they indicate a pause in hiring. With skills, the demand does not turn to lower (zero) skill demand when there is no demand for a certain type of worker; skill information is unavailable in years with missing data. To handle this issue, we average preadoption data (t_{-4} to t_{-1}) into one period and post-adoption data (t_0 to t_{+4}) into another. We estimate the effects of robot adoption with a two-way doubly-robust difference-in-differences design (Sant'Anna and Zhao, 2020), controlling for size, industry, the logarithm of wage in a commuting zone, and adoption cohort. We compare the average demand for various skills in each occupation in adopting plants before and after adoption with changes in plants that never adopted robotics (by the end of our sample period). This analysis is similar to the analysis we conducted for changes in employment.

As discussed earlier, adoption of robotics is usually confined to one of several stages of the production process (Figure 3) and therefore the need for employees with robotics skills is limited to that stage. Panel A of Figure 4 shows that the proportion of post-adoption postings requiring robotics skills is small and varies across occupations. We analyze the differences in skill requirements before and after adoption, separately for robotics and non-robotics jobs. Results are presented in Table 8 for technical skills and in Table 9 for general skills.

--- Insert Table 8 here ---

Table 8 shows that robot adoption significantly changes the demand for technical skills in robotic job postings but not in non-robotic job postings.[15] Robotic-related jobs demand 50 to 90 percent more design, production, and repair and maintenance skills in compared to their pre-adoption levels, both in high-skill and low-skill occupations. We interpret this significant increase in relation to never-adopters as the creation of new tasks necessary to work with robots. On the other hand, high-skill and low-skill robotic-related jobs demand around 40 percent less of quality control skills in compared to their pre-adoption levels. We interpret the decrease as evidence of displacement of tasks due to robots. Machine learning and automation other than robots also witness a significant upswing following robot adoption and in the case of robotic-related jobs, signaling complementarity between these technologies. Among high-skill robotic jobs, the demand for design skills experienced the largest increase. For medium-skill and low-skill, the increase in the demand for repair and maintenance was the largest.

Table 9 shows that robot adoption has a negligible effect on general skills both for the robotics postings and the non-robotics postings of adopters.[16] Of the three skills, only reasoning for high-skill robotic jobs is affected. The change is small relative to the average frequency it appeared in job postings before the adoption (around 11 percent).

[15] Appendix Table A14 shows the comparable results for the comparison with not-yet adopters.
[16] Appendix Table A15 shows the comparable results for the comparison with not-yet adopters.

In sum, we find that adopter plants do not change skill requirements for most occupations, supporting the argument that robot adoption adds workers instead of replacing incumbents with new workers with a different skill set. However, jobs that are directly involved in production and demand robotics skills—–which comprise a small proportion of a manufacturing plant's workforce—require different skill sets, indicating the partial displacement of some traditional skills such as quality control by robots, possibly because they cause fewer quality issues than humans. This is accompanied by enhancing design, production, maintenance, and repair skills required to support the effective operation of robots on the shop floor. This indicates possible replacement of some low-skill workers by robots as well as by workers in similar direct occupations but with enhanced skills.

Discussion and conclusions

Robots change work. Our findings indicate that while robots can displace certain production tasks, they also create new opportunities for employment and skill development in adopting plants and firms. The economy, at least during the 2010s into the early 2020s, has not reached the stage of 'lights out' plants. Robot adoption has been selective, focused on certain stages of the production process. Nor has the economy reached a stage where robots and AI can fully operate autonomously without human intervention. Robots that work on the production line require many functions carried out by humans who do not have to be on the shop floor as workers did before robotization. These tasks include planning, programming, installation, adjustments, oversight, and more. While these employees may be invisible on the production floor, they work with computers, watch live streaming from the floor, and intervene as needed. In some cases, workers collaborate with robots on the shop floor.

Our findings suggest that robots enhance employment and some skills in adopting plants and firms. They do so because robots may displace some production workers but require others to perform programming, installation, maintenance, repair, supervision and other activities that are carried out by humans. Robots also enhance competitiveness through productivity and quality enhancement, resulting in greater output that increases demand for employees in the non-robotic parts of a plant and in some upstream and downstream plants that belong to the same firm. It is not possible to identify with our data the magnitude of the spillover from the robotized part to the rest of the plant, but our analysis suggests that the spillover effect gets stronger as the introduction of robots impacts more non-robotized stages.

Robots certainly displace the tasks of some direct workers in the robotized stage of production but create other tasks that are carried out by workers in the same occupational classification. We cannot evaluate with our data whether the net employment effect of direct workers in the robotized stage is positive or negative, but we do find that the plant-level effect is positive. This may be entirely due to the spillover effect discussed above. In multi-plant firms in which some plants adopt robots but others do not, , demand for labor in non-adopting plants rises but much less than in the adopting plants. This is evidence for positive spillover effects at the firm level, with the spillover effect being much smaller than the direct effect at the plant level. The limited within-firm spillover effect is likely due to the fact that plants that belong to the same firm do not belong to the same value chain but many produce products for customers outside the firm.

There are negative spillover effects from adopting plants to non-adopting ones in firms that do not adopt robots. This displacement effect arises from the increased competitiveness of adopters. We find that the industry-level employment effect is close to nil. This may be explained by an increase in the total productivity of the industry due to the robotized plants that gain approximately the employment that is lost by non-adopters. As Aghion et al. (2022) remark in the context of similar findings in France, the overall effect of automation is increased output. Autor (2015) attributes this to technological progress, which explains historical growth in output without the disappearance of work.

There are several limitations to our study. Our findings are based primarily on changes and differences in the level of job postings. Firm demand for workers, as reflected by job postings, might be constrained by skill shortages and competition for similar skills in the labor market. Consequently, increased postings may not directly translate into employment growth. However, our findings suggest that demand associated with robot adoption generally leads not only to an increase in job postings but also in employment. Job postings and hirings capture changes only in the external labor market, which does not capture retraining of incumbent employees and transfer of employees across plants within the same firm. In the extreme, the use of retraining, transfer of employees across units of a firm, and reliance on contractors may result in no postings for employees with robotic skills (or posting only intermittently, resulting in misclassification of robot adopters as non-adopters). This may lead to an underestimation of the robots' employment effect. However, our results show significant increases in postings for production and other roles post robot adoption, perhaps less than the true effect. Furthermore, we are reassured that our findings regarding job postings translate into larger employment based on our analysis of a subsample for which we do have employment information as well as our analysis of the relationship between postings and employment changes in other datasets.

Technological advancements in robotics suggest that the vintage of robots may matter to their impact on work. We control the timing of the introduction of robots through our staggered difference-in-differences analysis. We did not specifically investigate whether the effect of robots has changed over time due to technological advancements and firms learning how to deploy them more effectively. However, most adoptions occur in the latter part of our sample period, hence they reflect recent robot technology in manufacturing. It is important to note that we excluded greenfield sites and warehouses from our sample, as the nature of robotic adoption and labor substitution in these environments may differ significantly. The introduction of AI in conjunction with robots may change the effects of robots on work. All these aspects—technological advancements, the role of greenfield sites, the impact in industries like warehousing, and the integration of AI with robotics—are fruitful areas for future research.

Several policy recommendations for government, business and educational institutions emerge from our study. (1) There is a need to support workers displaced by robotics, not so much in adopting plants but elsewhere in the economy. (2) Provision of training for reskilling workers to transition into new roles created by automation. (3) Relatedly, technical education should focus on programming, maintenance, and supervision of robotic systems and their integration with AI. (4) Encourage robot adoption by firms by enhancing their technical and human resource capabilities. (5) Improve data collection on robot adoption and its effects on employment to enable more detailed and comprehensive studies. It is important to support longitudinal studies to track the long-term impacts of robot adoption on different industries and regions.

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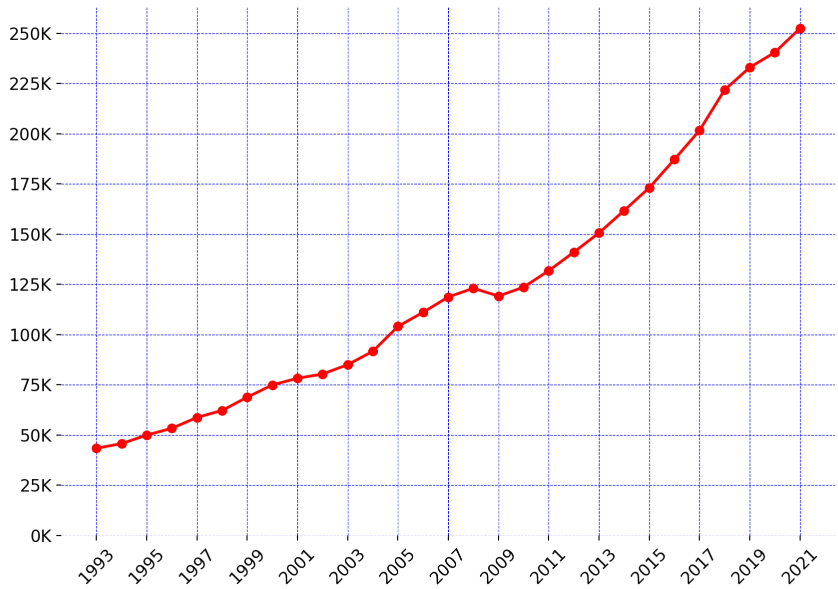
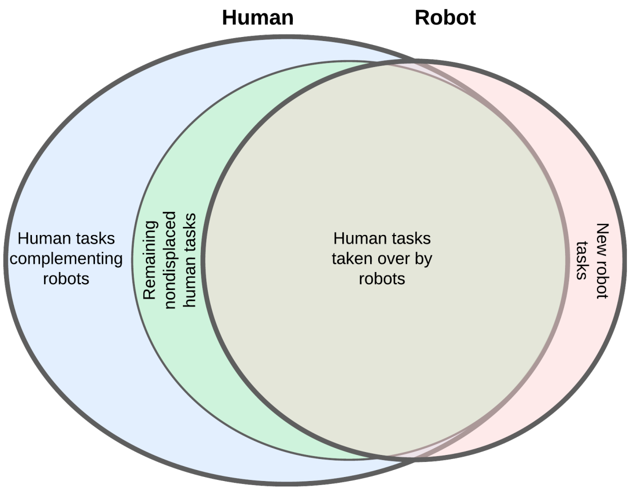
Figure 1: Stock of industrial robots in the US, 1993-2021



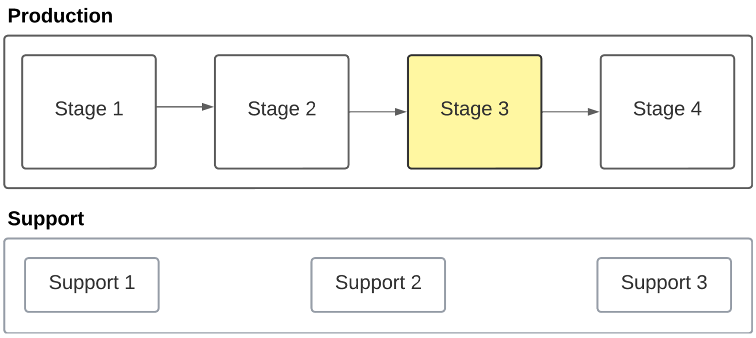
Notes: Stock of industrial robots based on installations from the International Federation of Robotics (IFR), assuming a depreciation rate of 10%, as in Graetz and Michaels (2018). The IFR defines industrial robots mainly by their physical tasks in industrial settings. However, advancements in AI and sensor technology now enable these robots to perform cognitive tasks like decision-making, process monitoring, and real-time response. In our study, which covers data up to 2022, we capture both the traditional physical roles of industrial robots and their growing cognitive capabilities as technology progresses.

Figure 2: Human-robot division of tasks in the robotized stage



Notes: Figure depicts how the robotized stage impacts the allocation of tasks between humans and robots. Some tasks are being displaced but new tasks emerge, illustrating complementarity and substitution happening simultaneously.

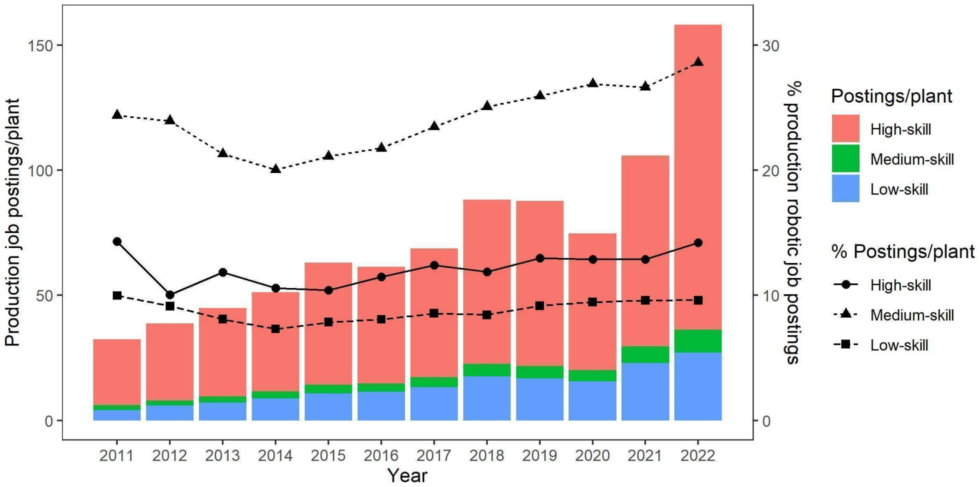
Figure 3: Robot application in a plant



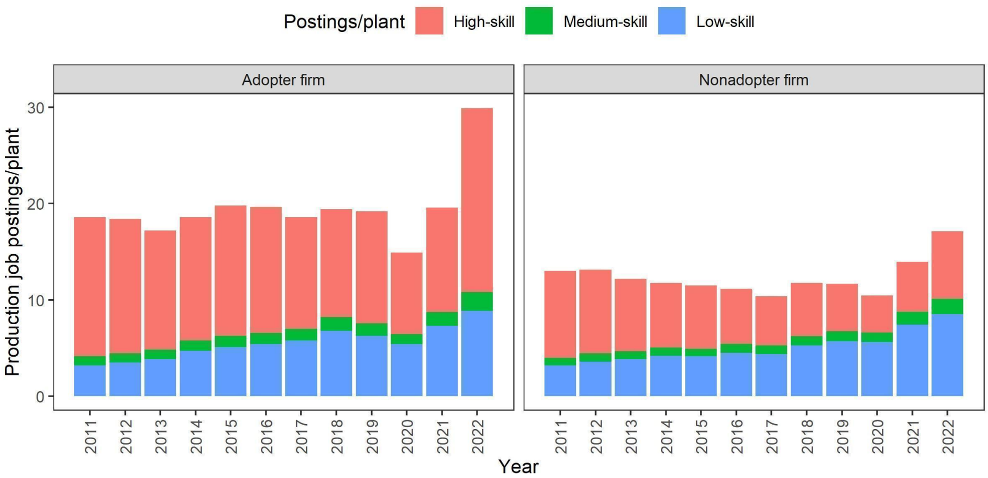
Notes: The highlighted box (Stage 3) represents the robotized production stage in a plant.

Figure 4: Average production robotics job postings per plant

(A) Robotic plant



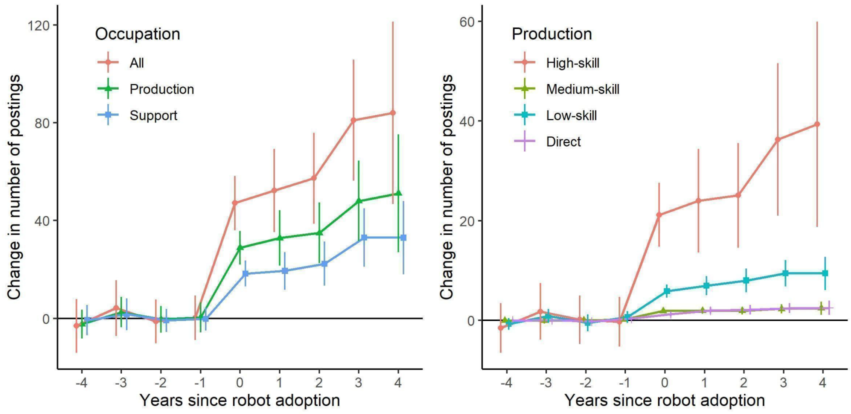
(B) Non-robotic plant



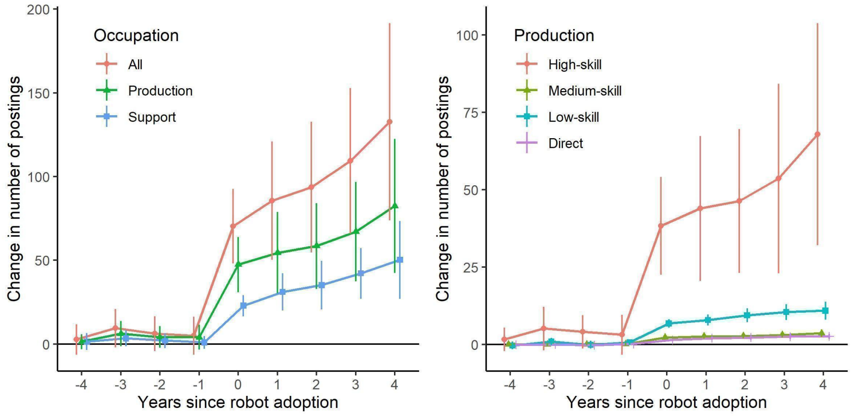
Notes: Figure shows in Panel A the total production job postings and the average percentage of robotics job postings from production job postings in a robotic plant and in Panel B the total production job postings in a non-robotic plant split into adopting and non-adopting firms. The percentage in Panel A is based on job postings within each occupational group (i.e., robotics job postings in occupation *i* divided by total job postings in occupation *i*).

Figure 5: Event study of robot adoption effect on job postings

(A) Adopter vs. not-yet adopter plants



(B) Adopters vs. never-adopter plants



Notes: Figure shows event time ATT. Table 3 shows overall ATT as aggregations of these. Postings in the year of adoption t_0 or in post-adoption years $t_1, t_{2,} t_3, t_4$ are compared to postings in t_{-1}; postings in pre-adoption years are compared to postings a year ago. Vertical solid lines represent 95-percent confidence intervals.

Table 1: Descriptive statistics

Variable	Never-adopter plants	Adopter plants: Pre-adoption	Adopter plants: Post-adoption
	(1)	(2)	(3)
A. Analytical sample (2010-2022)			
Number of firms	8,041	534	534
Number of plants	27,309	1,085	1,085
Number of postings			
All	5,091,407	186,934	698,476
Production	2,894,690	100,916	414,049
High-skill	1,701,562	78,697	313,405
Medium-skill	204,315	4,926	22,294
Low-skill	988,813	17,293	78,350
Direct	241,143	3,273	18,225
Support	2,196,717	86,018	284,427
Average number of postings per plant			
All	28.98	64.71***	146.71***
	(67.65)	(149.12)	(296.12)
Production	16.48	34.93***	86.97***
	(41.64)	(81.09)	(185.28)
High-skill	9.68	27.24***	65.83***
	(37.24)	(74.16)	(170.57)
Medium-skill	1.16	1.71***	4.68***
	(3.26)	(4.67)	(8.67)
Low-skill	5.63	5.99***	16.46***
	(10.40)	(11.79)	(24.03)
Direct	1.37	1.13***	3.83***
	(3.73)	(3.19)	(8.48)
Support	12.50	29.77***	59.74***
	(30.11)	(75.76)	(124.86)
B. Limited sample (2016-2022)			

Number of firms	2,159	93	93
Number of plants	4,578	118	118
Number of postings	581,151	13,600	35,639
Average number of postings per plant	29.97	58.04**	99.88**
	(65.38)	(130.45)	(141.76)
Average full-time employment per plant	314.09	584.02***	586.24
	(376.44)	(816.05)	(687.00)

Notes: Column 2 is based on four pre-adoption years (i.e., t_{-4} to t_{-1}). Column 3 is based on five postadoption years (i.e., t_0 to t_4). Standard errors are shown in parentheses. Stars in column (2) reflect the t-test significance level of the mean difference between (1) and (2). Stars in column (3) reflect the t-test significance level of the mean difference between (2) and (3). Full-time employment is calculated as total work hours per year divided by 2,000 (i.e., 40 hours/week × 50 weeks). Analytical sample in panel A is obtained from BGT. Limited sample in panel B is obtained from the Injury Tracking Application (ITA) administered by OSHA. Descriptive statistics for skills are shown in Table 7. Significance levels: * 10%, ** 5%, *** 1%.

Table 2: Descriptive statistics of adopting firms by size

Firm size	% Robotic plants per firm	Firms	Plants			Postings
			Robotic	Non-robotic	Total	
1 plant	100	101	101	-	101	16,121
2-5 plants	41.7	140	161	267	428	100,389
6-20 plants	18.98	161	304	1,485	1,789	500,225
21-100 plants	8.71	112	333	3,947	4,280	1,247,353
>100 plants	4.88	20	186	3,199	3,385	1,640,973
Overall adopter	37.58	534	1,085	8,898	9,983	3,505,061

Notes: Table shows descriptive statistics of firms owning at least one robotic plant. Sample plants are restricted to those having at least one pre-adoption and one post-adoption observations. Number of job postings is calculated from four pre-adoption to five post-adoption years of a plant (i.e., t_{-4} to t_4). Never-adopters (not shown) cover 7,615 firms, 18,411 plants, and 2,471,756 job postings.

Table 3: Robot adoption effect on job postings (difference-in-differences analysis)

Occupation	Pre-adoption postings	ATT	
		Adopter vs. not-yet adopter	Adopter vs. never-adopter
All	64.71	64.37***	98.36***
		(6.92)	(14.01)
Production	34.93	39.16***	62.03***
		(4.53)	(9.49)
High-skill	27.24	29.17***	50.02***
		(3.41)	(9.17)
Medium-skill	1.71	2.07***	2.89***
		(0.22)	(0.22)
Low-skill	5.99	7.92***	9.12***
		(0.64)	(0.67)
Direct	1.13	2.04***	2.22***
		(0.26)	(0.20)
Support	29.77	25.21***	36.33***
		(3.02)	(5.00)
Plants		1,085	28,394

Notes: Table shows the 5-year (t_0 to t_4) average treatment effects (ATT) for the number of job postings. These are annual ATT per plant. ATT divided by pre-adoption t_{-4} to t_{-1} mean postings of adopters (column 2) proxies a percentage change in postings. ATT are estimated using the multi-period difference-in-differences with inverse probability weighting method (Callaway and Sant'Anna, 2021). Standard errors (shown in parentheses) are clustered by plant. Covariates include the number of postings in the first year the plant appears in the data, the commuting zone's log of wages in 2007, and 3-digit NAICS code fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Table 4: Between-plant spillover effects of robot adoption (difference-in-differences analysis)

Occupation	A. Robotic plant: Pre-adoption (t_{-4} to t_{-1}) postings	A. Robotic plant: ATT	B. Non-robotic plant: Pre-adoption (t_{-4} to t_{-1}) postings	B. Non-robotic plant: ATT
All	72.18	112.02***	39.21	8.23***
		(19.22)		(0.94)
Production	38.97	70.95***	23.32	5.64***
		(12.84)		(0.54)
High-skill	30.48	58.41***	17.86	5.01***
		(12.29)		(0.51)
Medium-skill	1.89	3.04***	1.05	0.2***
		(0.28)		(0.04)
Low-skill	6.60	9.49***	4.40	0.44***
		(0.81)		(0.13)
Direct	1.23	2.18***	0.98	0.08
		(0.22)		(0.06)
Support	33.22	41.07***	15.89	2.59***
		(6.75)		(0.39)

Notes: Table shows the 5-year (t_0 to t_4) average treatment effects on the treated (ATT) for the number of job postings in plants owned by adopting firms. The comparison group is plants from never adopters. Non-robotic plants in panel B are duplicated for multiple adoption cohorts in a firm and stacked together. Sample in panels A and B have the same set of firms, which own at least one robotic plant and one non-robotic plant. Covariates include the number of postings in the first year the plant appears in the data, the number of plants having adopted robots in a cohort (only for panel B), the commuting zone's log of wages in 2007, and 3-digit NAICS code fixed effects. For robustness, Table A2 in the Online Appendix restricts the sample to large firms (i.e., firms with more than 20 plants). Significance levels: * 10%, ** 5%, *** 1%.

Table 5: Robot adoption effect on employment, 2016-2022 (difference-in-differences analysis)

	Plant-level	Firm-level
	(1)	(2)
Log(Full-time employment)	0.15**	0.14
	(0.06)	(0.11)
Mean Log(Preadoption employment)	5.60	6.44
Observations	32,480	15,468
Unit cohorts (plants/firms)	16,240	7,734
Units (plants/firms)	4,696	2,201
Robotic units (plants/firms)	118	99

Notes: Table shows the 3-year (t_0 to t_2) average treatment effects (ATT) for the log of full-time employment, comparing adopters with never adopters. ATT are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020), with average pre-adoption data (t_{-2} to t_{-1}) and post-adoption data (t_0 to t_2). Standard errors are shown in parentheses. Covariates include employment in the first year the plant appears in the data, the commuting zone's log of wages in 2007, cohort fixed effects, and 3-digit NAICS code fixed effects. The sample in column (2) includes firms with at least one robotic plant and one non-robotic plant. Significance levels: * 10%, ** 5%, *** 1%.

Table 6: Effect of industry-level robot penetration rates on employment in never adopters, 2016-2022 (panel estimation with instrumental variable regression)

	Period relative to adoption rate in t_0		
	0	1	2
Log(Full-time employment)	-0.000	-0.004**	-0.005**
	(0.002)	(0.001)	(0.002)
Mean robot penetration rates in $\$t_0$	22.22	22.22	22.22
	(23.21)	(23.21)	(23.21)
Mean DV	5.40	5.40	5.40
	(1.02)	(1.02)	(1.02)
Observations	8,542	8,542	8,542
Plants	3,992	3,992	3,992

Notes: Table shows the effects of changing the stock of robots per 1,000 workers in an industry by one unit on the log of full-time employment in (non-robotic) plants owned by non-adopting firms. Each cell shows the second stage coefficient and standard errors (in parentheses, clustered by industry) of instrumental variable (IV) regressions. In stage 1 (not shown), the number of US industrial robot stock per 1,000 workers is predicted by the number of EURO5 industrial robot stock per 1,000 workers and EURO5 research and development capital stock per 1,000 workers. EURO5 countries include Denmark, Finland, France, Italy, and Sweden. Included as controls, US industry-level real GDP, year fixed effects, and plant fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Table 7: Descriptive statistics for skills

Variable	Never-adopter plants (1)	Adopter plants: Pre-adoption (2)	Adopter plants: Post-adoption (3)
	A. Technical skills		
Design	0.36	0.49***	0.51
	(0.43)	(0.61)	(0.41)
Production	1.05	1.09	1.22***
	(0.81)	(1.00)	(0.81)
Repair and maintenance	1.03	0.86***	1.06***
	(0.84)	(0.96)	(0.79)
Quality control	0.14	0.12***	0.11*
	(0.15)	(0.17)	(0.11)
Machine learning	0.04	0.05	0.11***
	(0.13)	(0.23)	(0.26)
Automation	0.10	0.13***	0.18***
	(0.19)	(0.27)	(0.22)
	B. General skills		
Reasoning	0.52	0.55***	0.61***
	(0.37)	(0.42)	(0.32)
Character	0.39	0.27***	0.34***
	(0.40)	(0.35)	(0.30)
Social	0.64	0.66	0.65
	(0.41)	(0.46)	(0.34)

Notes: Skills are measured as the average frequency the skill appears in production occupations. Standard errors are shown in parentheses. Stars in column (2) reflect the *t*-test significance level of the mean difference between (1) and (2). Stars in column (3) reflect the *t*-test significance level of the mean difference between (2) and (3). Means by production occupations are available in Tables A12 and A13 in the Online Appendix. Significance levels: * 10%, ** 5%, *** 1%.

Table 8: Robot adoption effect on technical skills (difference-in-differences analysis)

	Design (1)	Production (2)	Repair and Maintenance (3)	Quality Control (4)	Machine Learning (5)	Automation (6)
			A. High-skill (22,929 plants; 117,362 plant-cohorts)			
ATT for robotics job	0.56***	0.51***	0.33***	-0.05***	0.21***	0.51***
postings	(0.05)	(0.06)	(0.04)	(0.01)	(0.03)	(0.03)
ATT for non-robotics	0.02	0.03	-0.02	-0.00	0.02*	-0.01
job postings	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Pre-adoption mean	0.71	0.99	0.35	0.14	0.08	0.09
			B. Medium-skill (12,189 plants; 51,524 plant-cohorts)			
ATT for robotics job	0.01	0.32***	0.60***	0.00	0.03**	0.26***
postings	(0.06)	(0.10)	(0.17)	(0.01)	(0.01)	(0.05)
ATT for non-robotics	-0.05	-0.00	-0.24**	0.01	0.01	-0.01
job postings	(0.04)	(0.07)	(0.10)	(0.01)	(0.01)	(0.03)
Pre-adoption mean	0.41	1.18	1.97	0.06	0.01	0.22
			C. Low-skill (21,605 plants; 108,975 plant-cohorts)			
ATT for robotics job	0.13***	0.71***	1.33***	-0.05***	0.06***	0.25***
postings	(0.04)	(0.08)	(0.12)	(0.01)	(0.02)	(0.03)
ATT for non-robotics	-0.01	0.08*	0.02	0.00	-0.00	-0.01
job postings	(0.02)	(0.04)	(0.05)	(0.01)	(0.01)	(0.02)
Pre-adoption mean	0.18	1.30	1.47	0.10	0.01	0.16
			D. Direct (11,617 plants; 48,983 plant-cohorts)			
ATT for robotics job	0.07	0.96***	0.04	0.01	-0.00	0.12**
postings	(0.05)	(0.16)	(0.16)	(0.03)	(0.00)	(0.05)
ATT for non-robotics	0.01	-0.07	0.17*	-0.00	-0.00	-0.01
job postings	(0.01)	(0.10)	(0.10)	(0.02)	(0.00)	(0.02)
Pre-adoption mean	0.06	1.38	1.22	0.05	0.01	0.02

Notes: Table shows the 5-year (t_0 to t_4) average treatment effects (ATT) for technical skills, comparing robot adopters with never-adopters. The dependent variable is the frequency of related terms appearing in job postings. ATT are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020), with pre-adoption data averaged into one period and post-adoption into another. Standard errors are shown in parentheses. Means of pre-adoption values (t_{-4} to t_{-1}) for each occupation are shown below the ATT. Plant-cohorts include unique plants that are replicated across cohorts to construct a stacked sample. Covariates include the number of postings in the first year the plant appears in the data, the commuting zone's log of wages in 2007, cohort fixed effects, and 3-digit NAICS code fixed effects. Table A12 shows parallel results for the comparison between adopters and not-yet adopters. Significance levels: * 10%, ** 5%, *** 1%.

Table 9: Robot adoption effect on general skills (difference-in-differences analysis)

	Reasoning	Character	Social
	(1)	(2)	(3)
A. High-skill (22,929 plants; 117,362 plant-cohorts)			
ATT for robotic job postings	0.08***	-0.03	-0.05*
	(0.03)	(0.02)	(0.03)
ATT for non-robotic job postings	0.02	0.01	0.03*
	(0.02)	(0.01)	(0.02)
Preadoption mean	0.69	0.28	0.78
B. Medium-skill (12,189 plants; 51,524 plant-cohorts)			
ATT for robotic job postings	-0.00	0.03	0.00
	(0.04)	(0.04)	(0.05)
ATT for non-robotic job postings	-0.03	0.03	0.01
	(0.03)	(0.03)	(0.04)
Preadoption mean	0.42	0.26	0.54
C. Low-skill (21,605 plants; 108,975 plant-cohorts)			
ATT for robotic job postings	0.05	-0.04	-0.05
	(0.03)	(0.03)	(0.03)
ATT for non-robotic job postings	-0.02	0.03*	0.00
	(0.02)	(0.02)	(0.02)
Preadoption mean	0.38	0.27	0.52
D. Direct (11,617 plants; 48,983 plant-cohorts)			
ATT for robotic job postings	0.08	-0.00	-0.04
	(0.06)	(0.06)	(0.07)
ATT for non-robotic job postings	0.07	0.10*	-0.01
	(0.05)	(0.06)	(0.05)
Preadoption mean	0.28	0.21	0.38

Notes: Table shows the 5-year (t_0 to t_4) average treatment effects (ATT) for technical skills, comparing robot adopters with never-adopters. The dependent variable is the frequency of related terms appearing in job postings. ATT are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020), with pre-adoption data aggregated into one period and post-adoption into another. Standard errors are shown in parentheses. Means of pre-adoption values (t_{-4} to t_{-1}) for each occupation are shown below the ATT. Plant-cohorts include unique plants that are replicated across cohorts to construct a stacked sample. Covariates include the number of postings in the first year the plant appears in the data, the commuting zone's log of wages in 2007, cohort fixed effects, and 3-digit NAICS code fixed effects. Table A13 shows parallel results for the comparison between adopters and not-yet adopters. Significance levels: * 10%, ** 5%, *** 1%.

Online Appendix for “Robots and Work”

Appendix A. Extensions, robustness checks, details of variable construction

Table A1 shows the effect of robot adoption when the adoption year is shifted to one year earlier (panel A) or later (panel B) than the adoption year identified through the first robotic job posting posted in a plant. For example, a plant that has an adoption year in 2015 is assigned a new adoption year in 2014 (panel A) or 2016 (panel B). The sample of plants is restricted to those used in the main analysis for job postings (Table 3).

Table A1. Robot adoption effect on job postings for shifting adoption year to *t-1* and *t+1*

Occupation	A. Adoption in *t-1*			B. Adoption in *t+1*		
		ATT			ATT	
	Pre-adoption postings	Adopter vs. not-yet adopter	Adopter vs. never-adopter	Pre-adoption postings	Adopter vs. not-yet adopter	Adopter vs. never-adopter
All	61.98	52.91***	80.70***	82.91	5.70	49.20***
		(6.26)	(3.87)		(8.45)	(5.01)
Production	32.92	33.59***	51.63***	46.12	2.17	28.99***
		(3.31)	(2.50)		(4.76)	(3.12)
High-skill	25.84	24.73***	41.06***	35.26	2.66	23.14***
		(3.01)	(2.28)		(4.29)	(2.82)
Medium-skill	1.62	1.63***	2.44***	2.40	-0.34	1.34***
		(0.27)	(0.14)		(0.29)	(0.17)
Low-skill	5.46	7.22***	8.13***	8.46	-0.14	4.51***
		(0.73)	(0.49)		(0.78)	(0.48)
Direct	1.02	2.16***	2.13***	1.67	0.43	1.39***
		(0.33)	(0.27)		(0.32)	(0.24)
Support	29.07	19.33***	29.07***	36.79	3.53	20.21***
		(3.28)	(1.56)		(4.24)	(2.03)
Plants		774	28,083		1,041	28,350
Robotic plants		774	774		1,041	1,041

Notes: Sample includes all plants. Covariates include first-year number of job postings, commuting zone's average log of wage, and 3-digit NAICS. Standard errors are clustered by firm. Significance: * 10%; ** 5%; *** 1%.

Table A2 presents the effect of robot adoption when the minimum number of robotic production job postings required to identify the year of adoption is raised from one to five (panel A) or ten (panel B). If the minimum is set to five (ten) postings, the adoption year is defined as the year when the cumulative number of robotic postings reaches at least five (ten). For example, if a robotic plant posts one robotic job in 2015, two in 2016, and two more in 2017, the year of adoption would be 2017. While the number of robotic plants remains unchanged, the adoption year may be delayed if a plant posts fewer than five (in Panel A) or ten (in Panel B) robotic job postings in the first year.

Table A2. Robot adoption effect on job postings when the minimum number of robotic postings required to identify the year of adoption is increased to five in panel A and to 10 in panel B

Occupation	A. 5 robotic job postings		B. 10 robotic job postings	
	Pre-adoption postings	ATT	Pre-adoption postings	ATT
All	83.90	64.23***	97.95	60.55**
		(22.31)		(26.36)
Production	46.83	40.72**	55.69	40.51**
		(16.44)		(18.72)
High-skill	35.66	30.81*	41.07	31.68*
		(16.20)		(17.91)
Medium-skill	2.40	2.32***	3.07	1.99***
		(0.42)		(0.50)
Low-skill	8.77	7.60***	11.55	6.84***
		(0.68)		(0.94)
Direct	1.86	2.04***	2.64	2.03***
		(0.23)		(0.34)
Support	37.07	23.51***	42.26	20.04**
		(6.01)		(8.22)
Plants		28,394		28,394
Robotic plants		1,085		1,085

Notes: Table shows the results of increasing the threshold of identifying the year of robot adoption from 1 robotic job posting in production occupations to (A) 5 robotic job postings and (B) 10 robotic job postings. The comparison group is never adopters. Covariates include first-year number of job postings, commuting zone's average log of wage, and 3-digit NAICS. Standard errors are clustered by firm. Significance: * 10%; ** 5%; *** 1%.

Table A3 shows the relationship between several measures of robot adoption from BGT and IFR. In column 1, the number of robotic plants from BGT is correlated with the number of robot operational stock from IFR. Column 2 shows the association between the number of robotic job postings from BGT and the number of new robot installations from IFR. Column 3 shows the association between the share of robotic plants and the number of robot operational stocks per 1,000 workers. All models include industry fixed effects.

Table A3. Relationship between our job-postings based measure of robot adoption and IFR's data on robots

	Robotic plants	Robotic job postings	Share of robotic plants
	(1)	(2)	(3)
Robot operational stock	0.0044***		
	(0.0008)		
New robot installations		0.1360***	
		(0.0144)	
Robot operational stock/1,000 workers			0.1477**
			(0.0327)
Fixed effects			
Industry	Yes	Yes	Yes
Industry-years	110	110	110
R^2	0.923	0.734	0.815

Notes: Standard errors are clustered by industry. Significance levels: * 10%, ** 5%, *** 1%.

Table A4. SOCs and assigned occupational categories

Occupation	2010 SOC code (number of postings)
a) Production	
High-skill	
Technical manager	11-3051 (140,920), 11-9041 (113,582), 11-1021 (103,362), 11-9111 (56,710), 11-9121 (47,889), 11-3061 (44,873), 11-3071 (39,854), 11-3021 (17,649), 11-9021 (13,432), 11-9013 (1,451)
Computer	15-0000 (1,670,256)
Engineer	17-2000 (1,089,905)
Medium-skill	
Technician	17-3020 (350,326), 17-3030 (837)
Low-skill	
Operator*	51-0000 (769,721), 49-0000 (414,937)
Direct**	53-7062 (140,633), 51-2092 (43,012), 51-2011 (39,943), 51-4121 (35,127), 51-9111 (22,833), 53-7064 (20,309), 51-2022 (14,896), 53-1021 (14,111), 53-1031 (13,046), 47-2141 (11,165), 53-7199 (4,119), 51-9121 (3,361), 51-2099 (3,312), 51-9122 (2,648), 51-4122 (2,241), 51-9123 (1,153), 51-2031(1,100), 51-2023 (748), 51-2091 (673), 51-2041 (538), 51-2021 (364), 47-3014 (13), 51-2093 (6)
b) Support*	11-0000 (833,795), 13-0000 (747,392), Unclassified (577,341), 43-0000 (494,466), 19-0000 (247,741), 41-0000 (191,485), 290000 (183,091), 27-0000 (151,108), 53-0000 (150,004), 47-0000 (86,812), 17-0000 (53,532), 33-0000 (43,335), 35-0000 (41,381), 23-0000 (32,965), 25-0000 (31,690), 37-0000 (30,684), 31-0000 (22,897), 21-0000 (12,550), 39-0000 (10,943), 45-0000 (5,585), 55-0000 (3,971)

Notes:
* Operator occupations include 6-digit SOC codes in 49 and 51 not listed in Direct occupations.
** Direct occupations include painters, assemblers, welders, packagers, and material handlers.
*** Support occupations include 6-digit SOC codes not listed in high-skill, medium-skill, and low-skill.

Table A5 shows the effect of robot adoption on subsamples with low and high degree of robotized production process. The degree of robotization is measured using two proxies: the share of robotic job postings in total plant production postings (panel A) and the share of unique robotic SOCs from unique production SOCs (panel B). Results show that a low-robotized production process has a higher positive spillover effect due to higher labor demand in non-robotized processes. Vice versa, a process with high share of robotization has a low spillover effect as substitution and complementarity effects are at play in most processes, giving less opportunities for the productivity effect to materialize.

Table A5. Within-plant spillover effects: Robot adoption effect by share of robotization of the production process

Occupation	A. Low share robotized		B. High share robotized	
	Pre-adoption postings	ATT	Pre-adoption postings	ATT
	A. Share of robotic production job postings in total plant production postings			
All	109.31	172.09***	12.93	25.89***
		(14.87)		(1.71)
Production	58.21	107.77***	7.91	18.26***
		(11.09)		(1.18)
High-skill	46.90	92.27***	4.42	10.37***
		(10.66)		(0.79)
Medium-skill	2.62	3.62***	0.65	1.88***
		(0.31)		(0.14)
Low-skill	8.69	11.89***	2.84	6.01***
		(0.75)		(0.66)
Direct	1.65	2.73***	0.53	1.63***
		(0.48)		(0.31)
Support	51.10	64.32***	5.02	7.63***
		(5.17)		(0.63)
Plants		27,852		27,851
Robotic plants		543		542
	B. Share of unique robotic production SOCs from unique production SOCs			
All	77.33	100.45***	49.45	79.38***
		(4.12)		(9.72)
Production	42.71	63.66***	25.53	49.46***
		(2.72)		(4.59)
High-skill	32.27	50.42***	21.16	39.23***
		(2.41)		(4.19)
Medium-skill	2.35	3.06***	0.93	2.58***
		(0.24)		(0.19)
Low-skill	8.09	10.18***	3.44	7.65***
		(0.78)		(0.60)
Direct	1.60	2.79***	0.57	1.58***
		(0.50)		(0.24)
Support	34.62	36.79***	23.91	29.93***
		(1.57)		(5.60)

Plants	27,854	27,849
Robotic plants	545	540

Notes: Robotic plants are split at (A) the median share of robotic job postings in the adoption year (t_0), 6.3 percent, and (B) the median share of unique robotic SOCs from unique production SOCs, 17.1 percent. The median is calculated based on 1,085 robotic plants. Covariates include first-year number of job postings, commuting zone's average log of wage, and 3-digit NAICS. Standard errors are clustered by firm. The comparison group is never adopters. Significance levels: * 10%, ** 5%, *** 1%.

The analysis in Table A6 aims to capture the cross-plant spillover effect within large firms that own at least one robotic plant. The sample includes adopting firms owning more than 20 plants. Panel A shows the effect of adoption in robotic plants. In panel B, an adoption year is assigned to a non-robotic plant as many times as the number of adoption cohorts in the adopting firm. For example, for a firm that adopted robots in 2014, 2015, and 2016, each non-robotic plant, conditional on having enough pre- and post-adoption observations, is duplicated three times and assigned the (pseudo) adoption years. For this reason, the unit of analysis for panel B is plant-cohort. Plants in panels A and B are compared with non-robotic plants owned by non-adopting firms.

Table A6. Between-plant spillover effects: Robot adoption in firms with more than 20 plants (difference-in-differences analysis)

Occupation	A. Robotic plant		B. Non-robotic plant	
	Pre-adoption postings	ATT	Pre-adoption postings	ATT
All	87.66	125.77***	39.98	8.28***
		(19.91)		(0.94)
Production	46.42	80.32***	23.85	5.86***
		(13.53)		(0.57)
High-skill	36.87	68.18***	18.35	5.47***
		(12.28)		(0.50)
Medium-skill	2.03	3.11***	1.05	0.17***
		(0.31)		(0.04)
Low-skill	7.52	9.03***	4.45	0.22
		(0.77)		(0.13)
Direct	1.42	1.91***	0.99	0.00
		(0.21)		(0.05)
Support	41.24	45.45***	16.13	2.43***
		(5.75)		(0.40)
Observations		12,078		38,882

Notes: Table shows the 5-year (t_0 to t_{+4}) average treatment effects on the treated (ATT) for the number of job postings per plant in large firms (firms owning more than 20 plants). Sample of non-robotic plants is duplicated for multiple adoption cohorts in a firm and stacked together. Sample of robotic and non-robotic plants have the same set of firms. Covariates include the number of postings in the first year the plant appears in the data, the number of plants having adopted robots in a cohort (for non-robotic plants), the commuting zone's log of wages, and 3-digit NAICS code fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

The analysis in Table A7 aims to capture the effect of robot adoption isolated from the effect of capital expansion. BGT data is merged with COMPUSTAT's public firm data through firm names to obtain capital expenditures. We evaluate whether the ATT differs between the model with and without firm-level capital expansion. The first row shows the ATT for all public firms. We perform a heterogeneity analysis by size for public firms in rows two and three to show that our results hold for firms with varying sizes. In rows four to six, we show the effect of capital expansion in small firms to address the concern that the firm-level variable does not sufficiently capture plant-level variations in expansion, particularly in firms that own numerous plants. By restricting the sample to firms with very few plants, firm-level expansion reflects more closely plant-level expansion. However, the sample size is very limited.

Table A7. Robot adoption effect on job postings (difference-in-differences) controlling for firm-level capital expansion expenses, plants in publicly traded firms

Occupation	Pre-adoption postings	ATT		Plants	Robotic plants
		No expansion	With expansion		
1. All public firms	83.26	107.59***	106.29***	8,972	509
		(12.80)	(12.67)		
2. Small public firms (20 or fewer plants)	63.05	69.96***	69.34***	2,576	124
		(18.52)	(18.34)		
3. Large public firms (more than 20 plants)	89.94	114.09***	111.83***	6,396	385
		(23.62)	(22.77)		
4. Public firms with 1 plant	13.25	20.18	19.59	292	8
		(13.65)	(14.91)		
5. Public firms with 1 and 2 plants	76.09	33.14*	30.45*	502	15
		(18.88)	(18.25)		
6. Public firms with 3 or fewer plants	51.55	19.30**	17.43**	634	26
		(7.86)	(6.98)		

Notes: ATTs reflect the change in all job postings in four (A) years or (B) quarters following robot adoption. The comparison group is never adopters. Covariates include first-year number of job postings, commuting zone's average log of wages, 3-digit NAICS, and the firm-level change in real capital expenditure normalized by real total assets (for models that include this variable). Capital expenditure (obtained from COMPUSTAT) includes expenditures for capital leases, increase in funds for construction, reclassification of inventory to property, plant and equipment, increase in leaseback transactions when included in the investing section of the statement of cash flows, any item included in the property, plant and equipment from the balance sheet, and logging roads and timber. The base year for real capital expenditures is 2015. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table A8. Industry distribution of plants

	Industry name	A. Full sample (2010-2022)			B. End of 2022		
		NR	R	Total	NR	R	Total
311	Food Manufacturing	2,599	60	2,659	1,674	54	1,728
312	Beverage and Tobacco Product Manufacturing	891	29	920	684	29	713
313	Textile Mills	2	0	2	1	0	1
314	Textile Product Mills	45	0	45	37	0	37
315	Apparel Manufacturing	33	4	37	20	3	23
316	Leather and Allied Product Manufacturing	22	0	22	20	0	20
321	Wood Product Manufacturing	336	4	340	271	3	274
322	Paper Manufacturing	501	5	506	361	5	366
323	Printing and Related Support Activities	585	7	592	428	7	435
324	Petroleum and Coal Products Manufacturing	438	10	448	301	10	311
325	Chemical Manufacturing	3,287	98	3,385	2,127	90	2,217
326	Plastics and Rubber Products Manufacturing	549	25	574	400	24	424
327	Nonmetallic Mineral Product Manufacturing	621	23	644	517	22	539
331	Primary Metal Manufacturing	822	25	847	548	19	567
332	Fabricated Metal Product Manufacturing	1,401	64	1,465	976	52	1,028
333	Machinery Manufacturing	1,918	110	2,028	1,349	97	1,446
334	Computer and Electronic Product Manufacturing	4,009	167	4,176	2,368	150	2,518
335	Electrical Equipment, Appliance, and Comp	541	43	584	311	39	350
336	Transportation Equipment Manufacturing	4,336	277	4,613	2,619	263	2,882
337	Furniture and Related Product Manufacturing	245	15	260	176	14	190
339	Miscellaneous Manufacturing	708	34	742	373	33	406
33	Unclassified	3,420	85	3,505	2,335	69	2,404
Total		27,309	1,085	28,394	17,896	983	18,879

Notes: 3-digit NAICS codes; NR stands for non-robotics postings and R stands for robotics postings

Table A9 shows how the percentage of postings of never adopter plants and, separately, the percentage of postings of adopter plants change with the adjusted penetration of robots (APR) at the industry-level, calculated as Acemoglu and Restrepo (2019) from IFR and EU KLEMS. The estimates indicate opposite effects of robots on adopters and never adopter plants. Specifically, one more robot per thousand workers is associated with a 0.87% decrease in the postings of never adopter plants between 2010 and 2020 and a 1.86% increase of the postings of adopter plants between 2010 and 2019.

Table A9. Change in log postings and APR

	Never-adopter plants		Adopter plants	
	2010-2019	2010-2020	2010-2019	2010-2020
EURO5 APR	0.1011	-0.872***	1.855**	0.632
	(0.349)	(0.254)	(0.760)	(0.549)
Mean of change in log postings	95.792	81.715	140.614	116.707
Mean of EURO5 APR	7.361	10.243	8.373	12.037
R^2	0.000	0.002	0.007	0.002
Observations	6,449	5,968	862	854

Notes: $EU5\ APR_{i(t_0,t_1)} = \sum_j \frac{R^j_{t_1} - (1+g_{i(t_0,t_1)})R^j_{t_0}}{L^j_{i,t_0-3}}$, where $R^j_{i,t}$ is the stock of robots in industry i, country j, year t from IFR; L^j_{i,t_0-3} is employment in thousand workers in industry i, country j, year $t_0 - 3$ from EU KLEMS; and $g_{i(t_0,t_1)}$ is the growth rate of output in industry i, country j from EU KLEMS. EURO5 includes Denmark, Finland, France, Italy, and Sweden. The dependent variable, change in the logarithm of postings, is multiplied by 100. Robust standard errors to heteroscedasticity. Significance levels: * 10%, ** 5%, *** 1%.

Table A10 shows the second-stage coefficients of IV regressions within two years following a change in the number of robot stocks per 1,000 workers in an industry. The dependent variable is the log of employment with data from multiple sources (i.e., KLEMS, the Occupational Employment and Wage Statistics, IPUMS CPS, the Statistics of US Businesses, and the Quarterly Workforce Indicators).

Table A10. The effect of industry-level robot penetration rates on industry-level log of full-time employment, 2010-2022 (panel estimation with instrumental variable regression)

Data Source	DV lag relative to penetration rate in t_0			Observations	Mean DV
	t_0	t_1	t_2		
KLEMS	0.0009	0.0026	0.0031	90	13.74
(All establishments)	(0.0018)	(0.0025)	(0.0028)		(0.82)
OES	0.0032**	0.0037*	0.0043*	90	13.74
(All establishments)	(0.0013)	(0.0020)	(0.0022)		(0.85)
IPUMS	0.0003	-0.0039	-0.0049	90	13.39
(Establishments ≥ 100 employees)	(0.0037)	(0.0044)	(0.0050)		(0.81)
SUSB	0.0036	0.0079*	0.0087*	90	13.35
(Establishments ≥ 100 employees)	(0.0028)	(0.0042)	(0.0046)		(0.90)
QWI	0.0024*	0.0028	0.0034	90	13.29
(Establishments ≥ 250 employees)	(0.0012)	(0.0017)	(0.0019)		(0.84)

Notes: The dependent variable is the log of employment with data from various sources. The independent variable is the number of robot stocks per 1,000 workers in industry k and year t. The instruments are the number of robot stock per 1,000 workers and the number of research and development capital stock per 1,000 workers in EURO5 countries. Standard errors (in parentheses) are clustered by industry. Covariates include US real GDP in industry k and year t, industry fixed effects, and year fixed effects. Sample from IPUMS and SUSB includes establishments with at least 100 employees; QWI, establishments with at least 250 employees; KLEMS and OES, all establishments. Significance levels: * 10%, ** 5%, *** 1%.

Table A11. Most frequently used terms in production occupations

Skill requirement	Terms (number of postings)
Design	system design (173,665), product design (122,384), engineering drawings (112,525), autocad (106,568), engineering design and installation (104,596), engineering design (98,764), object-oriented analysis and design ooad (88,278), mechanical design (67,798), microsoft visio (66,912), process design (66,667), computer aided drafting/design cad (64,964), catia (50,683), human machine interface hmi (46,868), design of experiments doe (45,247), circuit design (39,402), database design (38,413), design for manufacture/design for assembly dfm/dfa (35,461), electrical design (34,387), 3d modeling / design (33,229), user interface ui design (30,958)
Production	manufacturing processes (369,059), machinery (352,335), six sigma (286,170), welding (248,763), good manufacturing practices gmp (220,910), machining (216,006), lean manufacturing (215,267), lean six sigma (159,645), current good manufacturing practices cgmp (135,102), machine operation (133,122), calipers (95,172), soldering (85,193), failure mode and effects analysis fmea (79,605), grinders (79,112), lathes (77,286), failure analysis (76,890), kaizen (70,127), iso 9001 standards (65,350), machine tools (64,141), six sigma black belt (60,393)
Repair and maintenance	repair (782,529), predictive / preventative maintenance (275,604), hand tools (250,230), test equipment (219,672), schematic diagrams (206,405), calibration (144,731), power tools (124,870), wiring (119,244), micrometers (111,836), electrical systems (103,071), hvac (88,765), hydraulics (82,035), oscilloscopes (73,108), equipment operation (70,826), plumbing (69,548), equipment maintenance (63,120), painting (53,927), wiring diagrams (38,663), inspection records (35,670), equipment repair (33,812)
Quality control	quality assurance and control (502,794)
ML	python (243,844), machine learning (51,012), artificial intelligence (28,461), automated testing (25,773), apache hadoop (21,838), splunk (21,052), image processing (18,752), automation tools (16,877), chef infrastructure automation (16,039), deep learning (15,459), r (14,399), clustering (11,271), computer vision (11,250), tensorflow (8,818), neural networks (6,718), apache hive (6,678), mapreduce (6,158), natural language processing (6,064), laboratory automation (3,593), pattern recognition (3,476)
Automation	computer numerical control cnc (133,413), embedded software (70,682), programmable logic controller plc programming (50,140), electromechanical systems (26,649), automation systems (25,946), computerized numerical control lathes (14,804), servo drives / motors (12,001), rockwell automation (10,910), computeraided manufacturing cam (10,243), mastercam (8,000), devicenet (6,853), computer aided manufacturing cam (6,536), process field bus profibus (5,032), cnc machine (4,935), abb (4,621), machine vision (4,603), g-code (4,197), controlnet (4,096), zemax (4,002), motion control systems (3,752)
Reasoning	problem solving (1,167,194), research (648,171), creativity (328,315), analytical skills (187,502), basic mathematics (169,651), statistics (82,315), critical thinking (81,588), mathworks simulink (42,377), creative problem solving (37,005), clinical research (36,035), biostatistics (17,145), market research (12,037), mathcad (11,434), analytical chemistry (8,965), adobe creative suite (8,834), 8d problem solving (8,298), analytical testing (7,364), mathematical modeling (6,195), technology research (5,355), product research (4,865)

Character	detail-oriented (526,330), multi-tasking (288,232), self-starter (219,671), time management (188,153), meeting deadlines (106,030), positive disposition (84,505), prioritizing tasks (73,079), energetic (64,146), initiative (32,760), self-motivation (30,841), goal setting (14,332)
Social	communication skills (1,954,215), written communication (512,582), verbal / oral communication (300,008), presentation skills (241,993), oral communication (139,476), listening (79,812), team building (66,479), negotiation skills (51,376), prepare presentations (32,643), team management (23,849), business communications (22,742), persuasion (20,965), social media (14,502), effective communications (12,624), contract negotiation (10,630), technical presentations (4,383), presenting solutions (3,304), price negotiation (2,514), corporate communications (2,214), presentation design (2,022)

Table A12. Technical skills, means and standard deviations

Occupation	Non-adopter	Adopter			Non-adopter	Adopter		
		Pre-adoption	Post-adoption			Pre-adoption	Post-adoption	
			Non-robotics postings	Robotics postings			Non-robotics postings	Robotics postings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		A. Design				*D. Quality control*		
High-skill	0.55	0.66***	0.69	1.27***	0.18	0.16***	0.15	0.09***
	(0.63)	(0.71)	(0.53)	(1.05)	(0.22)	(0.24)	(0.16)	(0.21)
Medium-skill	0.32	0.45***	0.39*	0.47	0.08	0.06***	0.07	0.06
	(0.63)	(0.77)	(0.54)	(0.73)	(0.21)	(0.19)	(0.18)	(0.20)
Low-skill	0.14	0.21***	0.20	0.31***	0.13	0.10***	0.10	0.07***
	(0.32)	(0.48)	(0.34)	(0.63)	(0.21)	(0.20)	(0.15)	(0.21)
Direct	0.07	0.10*	0.13*	0.23***	0.07	0.06	0.07	0.09**
	(0.27)	(0.35)	(0.37)	(0.65)	(0.21)	(0.19)	(0.18)	(0.26)
		B. Production				*E. ML*		
High-skill	1.00	1.02	1.11**	1.52***	0.05	0.06	0.11***	0.31***
	(0.99)	(1.10)	(0.88)	(1.50)	(0.17)	(0.25)	(0.23)	(0.68)
Medium-skill	1.19	1.09**	1.24***	1.71***	0.02	0.02	0.03***	0.08***
	(1.20)	(1.26)	(1.06)	(1.61)	(0.21)	(0.10)	(0.18)	(0.46)
Low-skill	1.14	1.27***	1.33	2.04***	0.01	0.01	0.02	0.06***
	(0.96)	(1.16)	(0.84)	(1.67)	(0.12)	(0.11)	(0.13)	(0.31)
Direct	0.86	1.04***	1.02	2.41***	0.00	0.00	0.01**	0.02*
	(1.05)	(1.24)	(1.03)	(1.87)	(0.04)	(0.04)	(0.10)	(0.14)
		C. Repair and maintenance				*F. Automation*		
High-skill	0.47	0.36***	0.42***	0.83***	0.08	0.09	0.10	0.68***
	(0.68)	(0.53)	(0.54)	(1.09)	(0.21)	(0.26)	(0.16)	(0.85)
Medium-skill	2.26	1.93***	1.98	2.90***	0.16	0.21***	0.20	0.54***
	(1.92)	(1.79)	(1.63)	(2.30)	(0.38)	(0.48)	(0.35)	(0.73)
Low-skill	1.40	1.41	1.42	2.66***	0.11	0.15***	0.15	0.43***
	(1.22)	(1.34)	(0.99)	(2.36)	(0.27)	(0.36)	(0.24)	(0.67)
Direct	0.93	0.98	0.94	1.60***	0.01	0.02	0.03**	0.15***
	(1.22)	(1.18)	(1.11)	(1.80)	(0.11)	(0.13)	(0.13)	(0.40)

Notes: This table shows means and standard deviations for technical skills as the count of terms. Stars in (2) reflect the t-test significance level of the mean difference between (2) and (1). Stars in (3) and (4) reflect the mean difference between (3) and (2) and (4) and (2), respectively. Significance levels: * 10%, ** 5%, *** 1%.

Table A13. General skills, means and standard deviations

Occupation	Non-adopter	Adopter		
			Post-adoption	
		Pre-adoption	Non-robotics postings	Robotics postings
	(1)	(2)	(3)	(4)
		A. Reasoning		
High-skill	0.66	0.67	0.76***	0.82***
	(0.47)	(0.49)	(0.38)	(0.62)
Medium-skill	0.42	0.42	0.47**	0.52***
	(0.53)	(0.51)	(0.46)	(0.63)
Low-skill	0.39	0.39	0.44***	0.48***
	(0.42)	(0.44)	(0.37)	(0.61)
Direct	0.32	0.31	0.39***	0.42***
	(0.48)	(0.48)	(0.49)	(0.62)
	0.66	0.67	0.76***	0.82***
		B. Character		
High-skill	0.42	0.28***	0.36***	0.33***
	(0.47)	(0.36)	(0.35)	(0.47)
Medium-skill	0.36	0.25***	0.34***	0.32***
	(0.58)	(0.44)	(0.48)	(0.56)
Low-skill	0.40	0.29***	0.38***	0.34**
	(0.50)	(0.44)	(0.42)	(0.56)
Direct	0.42	0.30***	0.39***	0.31
	(0.62)	(0.59)	(0.58)	(0.57)
		C. Social		
High-skill	0.84	0.80**	0.83*	0.76*
	(0.53)	(0.52)	(0.41)	(0.60)
Medium-skill	0.53	0.54	0.54	0.54
	(0.61)	(0.60)	(0.49)	(0.64)
Low-skill	0.53	0.57**	0.55	0.52**

	(0.50)	(0.56)	(0.43)	(0.64)
Direct	0.41	0.44	0.44	0.34***
	(0.57)	(0.58)	(0.53)	(0.56)

Notes: This table shows means and standard deviations for general skills as the count of terms. Stars in (2) reflect the t-test significance level of the mean difference between (2) and (1). Stars in (3) and (4) reflect the mean difference between (3) and (2) and (4) and (2), respectively. Significance levels: * 10%, ** 5%, *** 1%.

Table A14 is a companion table to Tables 8 and 9. It shows the effect of robot adoption on technical skills in robotic and non-robotic job postings. The comparison group is not-yet adopters.

Table A14. Robot adoption effect on technical skills, adopter vs. not-yet adopter

Occupations	Plant-cohorts	Design	Production	Repair and maintenance	Quality control	ML	Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Robotics job postings			
High-skill	1,044	0.47***	0.63***	0.34***	-0.06***	0.10***	0.47***
		(0.07)	(0.09)	(0.06)	(0.02)	(0.03)	(0.03)
Pre-adoption mean		[0.69]	[1.01]	[0.33]	[0.14]	[0.04]	[0.09]
Medium-skill	448	0.08	0.48***	0.57**	0.02	0.03*	0.39***
		(0.10)	(0.16)	(0.28)	(0.03)	(0.02)	(0.07)
Pre-adoption mean		[0.42]	[1.17]	[2.00]	[0.06]	[0.01]	[0.21]
Low-skill	779	0.16***	0.60***	1.34***	-0.03	0.07***	0.18***
		(0.05)	(0.11)	(0.17)	(0.02)	(0.02)	(0.04)
Pre-adoption mean		[0.20]	[1.30]	[1.43]	[0.10]	[0.01]	[0.16]
Direct	229	0.08	0.95***	0.06	-0.01	-0.00	0.10
		(0.07)	(0.23)	(0.22)	(0.04)	(0.00)	(0.07)
Pre-adoption mean		[0.07]	[1.41]	[1.18]	[0.05]	[0.02]	[0.04]
				B. Non-robotics job postings			
High-skill	1,156	0.06	0.03	0.05	-0.03	-0.01	0.01
		(0.05)	(0.07)	(0.05)	(0.02)	(0.01)	(0.01)
Pre-adoption mean		[0.64]	[1.04]	[0.34]	[0.16]	[0.03]	[0.09]
Medium-skill	610	0.02	0.04	-0.14	0.01	0.01	0.03
		(0.09)	(0.12)	(0.21)	(0.03)	(0.01)	(0.04)
Pre-adoption mean		[0.45]	[1.10]	[1.98]	[0.06]	[0.02]	[0.20]
Low-skill	1015	-0.02	-0.04	0.24**	0.01	0.00	-0.02
		(0.03)	(0.06)	(0.10)	(0.01)	(0.00)	(0.02)
Pre-adoption mean		[0.22]	[1.29]	[1.34]	[0.10]	[0.01]	[0.14]
Direct	392	-0.00	-0.09	-0.03	0.00	-0.00	-0.00
		(0.03)	(0.10)	(0.12)	(0.02)	(0.00)	(0.01)
Pre-adoption mean		[0.13]	[1.01]	[1.01]	[0.05]	[0.00]	[0.01]

Notes: This table shows the 5-year (t_0, t_4) average treatment effects (ATT) for technical skills, comparing robot adopters with not-yet adopters. The dependent variable is the frequency of related terms appearing in job postings. ATTs are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020), with pre-adoption data aggregated into one period and post-adoption into another. Standard errors are shown in parentheses. Means of pre-adoption values (t_{-4}, t_{-1}) for adopters are shown in square brackets. Covariates include the number of postings in the first year the plant appears in the data, the commuting zone's log of wages, cohort fixed effects, and 3-digit NAICS code fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Table A15 is a companion table to Tables 8 and 9. It shows the effect of robot adoption on general skills in robotic and non-robotic job postings. The comparison group is not-yet adopters.

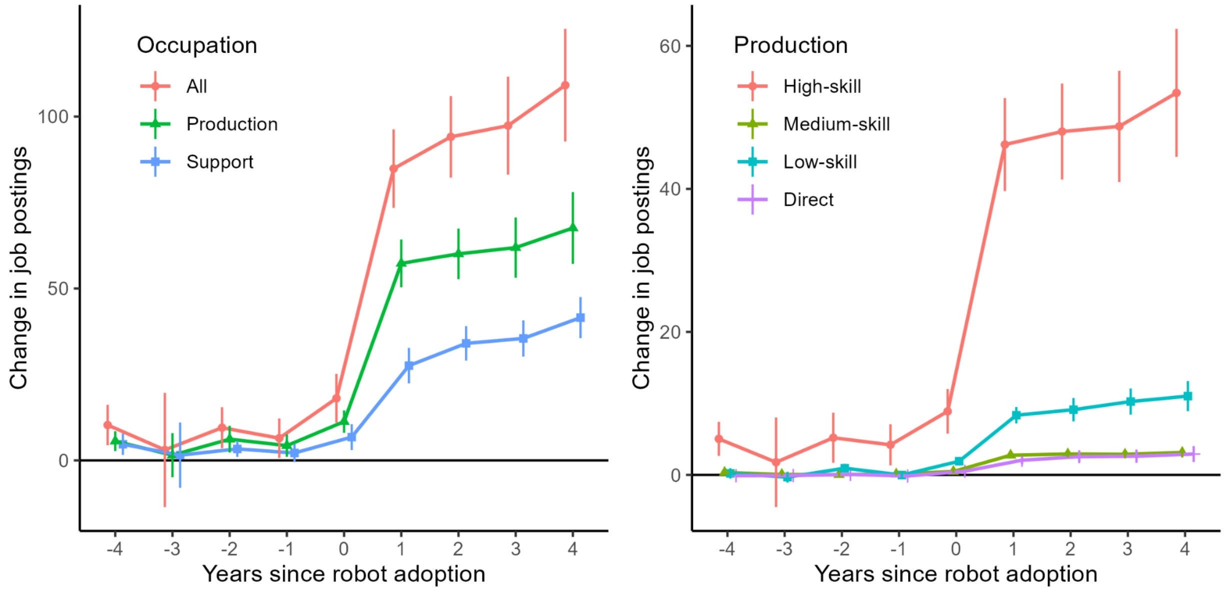
Table A15. Robot adoption effect on general skills, adopter vs. not-yet adopter

Occupations	Plant-cohorts	Reasoning	Character	Social
	(1)	(2)	(3)	(4)
		A. Robotics job postings		
High-skill	1,044	0.00	-0.01	-0.05
		(0.04)	(0.03)	(0.05)
Pre-adoption mean		[0.69]	[0.25]	[0.77]
Medium-skill	448	0.05	0.02	0.05
		(0.07)	(0.08)	(0.08)
Pre-adoption mean		[0.44]	[0.25]	[0.54]
Low-skill	779	0.09*	-0.04	-0.02
		(0.05)	(0.05)	(0.05)
Pre-adoption mean		[0.36]	[0.22]	[0.51]
Direct	229	0.11	-0.06	0.02
		(0.07)	(0.07)	(0.09)
Pre-adoption mean		[0.22]	[0.21]	[0.33]
		B. Non-robotics job postings		
High-skill	1,156	-0.04	0.04	-0.01
		(0.03)	(0.03)	(0.04)
Pre-adoption mean		[0.68]	[0.25]	[0.79]
Medium-skill	610	0.01	0.04	0.03
		(0.06)	(0.07)	(0.07)
Pre-adoption mean		[0.43]	[0.22]	[0.55]
Low-skill	1015	0.04	0.06	0.04
		(0.04)	(0.05)	(0.04)
Pre-adoption mean		[0.39]	[0.25]	[0.55]
Direct	392	0.14***	-0.03	-0.04
		(0.04)	(0.05)	(0.06)
Pre-adoption mean		[0.27]	[0.26]	[0.43]

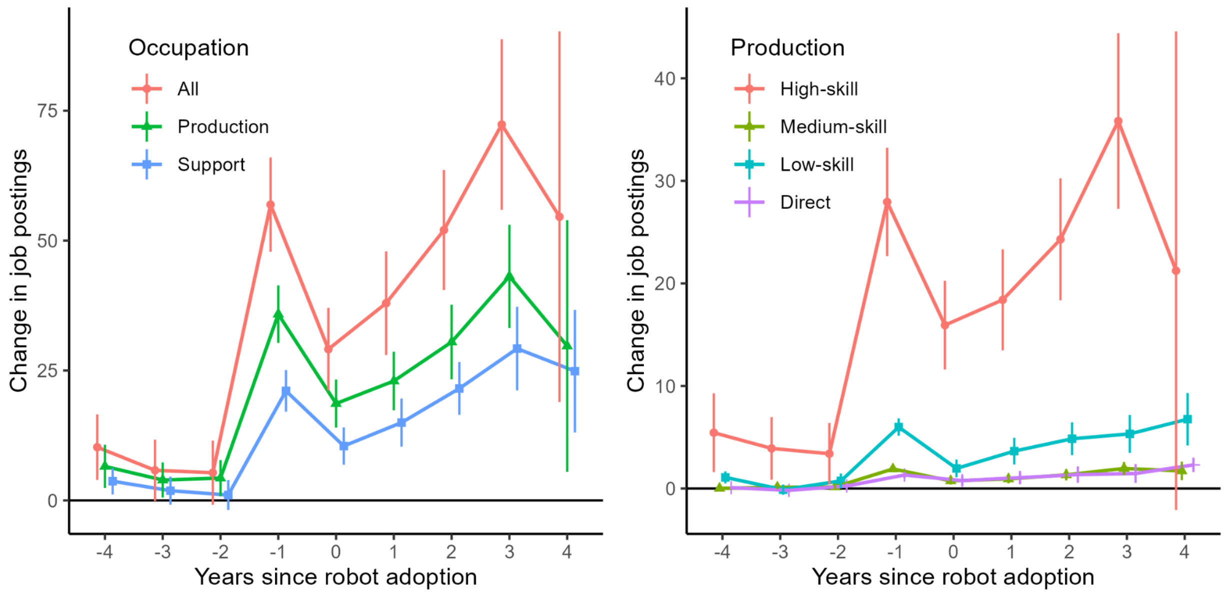
Notes: This table shows the 5-year (t_0, t_4) average treatment effects (ATT) for general skills, comparing robot adopters with not-yet adopter. The dependent variable is the frequency of related terms appearing in job postings. ATTs are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020), with pre-adoption data aggregated into one period and post-adoption into another. Standard errors are shown in parentheses. Means of pre-adoption values (t_{-4}, t_{-1}) are shown in square brackets. Covariates include the number of postings in the first year the plant appears in the data, the commuting zone's log of wages, cohort fixed effects, and 3-digit NAICS code fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Figure A1. Event-study of the effect of robot adoption on job postings for moving adoption year to *t-1* and *t+1*

(A) Moving adoption year to *t-1*



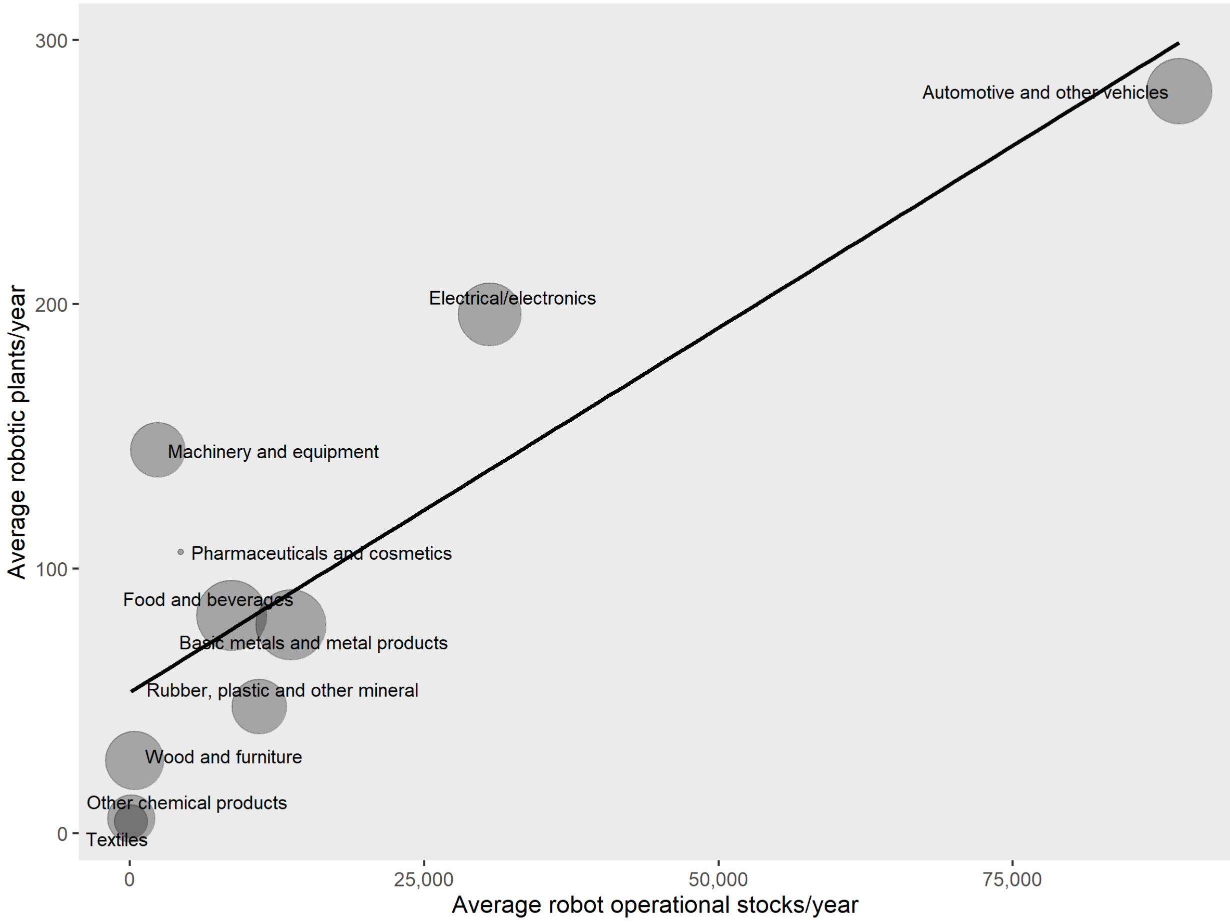
(B) Moving adoption year to *t+1*



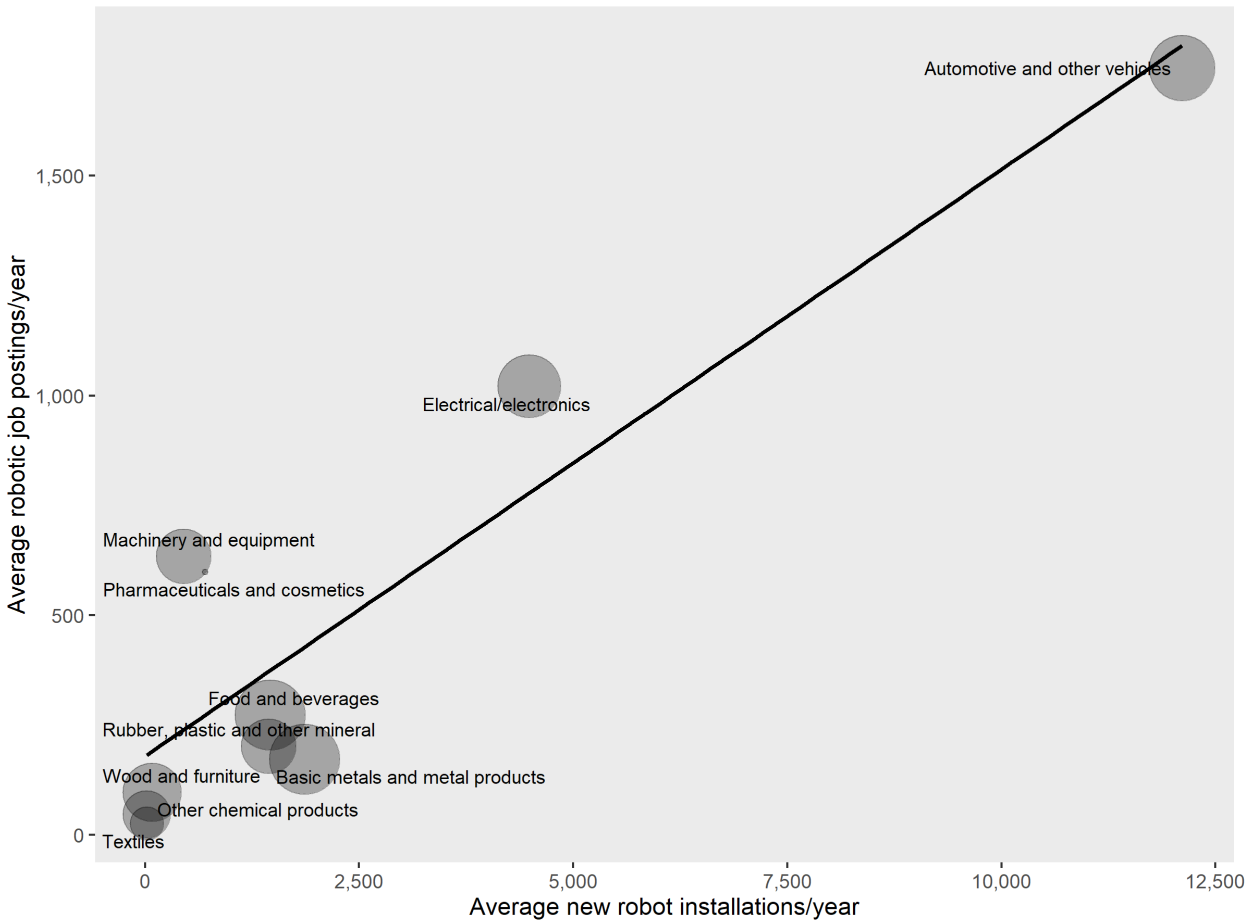
Notes: Figure shows the event-time ATT from moving the robot adoption timing to (A) one year earlier and (B) one year later than the original robot adoption year. For example, a robotic plant that adopted in 2015, panel (A) moves it to 2014 whereas panel (B) moves it to 2016. The control group is never adopters.

Figure A2. Relationship between alternative data sources for robots: International Federation of robotics (IFR) and BGT job postings

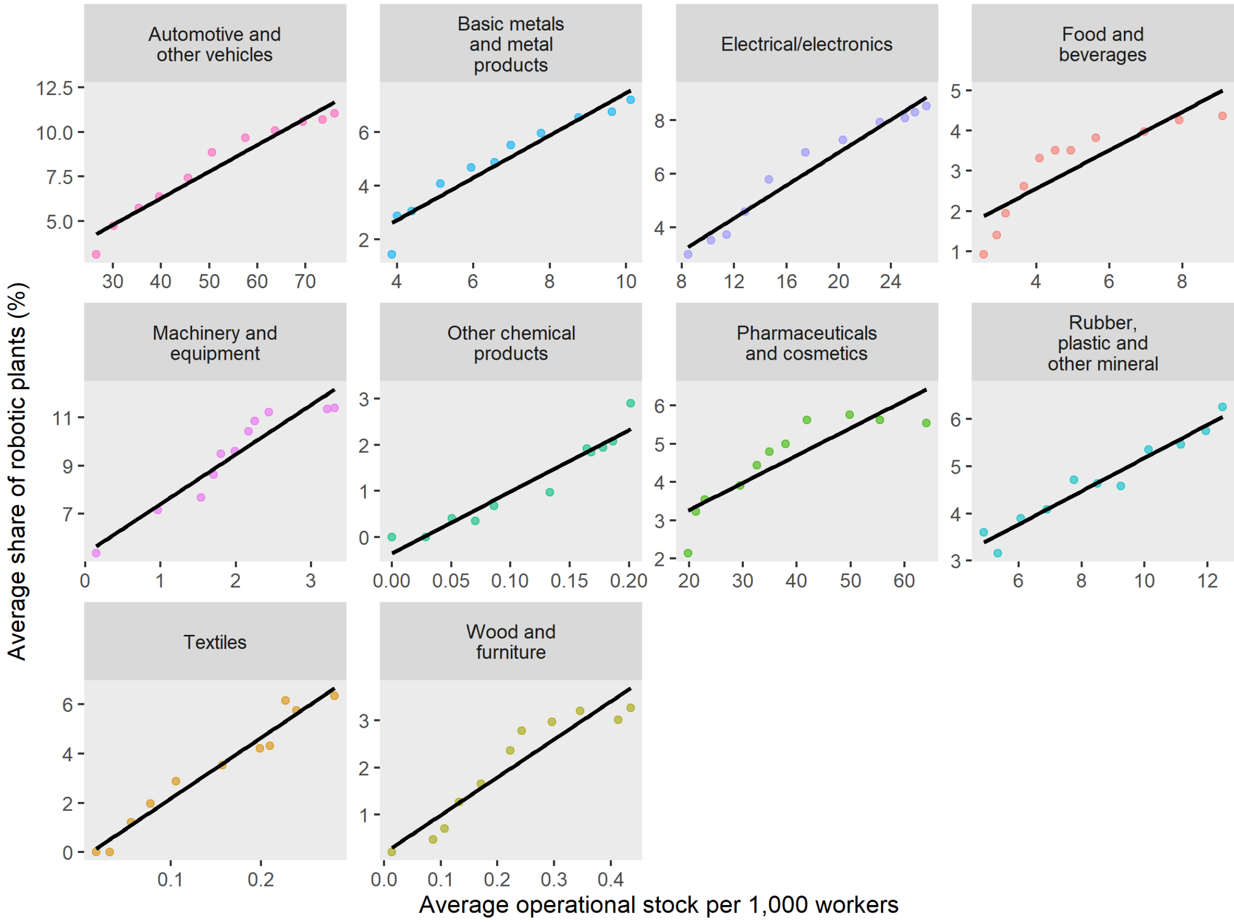
(A) Robot operational stock vs. robotic plants



(B) New robot installations vs. robotic job postings



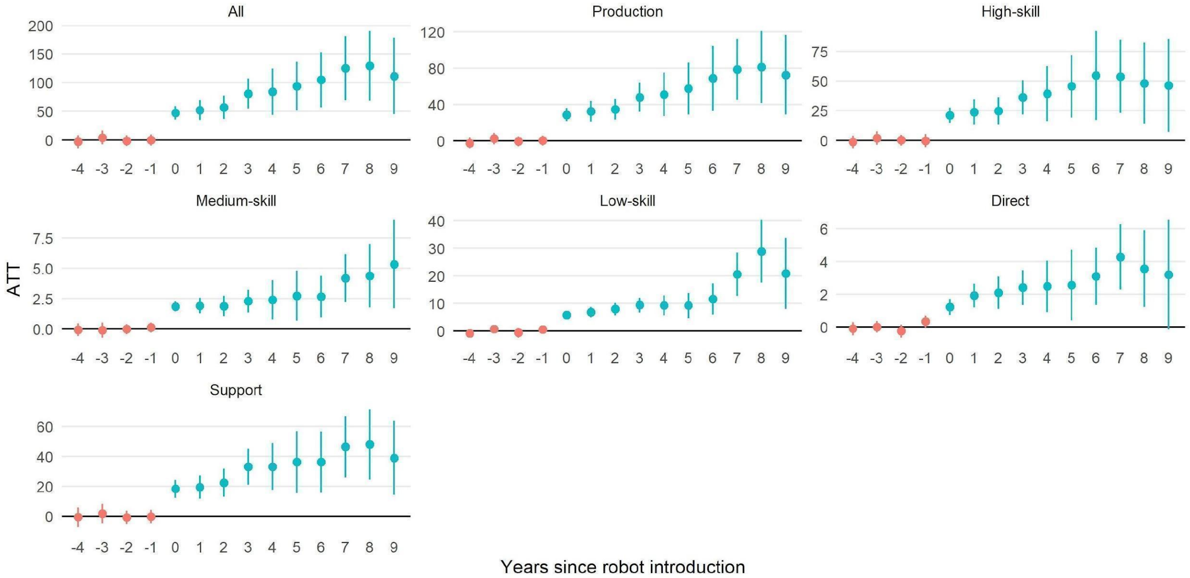
(C) Robot operational stock/1,000 workers vs. share of robotic plants



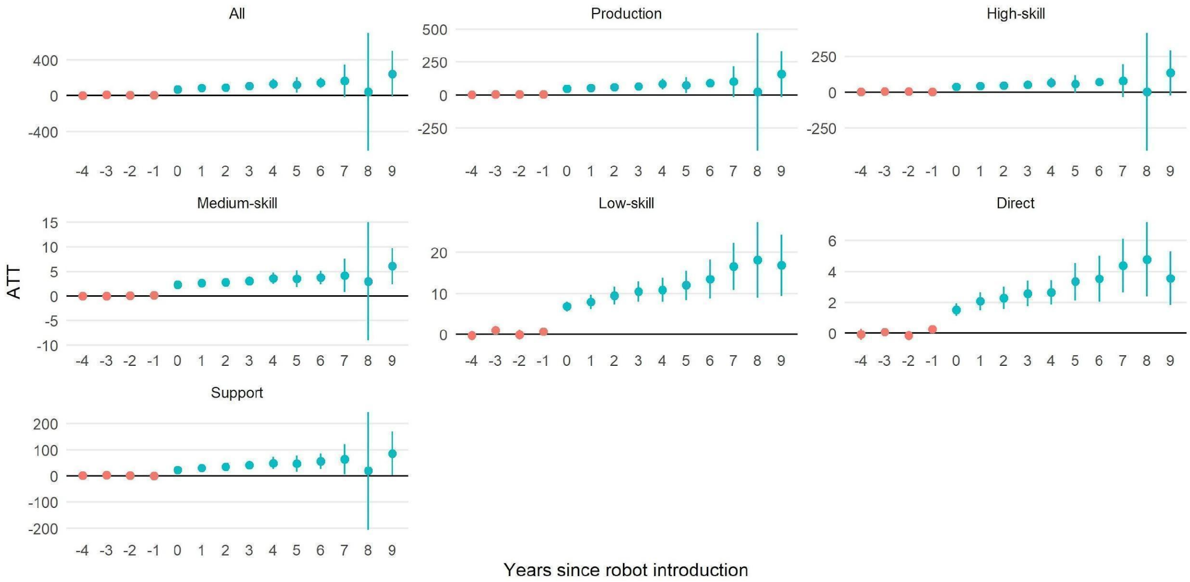
Notes: The horizontal axis represents the yearly and industry average stock of robots and robot installations from the International Federation of Robotics (IFR), while the vertical axis shows the percentage share of robotic plants from BGT. In panels (A) and (B), the size of each bubble reflects average US employment in an industry across years.

Figure A3. Long-term robot adoption effect on number of postings

(A) Adopter vs. Not-yet adopter



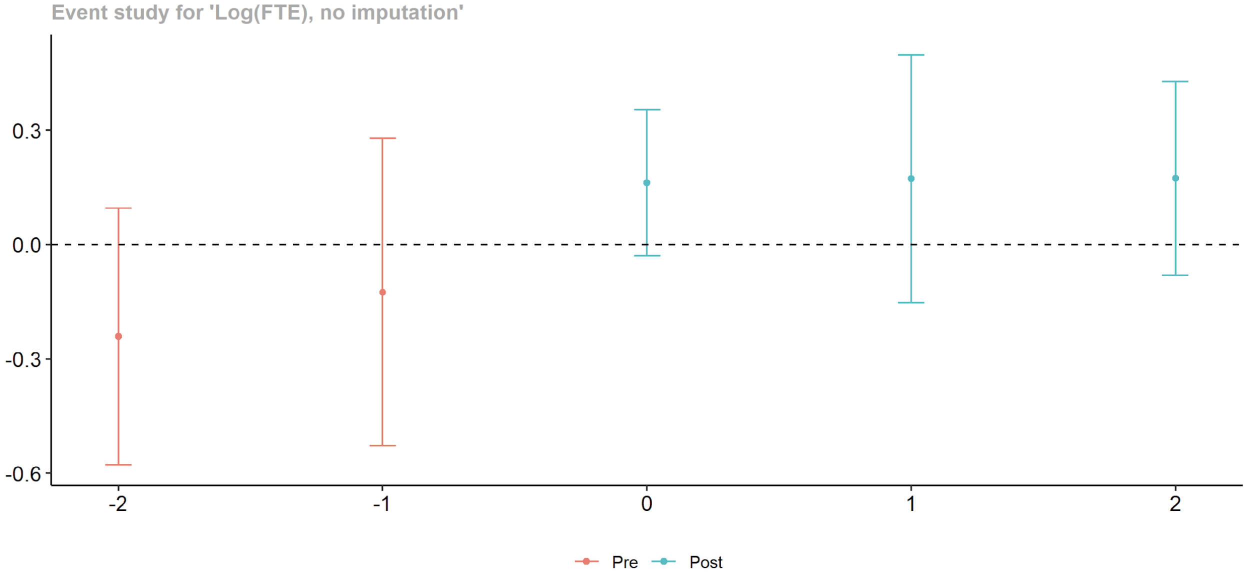
(B) Adopter vs. Never adopter



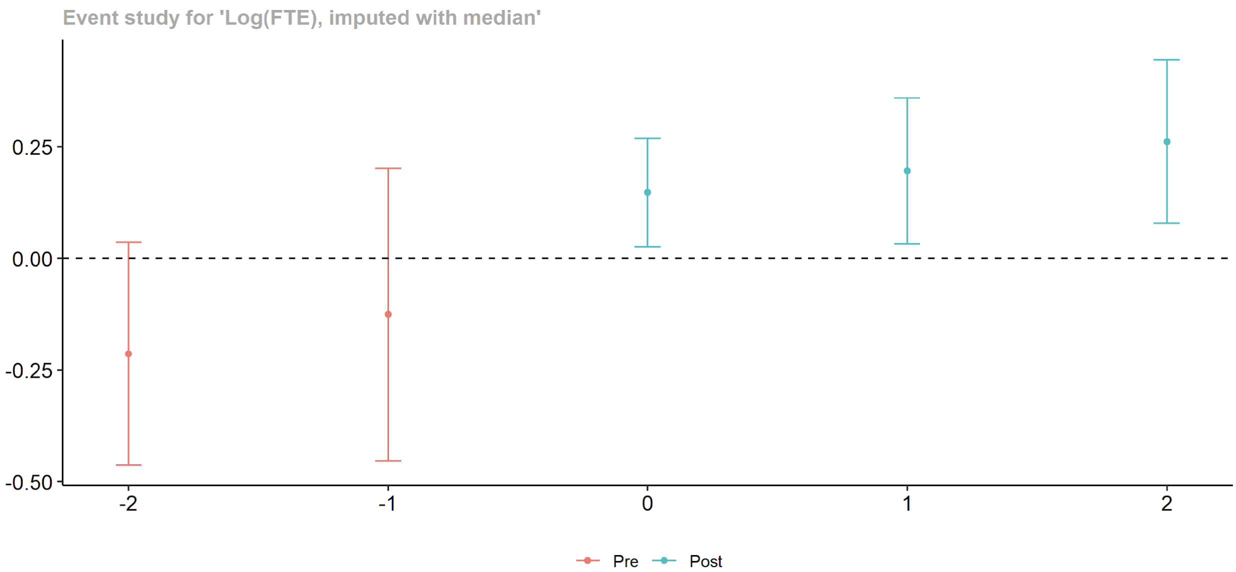
Notes: This figure shows annual ATT on the number of job postings by occupation, extending the postadoption periods to t_9. Panels (a) and (b) are estimated using an unbalanced sample of 1,085 and 28,475 plants, respectively, and include plant size, the commuting zone's log of wage, and 3-digit NAICS code fixed effects as covariates.

Figure A4. Event study of the effect of robot adoption on full-time employment

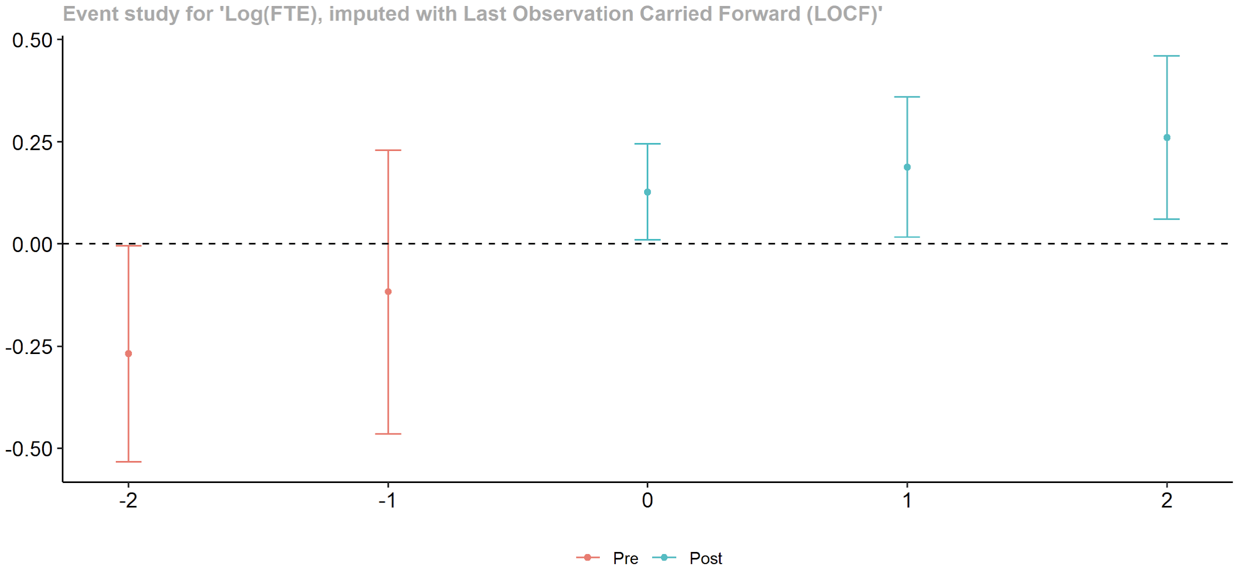
(A) No imputation



(B) Median of full-time employment for each plant



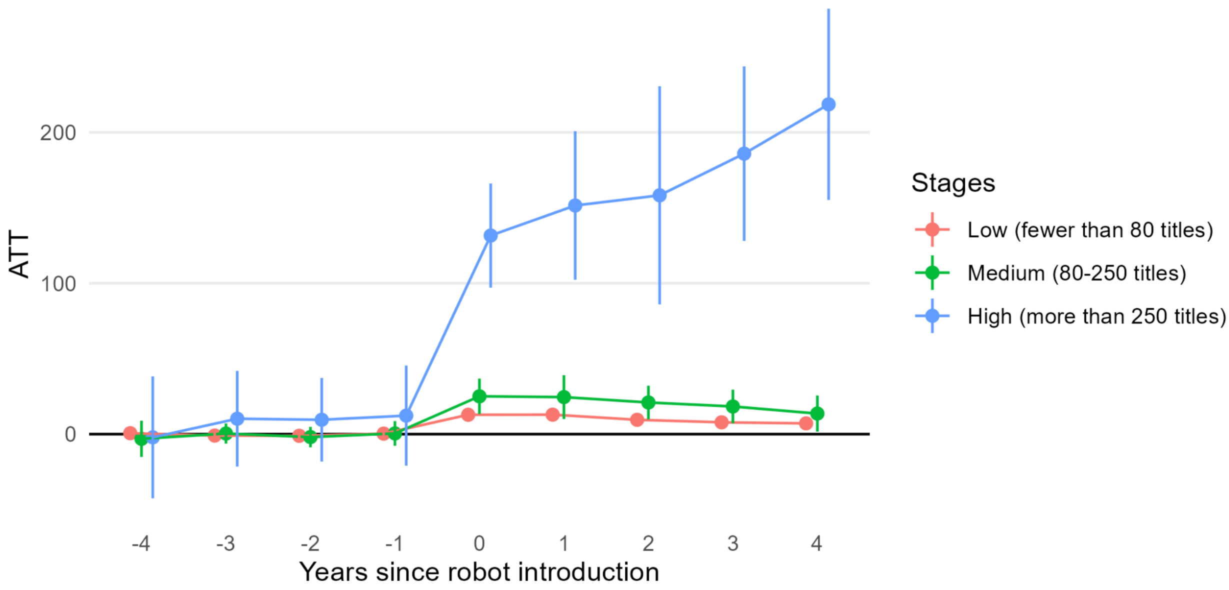
(C) Last observation carried forward



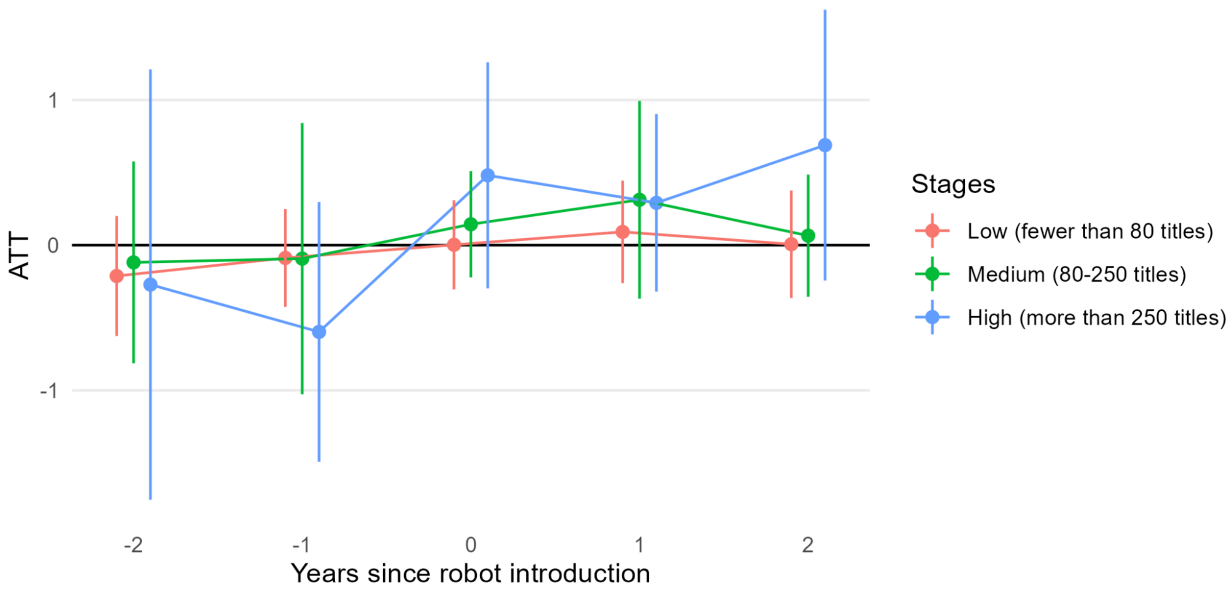
Notes: This figure shows event-time ATT for the log of full-time employment. Table 5 shows overall ATT as aggregations of results with no imputation. Panels B and C show alternative data imputation methods (other alternatives, available upon request, produce similar results). Vertical solid lines represent 95-percent confidence intervals.

Figure A5. Event-study of the effect of robot adoption on job postings and full-time employment by number of unique titles

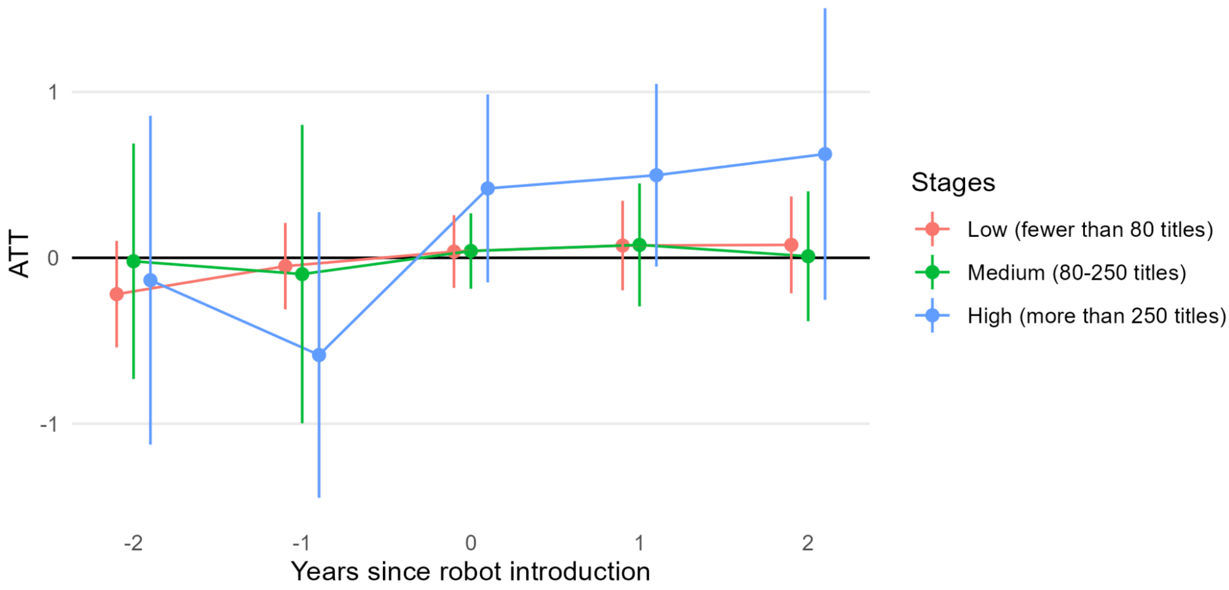
(A) Number of job postings (all occupations)



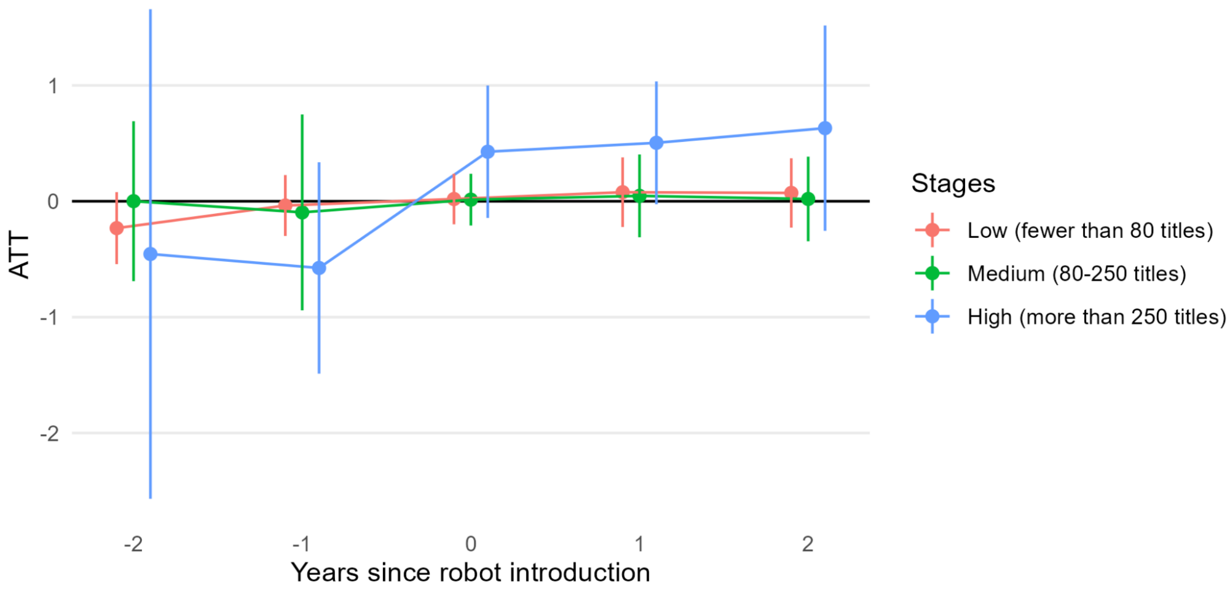
(B) Log of full-time employment (no imputation)



(C) Log of full-time employment (median)



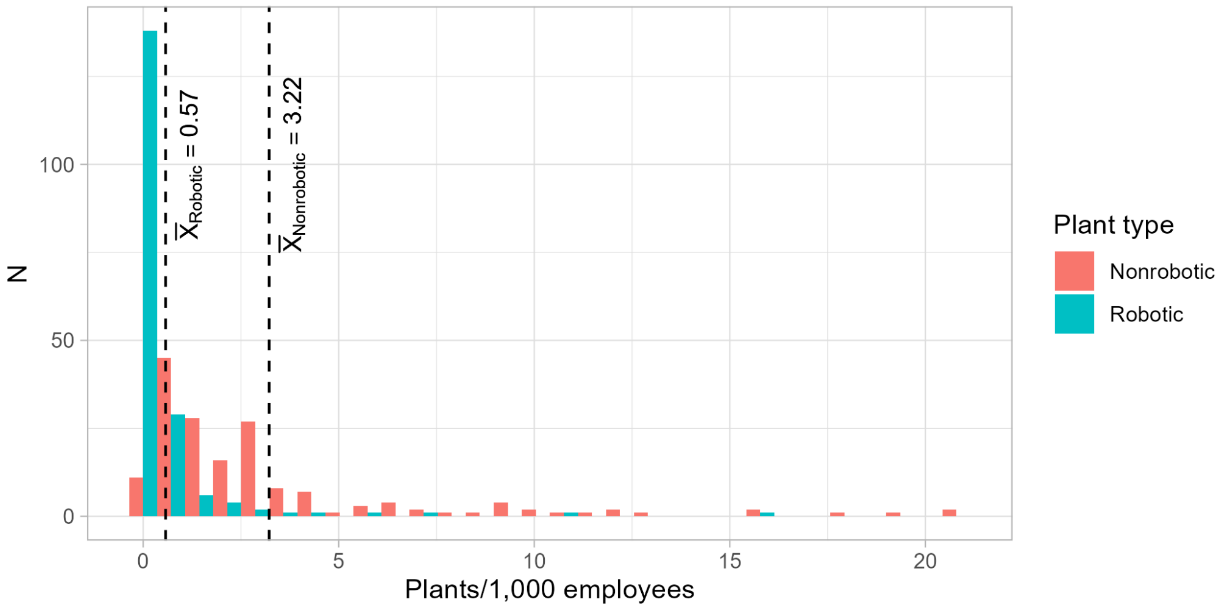
(D) Log of full-time employment (last observation carried forward)



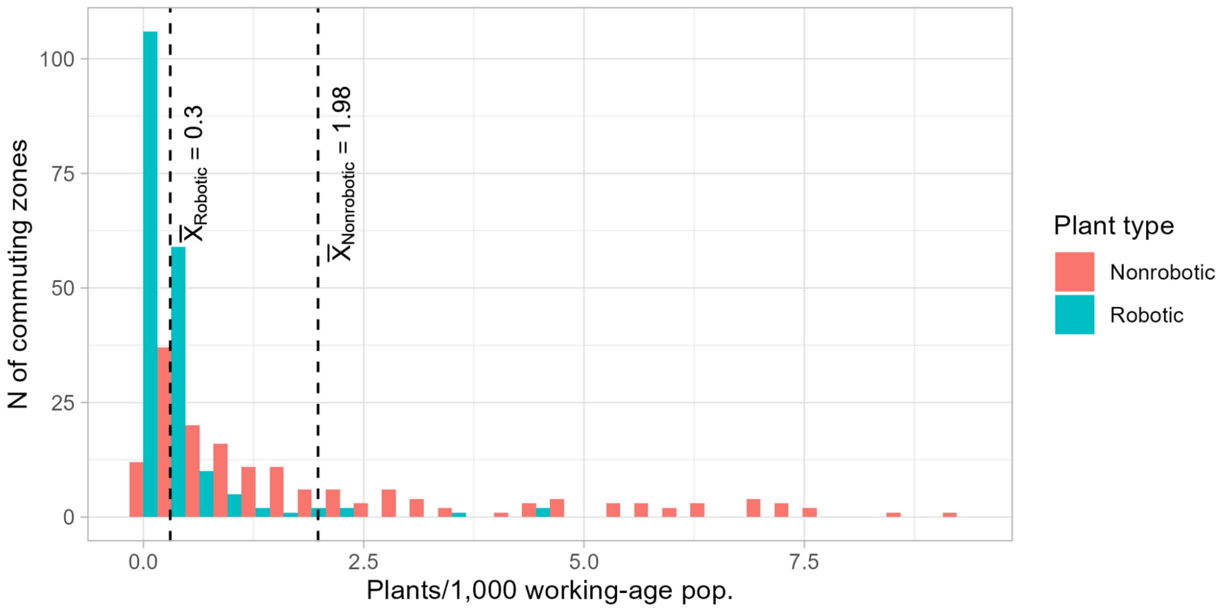
Notes: This figure shows event-time ATT for the number of job postings and the log of full-time employment. Panels C and D show alternative data imputation methods (other alternatives, available upon request, produce similar results). Vertical solid lines represent 95-percent confidence intervals.

Figure A6. Robotic and non-robotic plants density in Commuting Zones, 2019

(A) Number of plants per 1,000 manufacturing employees



(B) Number of plants per 1,000 working-age people



Notes: Figure shows the density of robotic and non-robotic plants per commuting zone in 2019. Plant density is measured as the number of robotic or non-robotic plants per (A) 1,000 manufacturing employees and (B) 1,000 working-age people in a commuting zone. The working age population includes individuals aged 20 to 64. Only commuting zones with at least one robotic plant are selected. To aid visualization, commuting zones in the top 5 percent of the plant density distribution are excluded. Data on employment and working-age population are obtained from the Census bureau.

Appendix B. Data

B.1. Robotic plants

We categorize job postings as either production or support based on SOC codes, with the specific codes outlined in Table A4. We classify a production job as robotic if it includes any of the following terms:'motoman robot programming', 'advanced robotics', 'robotic liquid handling', 'next generation robotics', 'pick and place robots', 'robot framework', 'robot operating system (ROS)', 'robot programming', 'robotic systems', and 'robotics.'

We identify the timing of adoption as the year in which the first production job requiring robotic skills is posted. We perform several robustness checks by evaluating the consequences for changes in the number of job postings if we use alternative criteria for the identification of the timing of introduction of robots. In Table A1 we shift the timing of adoption one year back and alternatively, one year forward. In Table A2 we identify the year of adoption as that in which at least 5 robotic jobs were posted, and alternatively 10 postings. The results in both tables show significant and positive effects of adoption, slightly different from those in Table 3.

We classify a plant as robotic if it has at least ten robotic job postings for production occupations. This threshold ensures a focus on plants with substantial robotic activity, as a substantial number of robotic job postings reflects the integration of robots into their production processes. Tables B1 and B2 show the reliability of this cutoff, as the ATTs stay significant when plants with fewer than 10 robotic job postings are moved from the list of never-adopter plants to the list of robotic plants. As indicated by the preadoption mean, these plants are smaller. The smaller average size contributes to smaller absolute effects, but the magnitudes of ATTs relative to preadoption means are comparable to those in Tables 3 and 5.

A plant may have already introduced robots before recruiting new workers with robotic skills in the external job market, hence generating substitution, complementarity, and productivity effects sooner than what is observable in job posting data. This may materialize into a positive or negative employment effect prior to the adoption year as defined in our approach. The absence of pre-adoption trend in the difference-in-differences analysis, however, suggests that this is not a major issue. A plant may adopt robots yet may not post robotic jobs because trains incumbent workers, transfers them from another plant in the same firm, or uses robot integrator contractors. This results in misclassifying such robotic plants as non-robotic, attenuating the estimated robot effect against our hypotheses.

A plant may introduce robots along with other capital expansion (e.g., in expectation of higher output demand in the future). The expansion may include hiring new workers and investing in new capital, including robots. As robot adoption and capital expansion happen simultaneously, the estimation from an (unconditional) difference-in-differences design combines the effect of the two events. To separate the robot adoption effect, we incorporate firm capital expansion—proxied by real capital expenditures normalized by real total assets from COMPUSTAT. Table A7 shows the ATTs are significantly positive, although slightly smaller. This shows that robot adoption has a separate effect beyond general plant expansion. The capital expansion measure is at the firm level, which may raise a concern that the expansion may not be distributed equally across plants. As a robustness check, we restrict the sample to adopting firms with three or fewer plants to ensure that the expansion happens in robotic plants. We still find a significantly positive effect within this subsample.

We restrict robotic plants to those that continue to post robotic jobs after the year of adoption but allow for gaps of one or two consecutive years, provided they post robotic jobs in at least one of the last two years of the sample period. These requirements account for the possibility that a plant may have low turnover in robotic jobs so may not need to post every year but want to ensure that they did not abandon robots, hence the requirement for the end of the sample period. In Table B3, we perform another robustness check to show that the criterion that a robotic plant is required to post at least one robotic job posting in one of the last two years does not bias our results. This exercise alleviates the concern that our results may be driven by "successful" robot adopters. The results are similar to Table 3. We note, however, that as the difference-in-difference analysis requires that robot adoption is "always on"—that is, once a plant adopts robotic technology it never abandons it—the inclusion of these plants may violate this assumption as the discontinuity in robotic job postings may indicate they abandon this technology.

Tables B1 and B2 examine the effect of robot adoption under two scenarios: When non-robotic plants with 1 to 9 robotic production job postings are reclassified as robotic plants (panel A), and when the sample of robotic plants is restricted to plants that post 1-9 robotic production job postings (panel B). This analysis addresses the concern that plants currently classified as non-robotic, because they post very few robotic job postings, may actually adopt robots that substitute for workers. Panel A of Tables B1 and B2 show that the ATTs are lower than those in Tables 3 and 5 but still significant. The lower ATTs is due to the smaller average plant size, as indicated by the pre-adoption number of job postings. Panel B of both tables show that these plants are unlikely to adopt robots that substitute for workers because they have positive posting and employment growth, although the magnitude is smaller.

Table B1. Robot adoption effect on job postings, evaluating the influence of no-robotic plants with 1-9 robotic production job postings

Occupation	A. Reclassification of non-robotic to robotic plants			B. Restricting to plants with 1-9 production robotic postings		
	Pre-adoption postings	ATT		Pre-adoption postings	ATT	
		Not-yet adopters	Never adopters		Not-yet adopters	Never adopters
All	42.86	52.54***	71.25***	35.74	25.63***	32.41***
		(3.86)	(10.50)		(3.50)	(3.03)
Production	24.16	31.89***	44.52***	20.65	15.01***	19.82***
		(2.36)	(7.15)		(2.35)	(1.94)
High-skill	17.07	24.22***	36.04***	13.75	10.77***	15.22***
		(2.13)	(6.91)		(2.12)	(1.82)
Medium-skill	1.40	1.65***	2.06***	1.30	0.81***	1.06***
		(0.12)	(0.15)		(0.13)	(0.12)
Low-skill	5.69	6.03***	6.42***	5.60	3.44***	3.54***
		(0.40)	(0.43)		(0.50)	(0.38)
Direct	1.27	1.40***	1.49***	1.32	0.67***	0.75***
		(0.14)	(0.13)		(0.15)	(0.12)
Support	18.70	20.65***	26.73***	15.09	10.62***	12.59***
		(1.56)	(3.78)		(1.40)	(1.21)
Plants		4,167	27,247		3,082	26,162
Robotic plants		4,167	4,167		3,082	3,082

Notes: Sample robotic plants include (A) plants that post at least one robotic production job posting and (B) plants that post 1 to 9 robotic production job postings that were previously classified as non-robotic. Covariates include first-year number of job postings, commuting zone's average log of wages, and 3-digit NAICS. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

Table B2. Robot adoption effect on log of employment, evaluating the influence of non-robotic plants with 1-9 robotic production job postings

variable	A. Reclassification of non-robotic to robotic plants	B. Restricting to plants with 1-9 production robotic postings
Log(Full-time employment)	0.100***	0.080***
	(0.024)	(0.025)
Mean Log(Preadoption employment)	5.53	5.51
Observations	28,016	27,780
Plant-cohorts	14,008	13,890
Plants	4,344	4,226
Robotic plants	523	405

Notes: Sample robotic plants include (A) plants that post at least one robotic production job posting and (B) plants that post 1 to 9 robotic production job postings that were previously classified as non-robotic. The comparison group is never adopters. ATTs are estimated with the two-way difference-in-differences estimator (Sant'Anna and Zhao, 2020). Standard errors are shown in parentheses. Covariates include employment in the first year the plant appears in the data, the commuting zone's log of wages in 2007, cohort fixed effects, and 3-digit NAICS code fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Table B3 shows the effect of robot adoption when robotic plants that do not post any robotic job postings in the last two years of the sample period are reclassified from non-robotic job postings into the sample of adopters. This exercise alleviates the concern that our results may be driven by "successful" robot adopters.

Table B3. Robot adoption effect on job postings, incorporating robotic plants with zero robotic job postings in the last two years of the sample period

		ATT	
Occupation	Preadoption mean	Not-yet adopters	Never adopters
All	62.98	67.83***	97.06***
		(13.42)	(18.23)
Production	34.27	41.61***	57.14***
		(9.18)	(10.10)
High-skill	26.61	32.21***	44.51***
		(9.03)	(9.61)
Medium-skill	1.60	2.11***	2.81***
		(0.23)	(0.24)
Low-skill	6.06	7.29***	9.83***
		(0.61)	(0.95)
Direct	1.17	1.88***	2.26***
		(0.23)	(0.21)
Support	28.71	26.22***	39.91***
		(4.60)	(8.05)
Plants		1,450	28,557
Robotic plants		1,450	1,450

Notes: Sample robotic plants include short-term adopters, defined as robotic plants that do not post any robotic job postings in the last two years of the sample period. Covariates include first-year number of job postings, commuting zone's average log of wages, and 3-digit NAICS. Standard errors are clustered by firm. Significance levels: * 10%, ** 5%, *** 1%.

B.2. Analytical sample

From 19,390,104 U.S. job postings in manufacturing (NAICS codes 31-33) between 2010 and 2022 that have a valid firm name, a geolocation, and contain at least two skills, we identify 1,306,254 establishments as unique firm-city-state observations.[17] These establishments include manufacturing plants, maintenance centers, training centers, distribution centers, research centers, sales centers (e.g., dealerships), headquarters, and others. In our study, we focus exclusively on manufacturing plants and maintenance centers—hereinafter referred to as 'plants'—that are configured for the integration of robotics into their manufacturing processes. To identify these plants, we applied a set of exclusion criteria, eliminating any establishment that meets any of the following conditions: a proportion of sales-related job postings exceeding 10 percent; fewer than two postings for high-skill positions; fewer than two postings for either medium-skill or low-skill positions; or an average of fewer than seven job postings annually in years with recorded postings. By applying these restrictions, we identified a sample of 37,959 plants with 9,203,823 postings deemed suitable for our analysis.[18]

Next, we implement a further set of selection criteria on the pool of 37,959 plants to define our analytical sample. First, we remove 3,032 plants that reported at least two consecutive years of zero job postings. Subsequently, we further refine the remaining sample by excluding 92 recruiter plants.[19] Following the initial exclusions, we further narrow down our sample by removing 2,916 plants that have not posted any technical robotic job postings in the last two years of their operation. Next, we exclude 654 adopter plants lacking data on their pre-adoption period. Each step of removal is applied sequentially to the subset of plants remaining after the previous step, ensuring a refined and specific analytical sample.

Firm names from the same employer may vary in how they appear in the BGT dataset. For example, '3M' (a company operating in industry, worker safety, healthcare, and consumer goods) may also appear as '3M Company' in another job posting. To minimize variations and improve the matching outcome, we perform standardization on firm names. This step is crucial for calculating, for example, the total number of plants per firm or job postings per plant, since the basis for aggregating the job postings and plants uses firm names. We perform the steps below, in which employer names are lower-cased and regular expressions are involved to capture a variety of terms.

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[17] Although the BGT dataset includes geolocations, which allow us to identify multiple establishments within a city, we use city-state combination as our definition of establishments. Based on our own investigation, these assigned geolocations are approximations of the actual locations. Moreover, establishments within a city may operate like one single establishment due to their proximity.

[18] The U.S. Census reported 55,871 establishments with at least 100 employees in 2020. The discrepancy with our data is because (1) the Census data include types of establishment other than plants, (2) our criteria is too restrictive and inadvertently remove some plants, and (3) not all establishments post online job advertisements.

[19] Several establishments in the original dataset are not manufacturing plants despite having the manufacturing industry codes (i.e., NAICS 31-33), but instead provide employment services, such as hiring on behalf of other manufacturing establishments and human resource consulting. These establishments may post robotic job postings and thus may introduce an error in our identification of robotic plants. To avoid this, we use several keywords (e.g., 'hr', 'human resourc', 'personnel', 'recruit', 'staff', 'employment') to identify and remove them from our sample.

Internet suffixes (e.g., ’com’, ’org’, ’gov’) are removed.

Non-alphanumeric characters replaced with space or nothing (e.g., ’*’, ’-’, ’#’, ’.’, ”’).

Irrelevant words (e.g., ’and’, ’amp’, ’u.s.’) are removed.

Common words are standardized (e.g., ’manufacturing’ to ’mfg’, ’technology’ to ’tech’, ’laboratories’ to ’lab’).

Firm legal forms (e.g., ’incorporated’, ’company’, or ’corporation’) and their misspellings (e.g., ’inc’, ’comapnies’, ’corporatoin’) are removed.

Extra spaces resulting from the previous steps are removed.

B.3. Matching Process of BGT and OSHA plants

Firm names in BGT and OSHA are matched with fuzzy matching after performing name standardization. We specify a maximum Jaro-Winkler distance threshold of 0.036155203, based on our examination of which value starts to yield a bad matching result. Establishments in both datasets are then matched through their cities and states in which they are located. This process yields 9,162 plants from 3,743 firms.

We further restrict this sample with the following criteria:

Removing outliers defined as plants with annual average employees and average work hours per employee outside the thresholds of [11.00, 7,412.05] for employees and [465.9086, 5,474.6914] for work hours. Values outside these thresholds indicate the 1-percent outliers. The rationale for excluding these extreme values is that they likely represent unusual cases or measurement errors that could distort the analysis, as we observe that a few establishments have an unusual number of employees relative to the reported annual work hours.

Including plants that are available in BGT and OSHA and have no missing commuting zone’s wage and full-time employment data during 2016-2022.

Removing robotic plants that adopted robots before 2017 (since plants that adopted robots in 2016 or earlier do not have pre-adoption data) or with missing pre- and post-adoption postings.

These criteria yield 5,788 plants from 2,563 firms.

Plants that report to OSHA are probably different from those who do not, so they are not likely to be representative in some respects of our analytical sample. However, there is no obvious reason to expect that robot adopters and non-adopters will have different responses to robot introduction than otherwise similar plants in the analytical sample.

B.4. Plant primary NAICS codes

Each job posting is associated with a 3-digit North American Industry Classification System (NAICS) code. A plant, particularly a larger one, may have job postings with various industry codes. We assign the largest frequency of 3-digit job posting-level NAICS code as the primary industry code to each plant. If a plant has two or more NAICS codes with the same largest frequency, we choose the code with the smallest number as the primary industry code. If a plant does not have any identifiable NAICS code, we choose the code that is most frequently assigned to other plants within the same firm as the primary industry code. The remaining unidentified plants are assigned NAICS 33.

Appendix C. Relationship between job postings and employment

We correlate the number of job postings with the log of number of employees in the OSHA dataset during 2016-2022. We have 13,732 observations from 4,434 plants to estimate the posting-employment relationship. Our preferred model (column (5) of Table C1) gives us the following estimates:

$$\Delta \log (Employment)_{it} = 0.0011 \times Postings_{it} - 8.46 \times 10^{-7} \times Postings_{it}^{2} \qquad (1)$$

Our model indicates that one job posting yields a 0.11-percent increase in employment, but the relationship weakens for larger plants, as indicated by the second term in the equation. This relationship is visualized in Figure C1. We use this estimate for converting job postings into the percentage change of employment per plant. Table 3 gives us the range for change in job postings; adopters increase job postings by 98 per year, compared to never adopters, following robot adoption. Plugging this number into the equation, the back-of-the-envelope estimate of the percentage increase in employment is 10.9 percent per year [95% CI: 5.6, 16.5].

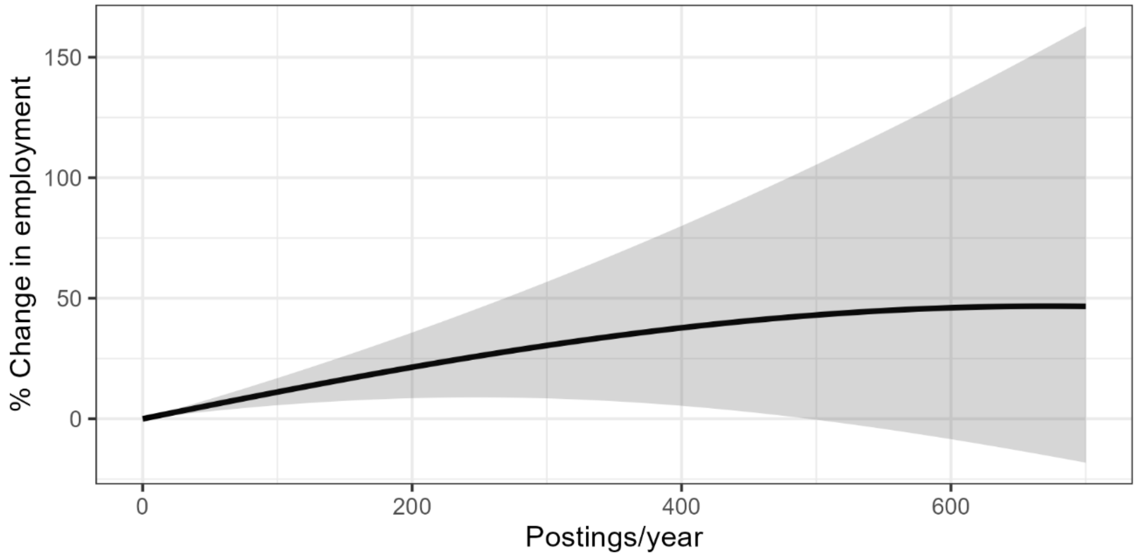
This range is close to the difference-in-difference estimate for employment from Table 5 (15 percent) and within the ballpark of previous studies on the employment effect of robots in other countries that employ difference-in-differences designs at the firm level. Koch et al. (2021) estimates that robot adoption expands employment among Spanish firms by five percent in the adoption year and ten percent by the end of the tenth year. In Finland, Hirvonen et al. (2022) shows that employment gradually increases following robot adoption and reaches 25 percent by the fifth year. Another study among French companies finds a steady 0.4 annual increase in the log of employment during ten postadoption years (Aghion et al., 2020). Dixon et al. (2021) in Canada estimate an average annual increase of 0.05 log point of employment during four years following robot adoption. In contrast, Bessen et al. (2023) find a negligible effect among large Dutch firms, whereas smaller firms contract by about 20 percent.

Table C1. Change in log of employment in relation to job postings, 2016-2022

Dependent variable:	Δ*log(Employment)*				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	0.0107**	0.0030	-	-	-
	(0.0038)	(0.0040)			
Postings	0.0002*	0.0005***	0.0011***	0.0004***	0.0011***
	(7.6 × 10-5)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Postings^2	-	-5.26 × 10-7*	-8.12 × 10-7**	-4.55 × 10-7*	-8.46 × 10-7**
		(2.32 × 10-7)	(2.48 × 10-7)	(2.25 × 10-7)	(2.8 × 10-7)
Fixed effects					
Plant	-	-	Yes	-	Yes
Year	-	-	-	Yes	Yes
Statistics					
Adjusted R^2	0.00056	0.00182	0.01228	0.01022	0.02404
Plant-years	13,732	13,732	13,732	13,732	13,732
Plants	4,434	4,434	4,434	4,434	4,434
Mean (SD) full-time employment	348.536 (442.452)	348.536 (442.452)	348.536 (442.452)	348.536 (442.452)	348.536 (442.452)
Mean (SD) postings	33.887 (64.862)	33.887 (64.862)	33.887 (64.862)	33.887 (64.862)	33.887 (64.862)

Notes: The dependent variable is the change in the log of full-time employment from year *t-1* to *t*. The full model is $\Delta \log\,(Employment)_{it} = 0.011 \times Postings_{it} - 8.46 \times 10^{-7} \times Postings_{it}^2$, where i denotes plants, t denotes years, γ_i is plant fixed effects, and τ_t is year fixed effects. Significance levels: * 10%, ** 5%, *** 1%.

Figure C1. Relationship between postings and change in full-time employment



Notes: This figure visualizes the relationship between postings and the predicted value of percent employment change using estimates from column (5) of Table C1. The area above and below the solid line is the 95-percent confidence bands.

Appendix D. Job postings, hirings, separations, and employment

We perform a simple exercise by correlating the industry average number of job postings per plant with the industry average new hirings and separations per establishment data from the Quarterly Workforce Indicators (QWI). These correlations allow us to derive estimates for annual changes in hiring and separations, and the corresponding net change in employment. The average new hiring and separations per establishment within a specific industry and year are computed by dividing the total number of industry-level new hires and separations by the total number of establishments, as sourced from the Statistics of U.S. Businesses (SUSB). To be comparable to our BGT sample, we restrict our sample to hiring and separations from larger establishments, specifically QWI establishments with more than 250 employees and SUSB establishments with more than 200 employees.

We conduct a regression analysis with these variables against the average number of postings per plant. To eliminate industry-specific variations, we incorporate 3-digit NAICS fixed effects in our analysis. Our model is $Y_{it} = Postings_{it} + \delta_i + \varepsilon_{it}$, where Y_{it} denotes new hires or separations in industry i in time t and δ_i denotes 3-digit NAICS fixed effects. Table D1 shows that one job posting per plant is equivalent to approximately 1.1 annual new hires and 0.89 separations per establishment. We multiply these coefficients with the ATT for each post-adoption period from the event-study analysis to estimate the annual change in new hires and separations, and by subtracting these values, we derive the net employment effect on a robot adopter. Table D2 shows that employment increases by around 6-8 workers annually following robot introduction. This is equivalent to 2.6-3.2 percent of the mean employment per establishment (i.e., 260 workers). This is an economically meaningful increase in net employment as our data indicate that robot adopters in the manufacturing sector are close to two thousand plants. For a sensitivity analysis, the new hiring coefficient has to decline or the separation coefficient has to increase by 0.23 points (corresponding to 20 and 25 percent of new hiring and separation current values, respectively) in order for net employment change to start to turn negative.

Table D1. Hiring, separation, and job postings per establishment

Dependent Variables:	New hiring	Separation
Model:	(1)	(2)
Variables		
Postings	1.123***	0.892***
	(0.217)	(0.239)
Fixed effects		
3-digit NAICS	Yes	Yes
Fit statistics		
Observations	226	226
R^2	0.956	0.969
Within R^2	0.315	0.243

Notes: Table shows estimates for the association between annual job postings and (1) new hiring and (2) separation. Observations are at the industry-year level, weighted by the number of establishments within the corresponding industry and year. Significance levels: * 10%, ** 5%, *** 1%.

Table D2. Net employment effect of robot introduction

Period	Event-time ATT for job postings	New hiring	Separation	Δemployment	% mean employment
(1)	(2)	(3)	(4)	(5) = (3) - (4)	(6)
0	70.35	79.00	62.75	16.25	2.19
1	85.63	96.16	76.38	19.78	2.67
2	93.73	105.26	83.61	21.65	2.92

Notes: Table shows estimates of the annual change in employment three years following robot introduction (column 5) derived from subtracting new hiring with separation. The estimates for new hiring and separation in columns 3 and 4 are calculated by multiplying ATTs in column 2 with the corresponding coefficients for the two variables in Table D1. ATTs are obtained from event study analysis of the unadjusted number of job postings. The mean employment per establishment is 740 workers.