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The Employment Consequences of Robots: Firm-level Evidence

by Jay Dixon

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Abstract

As a new general-purpose technology, robots have the potential to radically transform industries and employment. In contrast to previous studies at the industry level that predicted dramatic employment declines, this study finds that investments in robotics are associated with increases in total firm employment, but decreases in the total number of managers. It also finds that robot investments are associated with an increase in the span of control for managers remaining within the organization. This study provides evidence that robot adoption is not motivated by the desire to reduce labour costs, but is instead related to improving product and service quality. These findings are consistent with the notion that robots reduce variance in production processes, diminishing the need for managers to monitor workers to ensure production quality. Decreases in managerial headcount may also arise from changes in workforce composition. This study finds that investments in robotics are associated with decreases in employment for middle-skilled workers, but increases in employment for low-skilled and high-skilled workers, potentially changing managerial activities required by the firm. With respect to organizational change, this study shows that robots predict both the centralization and the decentralization of decision-making authority, but decision rights in either case are reassigned away from the managerial level of the hierarchy. This contrasts with previous studies on information technology that have generally found decentralizing effects on decision-making authority within organizations. Overall, the results of this study suggest that the impact of robots on employment and organizational practices is more nuanced than previous studies have shown.

Executive summary

Fears of artificially intelligent machines have lingered in the human imagination for thousands of years. Greek myths like those of Talus or Pandora told of artificial beings created by the gods wreaking chaos and destruction when they were sent to live among mortals on earth. Recent breakthroughs in artificial intelligence have expanded the production potential of machines. At the same time, this has focused attention on the potential for robots to wreak havoc on labour markets. Machines imbued with humanlike judgment and flexibility threaten to displace human workers from many of the tasks they currently perform in the economy.

However, it is possible that the impact of robots will not be very different from previous waves of automation that created enough tasks for humans to compensate for the workers that new machines displaced. Although switching workers to other tasks was often fraught and not all of them could benefit, past automation generated a roughly constant share of rapidly increasing output.

Whether robotic automation will lead to a permanent decline in the role of labour—or play out like its non-robotic predecessors—depends on how firms reorganize production after adopting robots. This study uses newly compiled firm-level administrative data from 1996 to 2017 to examine how Canadian firms that adopt robotic technology change their production processes and what happens to their workers when they do.

The study finds that robot adoption in Canada is not motivated by the desire to reduce labour costs, but instead by the desire to improve product and service quality. These improvements are associated with higher productivity. In contrast to previous studies at the industry level that predicted dramatic employment declines, this paper finds that investments in robotics are associated with increases in total employment in adopting firms. However, it also finds that these firms organize production around fewer managers, with each supervising more workers. These findings are consistent with the notion that robots reduce variance in production processes, reducing the need for managers to monitor workers to ensure production quality.

Decreases in managerial headcount may also arise because of changing managerial roles associated with changes in workforce composition. Investments in robotics are associated with decreasing middle-skilled employment alongside increases in the low-skilled and high-skilled workforce. Robots predict both the centralization (toward owners) and the decentralization (toward production workers) of decision-making authority, but decision rights in either case are reassigned away from the managerial level of the hierarchy. This contrasts with prior studies on information technology that have generally found decentralizing effects on decision-making authority within organizations.

Overall, the results of this study suggest that the impact of robot adoption on employment has not been apocalyptic for labour overall. However, changes in organizational practices associated with robot adoption will require a different mix of skills than many parts of the economy currently employ.

1 Introduction

This study examines how employment and organizations have changed in response to robot adoption. As robotics and artificial intelligence (AI) become increasingly used by firms as the next engine of innovation and productivity growth, their effects on labour, firm practices and productivity have become a subject of growing importance. According to extensive anecdotal evidence in the media, robots reduce overall employment and exacerbate income inequality, as rapid advancements in vision, speech, natural language processing and prediction capabilities have achieved parity with or exceed human capabilities across a range of tasks. These technological advancements have shifted the comparative advantage from humans to machines for a growing list of occupations (Brynjolfsson and Mitchell 2017; Felten, Raj and Seamans 2019; Frey and Osborne 2017), potentially leaving human labour with substantially fewer activities that can add value (Brynjolfsson and McAfee 2014; Ford 2015). This technology-based labour substitution may displace a significant proportion of the overall workforce, despite generating productivity gains (Acemoglu and Restrepo 2020; Autor and Salomons 2017; Ford 2015). If true, robot adoption is likely to cause significant changes in how firms organize production activities and manage their human capital (Bidwell 2013; Puranam, Alexy and Reitzig 2014; Zammuto, Griffith, Majchrzak and, Dougherty 2007).

Recent empirical studies that used data at the industry or geographic region levels found that robots were associated with drastic declines in overall employment (Acemoglu and Restrepo 2020; Dinlersoz and Wolf 2018; Graetz and Michaels 2018; Mann and Püttmann 2017). However, it has also been argued that robots are similar to past generations of general-purpose technologies (GPTs) that ultimately increased labour demand. In this competing view, even as labour is displaced, the new jobs created will more than compensate for the jobs lost (Autor and Salomons 2017). Preliminary evidence based on firm-level data supports this view and shows that robot-adopting firms become more productive and ultimately increase total employment (Koch, Manuylov and Smolka 2019). These new jobs are likely to complement robots, suggesting a compositional change in labour within firms. As robots offer new capabilities that differ from prior information technology (IT) investments (Brynjolfsson and Mitchell 2017), changes in human capital and the organization of production activities may also differ from those caused by IT and reflect those that are complementary to robots.

This study uses comprehensive data on businesses in the Canadian economy from 2000 to 2015 to show that robots are associated with increases in total employment, but the effect is not uniform across workers. Investments in robotics predict substantial declines in managerial employment, despite increases in non-managerial employment. This finding contrasts with prior IT that could not easily replace managerial and professional work (Autor, Katz and Kearney 2006; Autor, Levy and Murnane 2003; David and Dorn 2013; Dustmann, Ludsteck and Schönberg 2009; Murnane, Levy and Autor 1999). There is evidence that robots may affect managerial employment in two ways. First, robots may directly reduce the need to monitor and supervise workers, as they can substantially diminish human errors in the production process. Because worker supervision accounts for a substantial portion of work done by managers (Hales 1986), demand for managerial labour to supervise workers may decline with robot adoption. Second, robots may also indirectly affect managerial employment by changing the types of workers needed. Although the total number of non-managerial employees increases with robot adoption, this study also found that robot investments predict decreases in the employment of middle-skilled workers and increases in the employment of low-skilled and high-skilled labour. These changes in labour composition may lead to a decrease in managers (Malone 2003; Mintzberg 2013). Consistent with the findings of an increase in non-managerial employees and a decrease in the number of managers, this study found that robot investments predicted an increase in the span of control for managers remaining within the organization.

This study examined the motivations for robot adoption by firms, and the findings indicate that robot investment is not associated with the strategic importance of reducing labour costs, but is instead associated with an increase in the strategic importance of improving product and service quality. With regard to the allocation of decision-making authority within organizations, this study found that robot investments predicted both the centralization and the decentralization of decision-making authority away from the managerial level of the hierarchy. This suggests that, not only has managerial headcount decreased, but their decision-making authority has also diminished. This is different from earlier studies that found that IT generally led to the decentralization of decision-making rights (Acemoglu et al. 2007; Bresnahan, Brynjolfsson and Hitt 2002). Overall, the results show that changes in employment are related to complementary changes in organizational practices that are critical to the effective use of robots.

This study provides the most comprehensive evidence possible at the level of individual businesses on the employment and organizational effects of robot investments. The wide range of outcomes examined—employment, labour composition, span of control, strategic priorities and allocation of decision-making rights—suggests that robots have a substantive effect on both employment and the organization of production in different ways than previous technologies. This analysis also provides a deeper data-driven examination of how robots can change employment and organizational practices that are difficult to capture using country- and industry-level data (Raj and Seamans 2018). More broadly, the results of this study suggest that looking at individual organizations in detail can provide useful insights to the important debate about the consequences of robots for labour and organizations.

2 Theoretical considerations

The adoption of GPTs is often associated with substantial and widespread productivity gains across different sectors of the economy (Bresnahan and Trajtenberg 1995). To maximize the value of GPTs, firms must substantially reorganize their work activities and change the nature of work and human capital requirements (Autor, Levy and Murnane 2003; Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson, Rock and Syverson 2018). As a recent and rapidly proliferating GPT (Brynjolfsson, Rock and Syverson 2018; Cockburn, Henderson and Stern 2018), robots have the potential to transform employment, firm practices and the economy (Agrawal, Gans and Goldfarb 2018; McAfee and Brynjolfsson 2017).

2.1 Robots and total employment

The effect of robots on employment is still undetermined. Research examining the effect of robots on labour is still nascent, with only a few studies examining the substitutability of robots on work (Acemoglu and Restrepo 2020; Arntz, Gregory and Zierahn 2016; Frey and Osborne 2017; Mann and Püttmann 2017; Manyika et al. 2017). However, most of these preliminary studies predict dire consequences resulting from the labour displacement attributable to robot adoption. For example, Frey and Osborne (2017) found that up to 47% of all jobs in the United States could be displaced. Using a task-based approach that divided each occupation into a set of concrete tasks, Organisation for Economic Co-operation and Development researchers found that 70% of tasks performed by labour could be automated (Arntz, Gregory and Zierahn 2016). Other studies that used the task-based approach found that over 50% of work tasks were vulnerable to automation (Manyika et al. 2017), leading to both labour displacement and wage reductions (Bessen et al. 2019). Using a measure of robot penetration at the industry level in the United States, Acemoglu and Restrepo (2020) found that one robot could replace roughly six people. Graetz and Michaels (2018) used similar data on robot adoption for 17 countries and also found robot adoption to be associated with a reduction in work hours for low-skilled labour.

The findings of these initial studies are in stark contrast with earlier generations of technologies that have been found to increase employment in conjunction with productivity, ultimately leading to labour's share of productivity remaining constant. Instead of reducing employment, robots may positively affect employment through (1) productivity increases from labour substitution inducing demand for other goods and services that require non-automated tasks; (2) capital deepening that increases the effectiveness of robots, which can increase productivity without further reducing labour; and (3) the creation of new tasks or increased demand for existing tasks that are complementary to those of robots (Acemoglu and Restrepo 2018; Brynjolfsson, Rock and Syverson 2018). Initial results from surveys of Spanish manufacturing firms suggest that organizations that adopt robots experience both productivity and employment gains (Koch, Manuylov and Smolka 2019).

These differing results are attributable in part to difficulties in observing these countervailing effects in an entire economy using data at the industry and geographic region levels. Studies at these levels of analysis cannot clearly examine how firms use robotics to substitute or complement labour. As prior literature examining the link between IT and productivity has shown, analysis at more aggregated levels can often lead to markedly different conclusions from empirical studies conducted at the firm level (Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson and Hitt 1996). These differences can arise from the substantial heterogeneity in productivity growth across firms that cannot be clearly observed at the industry level or other aggregated levels of analysis (Syverson 2004). For example, robot-adopting firms may experience productivity and employment gains while non-adopting firms in the same industry experience employment and productivity losses. If this is true, even if robots are observed to cause employment losses at the industry level, it remains unclear whether robots displace workers within robot-adopting firms or whether workers are instead displaced in non-adopting firms because of a decrease in competitiveness. Without a clear understanding of these underlying mechanisms, it is particularly challenging to make meaningful inferences, with similar empirical issues hampering early attempts to understand the effects of IT investment on organizations. Ultimately, it was critical to obtain more precise measurement of both IT and organizational capabilities at the firm level to resolve the IT–productivity paradox discovered by earlier studies and uncover the factors behind the heterogeneous effects of IT on firm outcomes (Brynjolfsson, Hitt and Yang 2002). This study uses a firm-level measure of robot investments for the population of firms in Canada to empirically investigate the competing hypotheses of whether robot-adopting firms increase or decrease employment in firms.

H1a: Robot investments are associated with increases in total employment.

H1b: Robot investments are associated with decreases in total employment.

2.2 Robots and non-managerial employment

Regardless of the effect on total employment, workforce composition is likely to change with robot adoption as demand for different skills changes within the firm. This is similar to what occurred in prior generations of skill-biased technological change. For example, the rise of IT in the late 1990s led to a reduction in the demand for low-skill and middle-skill occupations as routine tasks became automated, and a corresponding increase in demand for non-routine and cognitively challenging tasks, including managing employees (Autor, Katz and Kearney 2006; Autor, Levy and Murnane 2003; Card and DiNardo 2002; Murnane, Levy and Autor 1999). Similar to these studies, low-skilled workers were defined in this study as those working in occupations requiring a high school degree or less, middle-skilled workers were defined as those working in occupations requiring vocational or trades accreditation or an associate degree, and high-skilled workers were defined as those working in occupations requiring at least an undergraduate university degree. Although it has been argued that non-routine and cognitively challenging tasks are difficult to automate

(Autor, Levy and Murnane 2003; Murnane, Levy and Autor 1999), the increasing sophistication of robots is likely to automate tasks that were previously unaffected by automation.

With advances in vision, speech and prediction capabilities, robotics has advanced beyond automating simple routine tasks, and robots have now become capable of performing more cognitively complex work, as well as tasks involving specific types of manual dexterity. Middle-skilled workers are more likely to perform these tasks that robots are becoming more able to automate. For example, in the health care and pharmaceutical industries, robots have been used to handle and prepare materials, follow complex protocols to prepare and analyze samples, and help coordinate patient care without human intervention (Gombolay et al. 2018). Firms with significant warehousing operations have also experienced similar effects. Robots have automated a large range of warehousing logistics activities by effectively transporting objects between locations without human intervention. By relieving humans of lifting and handling awkward, heavy objects during inventory management, robots not only avoid injuries but also provide consistency in product quality and decrease overall delivery time. In manufacturing, industrial robots can substantially reduce variance in product quality. Machine vision enables robots in the automotive industry to consistently install and weld parts onto car bodies with a high degree of precision, minimizing errors in the production process. This can involve difficult manual manipulations such as 360-degree multi-arm rotations with many repetitions. Robots can be programmed to perform these tasks precisely over a long period of time. As a result, robots can substantially reduce both unintended human errors, such as those arising from fatigue, and deliberate actions, such as gaming production quotas, that have previously impeded productivity and effective management (Helper and Henderson 2014).

These illustrative examples suggest that robots can automate certain complex tasks that were primarily the responsibility of middle-skilled workers, including technicians, machinists and operations personnel from a variety of industries that are responsible for following complex protocols to ensure production quality. These tasks may also involve certain types of manual dexterity that require significant learning over time for humans. With robots, many of these tasks can be automated using algorithms, eliminating human errors and the need to provide training for these skills. By reducing production quality variance, robots can decrease the demand for middle-skilled work, as these tasks are vulnerable to robot-based automation.

H2: Robot investments are associated with decreases in middle-skilled employment.

However, investments in robotics may also create demand for human labour and tasks that complement robots. While demand for middle-skilled work may decrease through direct substitution, demand for complementary work—either lower or higher skilled—may increase with robot adoption. For firms that redesign their production processes to leverage the capabilities that robots can offer, productivity may increase, ultimately leading to increases in employment for specific types of workers. Despite recent technological advances, robots are often unable to fully automate most production processes. For many of these so-called residual tasks, human labour remains a more efficient and cost-effective solution (Autor, Levy and Murnane 2003; Brynjolfsson and Mitchell 2017). For example, Elon Musk famously scaled back investments in automation in the Tesla factory and reintroduced human workers after too much automation slowed the production of the Model 3 electric vehicle and delayed its market launch (Hawkins 2018). To use robots effectively, human capital must also be reorganized and reassigned to assist with production. For example, Amazon significantly redesigned work in its warehouses to use its Kiva Robotic systems effectively. As part of this redesign, robots are used to travel between locations within the warehouse, but human workers pick and pack the products delivered by the robots. In this case, instead of using middle-skilled workers to manage inventory by walking from shelf to shelf to examine and handle products, robots and algorithms can automate this process and bring inventory to human workers directly. These human workers then pick up the items and place them into shipping boxes. Researchers have also systematically matched occupations to what machine learning can do and found that many of the manual skills performed by low-skilled labour cannot be replaced easily with technology (Brynjolfsson and Mitchell 2017; Felten, Raj and Seamans 2019). While machine learning is not identical to robot technology, robotics relies heavily on machine learning to make inferences, which can be a useful indicator of the potential impact of robots on work.

Current evidence suggests that, although robots can increase manual dexterity for certain tasks, they cannot yet effectively perform many manual tasks that humans can do easily. As a result, productivity increases arising from robot investments will lead to increases in demand for low-skilled workers doing these residual tasks.

H3: Robot investments are associated with increases in low-skilled employment.

Demand for high-skilled workers may also increase with robot adoption. As illustrated in the example of how Amazon reorganized warehouse work activities after robot adoption, the majority of productivity gains from technology adoption come from the complementary redesign of work (Bresnahan, Brynjolfsson and Hitt 2002; Hammer 1990). Implementing the necessary process improvements and work reorganization requires highly skilled professionals (Bresnahan, Brynjolfsson and Hitt 2002; Hammer 1990; Helper and Henderson 2014; Huselid and Becker 1997; Ichniowski, Shaw and Prennushi 1997), some of whom are needed to program, repair, customize and work with robots (Acemoglu and Restrepo 2020; Autor and Salomons 2018; Brynjolfsson and Mitchell 2017).

However, demand for high-skilled workers may also increase for those that do not work with robots directly, as automating certain routine tasks can free up resources to engage in more cognitively complex tasks. For example, when hospitals adopt robots to lift patients out of beds, nurses are not only relieved of the physical strain of tasks that are more likely to cause injuries, but are also given more time to interact with patients and participate in clinical treatment (Gombolay et al. 2018). Similarly, by algorithmically providing pills and other medications to patients directly (Bepko, Moore and Coleman 2009), nurses can spend more time ensuring compliance and making other clinical decisions. In the manufacturing sector, where a majority of the routine production process is done by robots and low-skilled labour, time and resources can be freed up for high-skilled professionals to design and market new products and optimize production processes (Felten, Raj and Seamans 2019). Programmable robots can also increase a firm's flexibility to serve different types of orders and provide a greater range of products. This can further increase the demand for high-skilled workers who can design a wider variety of products.

Consistent with these findings, Autor and Dorn (2009) found that investments in computer technologies over the last several decades contributed to the widespread increase in high-skilled jobs involving creative, problem-solving and coordination tasks. Similarly, Felten, Raj and Seamans (2019) found that investments in AI were correlated with the increased employment of high-skilled workers such as software engineers. Therefore, the employment of high-skilled workers is also expected to increase after robot adoption.

H4: Robot investments are associated with increases in high-skilled employment.

2.3 Robots and managerial employment

Managerial employment may also change significantly with robot adoption. When production is automated using robotics, human errors are substantially reduced and variance in production quality decreases (Verl 2019). Unlike humans, robots can precisely perform the same complex process repeatedly for long periods of time without experiencing fatigue, resulting in both productivity increases and fewer errors in the production process. Agency problems arising from information asymmetries also do not exist with robots, as they do not operate in their own self-interest the way humans might in work settings (Eisenhardt 1989; Hong, Kueng and Yang 2019;

Jensen and Meckling 1976). Because of the substantial cost of employee monitoring for firms (Dickens et al. 1989, 1990) and considerable time spent by managers monitoring employee activities (Hales 1986, 1999), using robots in the production process can substantially reduce the need to monitor work effort and quality closely. Through both a reduction in production process variance and a lack of agency costs associated with managing robots, the level of monitoring required to ensure production quality is likely to decline. Because monitoring and control constitute a significant portion of managerial activities (Kolbjørnsrud, Amico and Thomas 2016), the demand for managerial labour is likely to decrease after robot adoption.

While robots can reduce demand for managers by decreasing the need to monitor employees during the production process, they may also affect managerial work by changing the composition of non-managerial employees within the organization. If robot adoption is associated with a decline in middle-skilled workers and an increase in high-skilled and low-skilled workers, managerial activities may change for the newly transformed workforce. Managing low-skilled workers can be very different from managing other types of employees, as low-skilled work is typically more standardized and—consequently—easier to monitor and evaluate than higher-skilled work (Mintzberg 1980; Perrow 1967). Furthermore, an individual manager can potentially supervise many more employees if digital tools automate aspects of the monitoring process for standardized work. For example, technology can be used to organize and report the output of simple routine tasks and even make predictions about work outcomes (Aral, Brynjolfsson and Wu 2012), especially for standardized work where inputs and outputs can be specified and clearly measured (Brynjolfsson and Mitchell 2017). In the case of Amazon, the productivity of warehouse workers is tracked in real time and an automated system generates recommendations for employee warnings and terminations when productivity targets are not met. Having an objective measure of productivity recorded using automation technology also reduces disruptive conflicts between managers and subordinates, as objective productivity measures are more difficult to dispute (Scully 2000; Wu 2013). As the proportion of low-skilled workers in the organization's workforce increases, fewer managers may be needed within the organization.

In addition to differences in managing low-skilled work, managing high-skilled professionals is also likely to differ from managing middle-skilled workers. High-skilled workers often engage in more cognitively challenging tasks that provide higher added value, such as product design and production optimization. Managing these types of workers is likely to differ substantially from managing workers doing routine manual tasks (MacDuffie 1997; Parker and Slaughter 1988). Supervising low-skilled and middle-skilled workers primarily involves ensuring employees arrive on time, verifying compliance with rules and regulations, monitoring employees' work procedures and output, issuing commands, and training employees to do their job properly (Helper and Henderson 2014; Taylor 1911). In comparison, employees who do more cognitively complex work are often experts themselves in dealing with problems outside routine operations and can resolve production problems better than their managers (Helper, MacDuffie and Sabel 2000; Kenny and Florida 1993). These employees are often empowered to make more decisions because they are more capable than their managers of solving relevant problems (Huselid and Becker 1997; Ichniowski, Shaw and Prennushi 1997). As a result, managing these employees may involve less direct issuing of commands and more advising and empowerment of employees to solve problems (Malone 2003; Mintzberg 1973, 2013).

While it is expected that the span of control for managing low-skilled workers will increase, this expected change is ambiguous when the subordinates in question are high-skilled workers. If workers require more advising and coaching from managers, managerial span of control may decrease (Malone 2003, 2004). It has also been argued that high-skilled workers pose unique challenges to the efficiency of organizational hierarchies because of their greater need for communication and conflict resolution, which can be mitigated by decreasing span of control (Bell 1967; Meyer 1968). However, the effective use of high-skilled labour often leads to granting them greater autonomy (Bresnahan, Brynjolfsson and Hitt 2002), potentially increasing the span of control (Simon 1946). Previous literature examining the relationship between skill composition changes and span of control in the presence of technology adoption has been limited, but the evidence that is available generally finds net positive effects on span of control (Scott, O'Shaughnessy and Cappelli 1994). If decreases in the demand for managerial labour arising from reduced monitoring requirements and skill composition changes dominate potential increases because of productivity gains, demand for managerial labour may ultimately decline. Based on these arguments, it is expected that managerial employment will decrease with robot adoption.

H5: Robot investments are associated with decreases in managerial employment.

3 Data and measures

3.1 Data

To measure robot investment at the firm level, this study uses data provided by the Canada Border Services Agency (CBSA) that capture the purchases of robots imported by Canadian firms from 1996 to 2017. The global production of robotics hardware is highly concentrated in relatively few countries, such as Japan, Germany, the United States and—increasingly—China. In comparison, Canada does not produce a meaningful quantity of robotics hardware domestically. Therefore it must import robots from foreign producers, which makes it possible to use data on import transactions to measure robot adoption by firms. For all import transactions, the CBSA classifies goods according to Harmonized System (HS) codes, and it classifies industrial robots separately from other types of technology, machinery and equipment. In addition to the HS code, the name of the exporting firm, product country of origin, name and address of the importing firm, business number of the importing firm (a unique government-issued identifier for Canadian businesses), and value of the transaction are recorded. See Dixon (2020) for details on the construction of these data.

Because this study uses import data, the definition of "robot" is ultimately based on what type of import transactions are being classified as robots. As a starting point, the International Federation of Robotics (IFR) defines industrial robots as having the characteristics of being (1) automatically controlled, (2) reprogrammable, (3) a multipurpose manipulator in three or more axes, and (4) used in industrial automation applications. The IFR provides a number of examples of robots and their primary functions in its published material and on its website. This material includes activities such as assembly, welding, painting, packaging, picking and placing, and handling materials for metal casting. In principle, firms that are members of an IFR-affiliated industry association are likely to use a definition of robot that is consistent with the IFR.

To examine the measure of robotics investment in greater detail, searches were manually conducted in the public domain for transactions accounting for 95.0% of the total value of robot purchases in the data. Members of IFR-affiliated industry associations (e.g., Robotics Industry Association, Japan Robot Association) accounted for 58.4% of the total value of imports in the data. Firms that were not robotics association members but that advertised selling the same type of robots accounted for another 13.3% of the import value. Most often, these firms were specialized in installing and integrating robots that were actually produced by association members. An additional 2.0% of the total transaction value involved exporting firms that were not affiliated with a robotics industry association but manufactured robots for scientific laboratories. According to the data, these robots were imported primarily by firms in the health care industry and were used to automate a variety of repetitive tasks in biology and chemistry research, such as pipetting.

An additional 19.0% of the total value was attributable to importing firms in robot-intensive industries—primarily the automotive industry, but also machine tools and plastics manufacturing.

Some firms in these industries are members of robotics industry associations, but the data in this study have more comprehensive coverage of firms that invest in robots. Because of the well-documented prevalence of robot use in these industries and from examining the types of robots used by the importing firms in these transactions, it was possible to infer that these transactions reflected investments in robotics similar to those involving robotics association members. For the remaining 2.3% of the import value, firm websites confirmed that robots were being used in a variety of activities, including performing repairs and handling materials in hazardous environments (e.g., pipelines and nuclear power plants), and were also being used in construction and demolition.

The robot investment data used in this study were merged with two datasets maintained by Statistics Canada that contain measures of firm characteristics: (1) the National Accounts Longitudinal Microdata File (NALMF), a panel dataset that contains measures of aggregate firm-level employment and economic inputs derived from taxfiling data from 2000 to 2015, and (2) the Workplace and Employee Survey (WES), which was developed and administered by the former Business and Labour Market Analysis Division and Labour Statistics Division at Statistics Canada. The WES consists of both an employer component, which contains comprehensive information on employment and management practices at the organizational level, and a linked employee component, which measures individual-level job characteristics and activities. The employer survey sample is a random stratified sample in a panel structure. It is representative of the population of business establishments in the Canadian economy in each year. For the employee sample, individual employees were randomly chosen within each organization and surveyed for two consecutive years, with Statistics Canada resampling individuals from each organization after each two-year cycle was completed. The WES employer survey data used in this study are for 2001 to 2006, while the WES employee survey data used represent employees followed from 2001 to 2002 and 2003 to 2004.

Several adjustments to both the NALMF and WES samples were made to more precisely capture firms of sufficient size that purchased robots with the intention of implementing them as an end user for production. Only firms with at least 10 employees were included in this study, and firms in the finance and insurance sector (North American Industry Classification System [NAICS] code 52) and the real estate and rental and leasing sector (NAICS code 53) were removed, as they were found to be involved primarily in leasing robots to other firms and comprised a negligible percentage of total robot imports into Canada. Firms in service industries that were involved in programming imported robots for the purpose of reselling them to other firms (NAICS codes 5413, 5414, 5415 and 5416) and firms in the wholesale trade sector (NAICS code 41) were also removed. In the final data used for analysis, the NALMF sample contained a total of 168,729 firms, the WES employer sample contained 3,981 business establishments and the WES employee sample contained 7,958 individual employees.

3.2 Robot capabilities

Dixon (2020) found that robots were especially active in the automotive and machinery and equipment assembly sectors, as well as in the plastics processing, and minerals and metals manufacturing industries.

In automotive manufacturing, robots are usually organized along a structured assembly line to fetch and position parts; fasten, rivet or weld parts together; and apply coatings or paint to the assembled parts. Robots are also prominent in the electronics assembly industry, where "pick-and-place" robots select circuits and place them on circuit boards or silicon wafers. They handle small, delicate parts with precision, selecting among different types and pressing them onto circuit boards. They can also visually inspect circuit boards, test the connections and etch circuit boards. Robots may also be involved in packaging finished products. In addition to improving quality, one of the main motivations for adopting robots in the electronics industry is the increase in flexibility they provide in serving different orders, as they can switch from large volume orders to smaller batches.

Robots are also used extensively in the processing of plastics, where they primarily perform secondary machine-tending roles. They also apply labels and move parts to other areas where they are further modified or packaged for shipment. In the injection moulding of plastic parts and packaging materials, they are also used to select items and apply labels. Overall, in the plastics processing industry, robots can replace a substantial proportion of repetitive manual labour.

In minerals and metals manufacturing, robots are involved in loading and unloading metal blanks into computer numerical control machine tools, repositioning semi-finished parts during the machining process and deburring afterwards. A primary motivation for robot adoption by firms in die-casting industries is the improvement of worker safety. Foundries are dangerous work environments in which robots—or workers—are subjected to intense heat and toxic fumes. Once moulded, the parts then need to be cooled, modified and inspected. Robots can control for quality in all of these steps. When the quality of the moulded parts depends on the skill of individual workers, robots offer much greater consistency. Individuals working alongside robots are also able to work much more safely and efficiently.

In addition to these industry-specific applications, palletizing is a ubiquitous application that robots can facilitate across many industries. Robots can recognize, pick up, orient and stack packages on pallets. They can also move easily between various quantities of packages of different sizes and varieties. Combined with the ability to control for quality, robots can efficiently place items in packages and seal and label them with machine-readable codes. This not only increases efficiency and precision, but also reduces injuries associated with palletizing large objects.

3.3 Measures

Below are the measures that were used in the main baseline tests:

Robot investment: A measure of robot capital stock was created by using the data that capture imports of robotics hardware and adding all robot purchases by each firm recorded in each year. To adjust the robot capital stock measure for economic depreciation, a useful life of 12 years was assumed based on IFR guidance.

Employee count, hiring and departures: To measure the total number of employees within the firm, the total count of employees provided in the NALMF data for each firm-year was used. This count was obtained from payroll deduction remittance forms submitted by all Canadian firms to the Canada Revenue Agency. Counts of managerial and non-managerial employees were recorded as responses in each year of the WES employer survey. The total number of new employee hires and departures was also recorded for each year of the survey data for both managerial and non-managerial employees. Non-managerial employee headcount was also reported by skill type (i.e., middle-skilled, low-skilled and high-skilled).

Strategic importance of labour cost reductions and quality improvements: To measure the strategic importance of labour cost reductions and quality improvements to the firm, a section of the WES employer survey asking respondents to “please rate the following factors with respect to their relative importance in your workplace general business strategy” for the years 2001, 2003 and 2005 was used. Respondents were asked to choose the importance of each factor on a Likert scale with the following possible responses: (1) not applicable, (2) not important, (3) slightly important, (4) important, (5) very important and (6) crucial. For this study, the factors of reducing labour costs and improving product and service quality were considered separately for analysis. For the measure of strategic priority of each factor, the values of (2) on the Likert scale were redefined to be equal to (1), and the scale was reset to ascend from 1 to 5, as an increase from the original (1) to (2) and vice versa does not clearly capture the changes in strategic priority this study aims to measure.

Decision-making authority for training and choice of production technology: The WES employer survey data contain detailed information on decision-making authority for tasks in different layers of the organizational hierarchy. This information was drawn from survey questions similar to those used by Bresnahan, Brynjolfsson and Hitt (2002), and Bloom et al. (2014) to measure worker autonomy. The survey asked “who normally makes decisions with respect to the following activities?” For this study, the activities of training and choice of production technology were considered, as they are directly relevant to the firm’s investments in human capital and use of robotics for productivity. For the 2003 and 2005 waves of the survey, survey respondents were given the following five possible responses to the question on who makes decisions: (1) non-managerial employees, (2) work supervisors, (3) senior managers, (4) individuals or groups outside the workplace (typically corporate headquarters for multi-establishment firms), and (5) business owners. To create distinct categories that correspond to hierarchical levels within organizations, three dummy variables were used. Each variable was equal to 1 if decision-making authority over the task was assigned to (1) non-managerial employees, (2) work supervisors or senior managers (to capture managerial employees), or (3) business owners or corporate headquarters.

Supervisor span of control: To capture supervisor span of control, the WES employee survey asked individual respondents whether they “supervise the work of employees on a day-to-day basis,” and, if so, to report the total number of employees who either report to them directly or who report to their subordinates. In this study, this total count was used as a measure of supervisor span of control, and only managers who were not promoted during the two-year period they were followed in the data were considered.

Work schedule unpredictability: To assess the unpredictability of employees’ work schedules, the WES employee survey asked respondents “how far in advance do you know your weekly hours of work?,” with the following possible responses: (1) always known, (2) more than one month (more than 31 days), (3) one month (22 to 31 days), (4) 3 weeks (15 to 21 days), (5) 2 weeks (8 to 14 days), (6) 1 to 7 days and (7) less than 1 day. For the main measure of work schedule unpredictability, the numerical value associated with each response was used, with increasing values denoting a shorter time period in which employees know their work schedule in advance.

Controls: A number of control variables were also used in this analysis. In all NALMF and WES employer sample specifications, organization fixed effects were included to address concerns of unobserved heterogeneity across firms and year fixed effects to control for aggregate shocks and trends. In the WES employee sample regressions, models were also estimated including individual employee fixed effects. This study controlled for organization size, which was measured by logged total assets in the NALMF sample, logged total revenues in the WES employer sample and logged total employees in the WES employee sample. A dummy variable control for firms with multiple business units in the NALMF sample and for organizations that were part of a multi-establishment firm in the WES employer sample was included. In the WES employer sample analysis, separate dummy variables were used to control for business establishments with an organized union or that implemented outsourcing as an organizational change.

4 Empirical strategy

A primary concern in estimating the effect of robotics is that robot adoption is unlikely to be random, which could potentially bias the coefficient estimates. This issue is addressed in two ways in addition to the robustness tests conducted.

First, for the total employment regression (using the NALMF sample), robot investment is instrumented for using the percentage of workers in each four-digit NAICS code in occupations with high manual dexterity and low verbal ability in 1995 multiplied by the inverse of the median price per robot in Canada for each year. Measures of occupation-level manual dexterity and verbal ability were obtained from the Career Handbook 2003, a dataset created by Employment and Social Development Canada, which contains ratings of the level of manual dexterity and verbal ability associated with over 920 distinct occupations on a four-point scale. High and low levels were defined as the top and bottom two points on the scale, respectively. The median price per robot for each year in Canada was calculated from the import data provided by the CBSA. The percentage of workers in each four-digit NAICS code in occupations with high manual dexterity and low verbal ability in 1995 provides a cross-sectional measure of industries that have a higher proportion of workers who may engage in activities that more closely match the capabilities of robots, which is multiplied by the inverse median robot price in Canada to create a time-varying instrumental variable. As robot prices decrease over time, industries with a higher percentage of workers doing work similar to the capabilities of robots are presumably more likely to adopt them. This is used as an instrument to argue that both cross-sectional industry employment composition in 1995 and the national median price of robots serve as plausibly exogenous predictors of firm-level robot adoption.

Second, coarsened exact matching (Iacus, King and Porro 2012) was used to match robot-adopting organizations with non-robot adopting organizations on key observables, and the estimation of the main regressions was repeated on matched samples for comparison. For the NALMF sample, robot-adopting firms in the sample were matched to non-robot adopting firms by industry (measured by four-digit NAICS code), year, province, whether the firm is a multi-unit enterprise, total assets, firm age, average annual earnings of the firm's employees and capital stock. Matching was done exactly by industry, year, province and multi-unit status, with coarsening allowed for the other variables. For the WES sample, matching was done exactly by industry, year and province, with coarsening allowed for total revenue, age of the organization, average annual employee earnings and capital stock.

5 Results

5.1 Main findings

Firms are adopting robots to increase productivity (see Appendix Table A1). However, that does not appear to come at the expense of total employment. Results of the baseline tests of the relationship between robot investments and total employment are presented in Table 1, columns 1 and 2, for both the full and matched samples created using coarsened exact matching. As columns 1 and 2 show, the coefficient for the measure of robot investment is positive and statistically significant, predicting an increase in total employment and supporting Hypothesis H1a. Column 3 presents the results from the instrumental variable estimation, which are directionally consistent with both columns 1 and 2 and are very similar in magnitude to the matched sample results in Column 2. For both the matched sample and instrumental variable estimations, a 1% increase in robot investment predicts a roughly 0.015% increase in total employment within the firm. Considering robot capital represents only 0.05% of the factor share, this is a substantial effect and suggests that there are complementary firm practices associated with robots. As an additional step, the same regression shown in Column 1 was estimated, but the robot investment measure was replaced with a series of time-indexed dummy variables for the years before and after robot adoption. The dummy variable coefficients were plotted graphically in Chart 1. Prior to robot adoption, there was no evidence of differences in total employment trends with non-robot adopting firms, but an increase in total employment occurred beginning in the first year of robot adoption. The results of the relationship between robot investments and non-managerial employment by different skill types are shown in Table 1, columns 4 to 9. As columns 4 and 5 show, there is consistent evidence of a negative and statistically significant relationship with middle-skilled employment, which supports Hypothesis H2. There is also evidence of a positive and statistically significant relationship for both low-skilled (columns 6 and 7) and high-skilled (columns 8 and 9) employment, which supports hypotheses 3 and 4.

Table 1-1
Total employment and non-managerial employment by skill type regressions — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Regression type	Fixed effects	Fixed effects	Two-stage least squares	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	NALMF	NALMF	NALMF	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Full	Matched	Full	Matched	Full	Matched
Dependent variable	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total middle-skilled)	ln(Total middle-skilled)	ln(Total low-skilled production)	ln(Total low-skilled production)	ln(Total high-skilled)	ln(Total high-skilled)

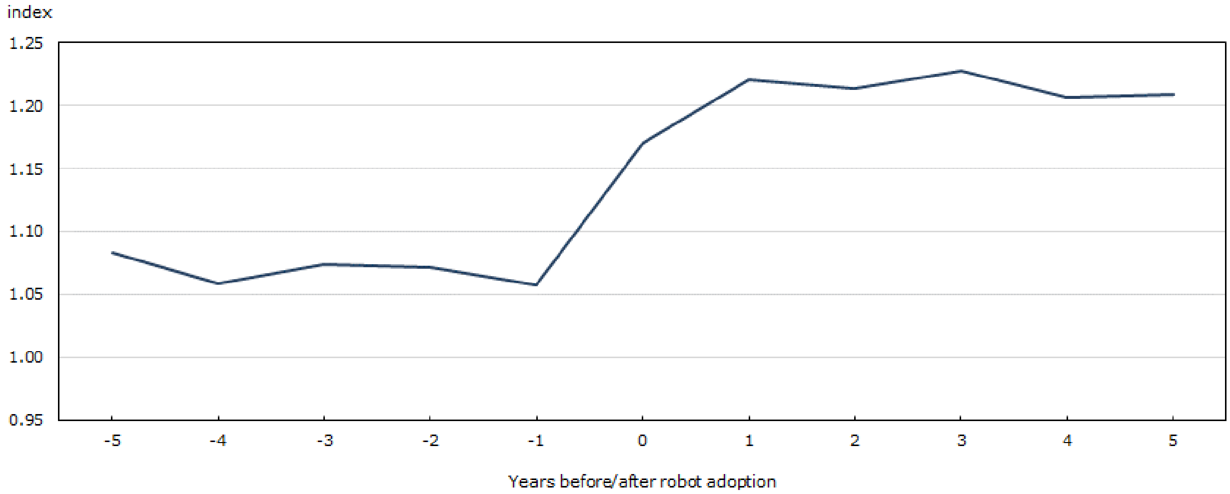
Note: NALMF: National Accounts Longitudinal Microdata File; WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), Workplace and Employee Survey and National Accounts Longitudinal Microdata File.

Table 1-2
Total employment and non-managerial employment by skill type regressions — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
ln(Total assets)									
Coefficient	0.191 ***	0.215 ***	0.346 ***	...	...	...	...	...	...
Standard error	0.013	0.037	0.016	...	...	...	...	...	...
ln(Total revenues)									
Coefficient	...	...	...	0.147	0.106	0.122	0.398 **	0.040	0.037
Standard error	...	...	...	0.103	0.094	0.086	0.162	0.071	0.074
Multi-unit enterprise									
Coefficient	0.139 ***	0.144 ***	0.500 ***	-0.077	-0.396 ***	-0.235 *	-0.049	0.090	0.486 **
Standard error	0.014	0.022	0.027	0.095	0.062	0.132	0.074	0.063	0.175
Unionized									
Coefficient	...	...	...	0.389 ***	-0.092	0.200	2.052 ***	-0.219 **	-1.041 *
Standard error	...	...	...	0.115	0.669	0.161	0.477	0.095	0.523
Outsourcing									
Coefficient	...	...	...	-0.001	0.419 **	0.048	-0.335	0.171 **	0.162
Standard error	...	...	...	0.086	0.187	0.104	0.322	0.068	0.151
ln(Robot capital stock)									
Coefficient	0.007 ***	0.015 **	0.015 ***	-0.086 ***	-0.031 **	0.061 ***	0.021 **	0.016 **	0.018 **
Standard error	0.002	0.006	0.004	0.014	0.012	0.021	0.009	0.007	0.008
Industry fixed effects	No	No	Yes	No	No	No	No	No	No
Province fixed effects	No	No	Yes	No	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations (number)	929,162	41,399	865,759	17,449	1,746	17,449	1,746	17,449	1,746
Adjusted R-squared	0.92	0.94	...	0.70	0.74	0.72	0.83	0.59	0.76

... not applicable
* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Notes: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), Workplace and Employee Survey and National Accounts Longitudinal Microdata File.

Chart 1
Change in employees (indexed to firm's first year in sample)



Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics.
Sources: Statistics Canada, Robots! (import data) and Workplace and Employee Survey.

The results for the tests on the relationship between robot investment and managerial and total non-managerial employment are shown in Table 2, again presenting both full and matched sample results. In columns 1 and 2, there is evidence of a negative and statistically significant relationship between robot adoption and managerial employment. Similar to the exercise done in Chart 1, the same regression shown in Column 1 was estimated, but the robot investment measure was replaced with a series of time-indexed dummy variables for the years before and after robot adoption, and the coefficients were plotted graphically in Chart 2. Prior to robot adoption, there was no evidence of differences in total managerial employment with non-robot adopting organizations, but a substantial decrease in managerial employment occurred beginning in the first year of robot adoption. Table 3 shows how robot investment may predict the hiring and departures of managerial and non-managerial employees. Robot adoption predicts a decrease in the hiring of new managers (columns 1 and 2), but an increase in the number of managerial departures (columns 3 and 4), suggesting that both contribute to the change in managerial headcount.

Table 2-1
Managerial and non-managerial employment, hiring, and departure regressions — Model specifications

	Model 1	Model 2	Model 3	Model 4
Regression type	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Matched
Dependent variable	ln(Total managers)	ln(Total managers)	ln(Total non-managerial employees)	ln(Total non-managerial employees)

Note: WES: Worplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 2-2
Managerial and non-managerial employment, hiring, and departure regressions — Regression results

	Model 1	Model 2	Model 3	Model 4
ln(Total revenues)				
Coefficient	0.084 **	0.009	0.242 ***	0.389 ***
Standard error	0.033	0.168	0.053	0.093
Multi-unit enterprise				
Coefficient	0.032	0.307	0.046	1.199
Standard error	0.096	0.434	0.049	0.847
Unionized				
Coefficient	0.168	0.594	0.025	-2.309 ***
Standard error	0.108	0.472	0.033	0.488
Outsourcing				
Coefficient	0.001	0.160	0.005	-0.205 *
Standard error	0.059	0.152	0.059	0.115
ln(Robot capital stock)				
Coefficient	-0.080 ***	-0.073 ***	0.005 **	0.016 **
Standard error	0.011	0.014	0.002	0.008
Year fixed effects	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations	17,449	1,746	17,449	1,746
Adjusted R-squared	0.69	0.75	0.88	0.86

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey (WES) data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 3-1
Managerial and non-managerial hiring, and departure regressions — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Regression type	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Matched	Full	Matched	Full	Matched
Dependent variable	ln(Total managerial hires)	ln(Total managerial hires)	ln(Total managerial hires)	ln(Total managerial hires)	ln(Total non-managerial hires)	ln(Total non-managerial hires)	ln(Total non-managerial departures)	ln(Total non-managerial departures)

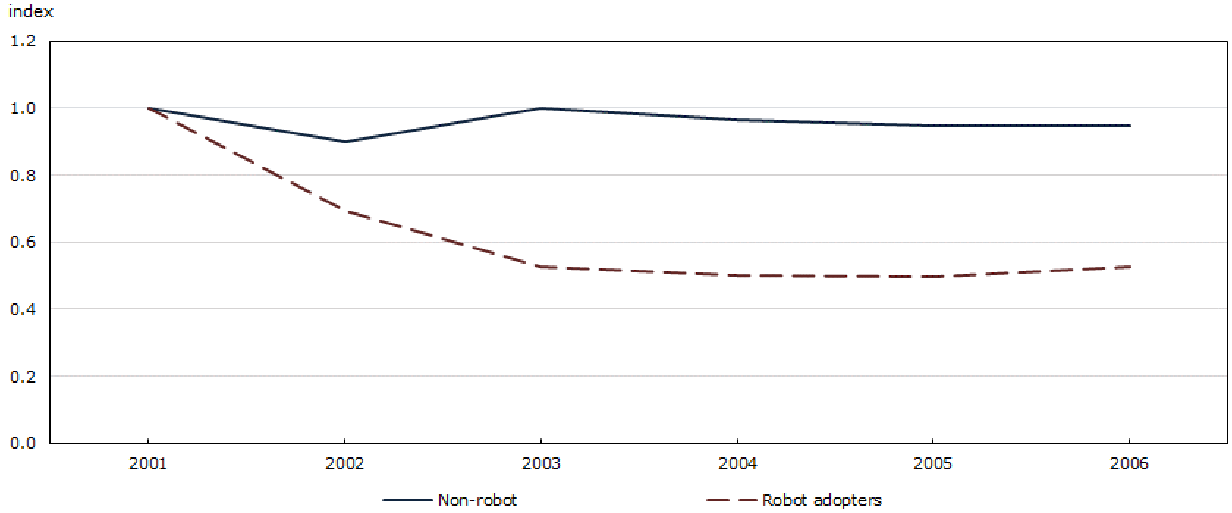
Note: WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 3-2
Managerial and non-managerial hiring, and departure regressions — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ln(Total revenues)								
Coefficient	0.053	0.066	0.023	0.024	0.209 **	0.045	0.077	0.203 *
Standard error	0.070	0.183	0.037	0.044	0.082	0.161	0.084	0.112
Multi-unit enterprise								
Coefficient	0.030	-0.343 *	-0.050	-0.061	-0.124	-0.584	0.178	0.006
Standard error	0.149	0.185	0.078	0.223	0.208	0.419	0.118	0.192
Unionized								
Coefficient	0.279 **	0.514	-0.019	-0.159	-0.149	-1.139 ***	0.292 ***	0.119
Standard error	0.124	0.523	0.067	0.106	0.104	0.301	0.100	0.117
Outsourcing								
Coefficient	0.116	0.109	-0.049	0.089	0.158	-0.343 **	0.062	0.053
Standard error	0.086	0.101	0.050	0.115	0.119	0.173	0.079	0.084
ln(Robot capital stock)								
Coefficient	-0.032 ***	-0.037 ***	0.025 ***	0.031 **	0.044 ***	0.028 **	0.037 ***	0.018 ***
Standard error	0.009	0.013	0.004	0.012	0.007	0.014	0.009	0.006
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (number)	17,449	1,746	17,449	1,746	17,449	1,746	17,449	1,746
Adjusted R-squared	0.19	0.22	0.06	0.03	0.60	0.46	0.33	0.15

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Notes: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Chart 2
Number of managers (indexed to 2001)



Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics.
Sources: Statistics Canada, Robots! (import data) and Workplace and Employee Survey.

As additional confirmation, a test was conducted to determine whether total employment increases can be explained by an increase in total non-managerial employment. The results of this test are shown in Table 2, columns 3 and 4. If the total employment or managerial employment results are attributable to measurement error in either variable, it is unlikely that a corresponding change in non-managerial employment would be observed. The coefficient for robot investment is positive and statistically significant, consistent with total employment increases being driven by non-managerial employees. In Table 3, columns 5 to 8 examine whether these results can be explained by changes in hiring or turnover for non-managerial employees. The coefficient for robot investment is positive and significant across all specifications, suggesting that investments in robotics increase both non-managerial hiring (columns 5 and 6) and non-managerial departures (columns 7 and 8). While both hiring and turnover increase, the net effect of the two (Table 2, columns 3 and 4) ultimately predicts a net gain in total employment for non-managerial employees. Increases in hiring and departures for non-managerial employees also suggest a compositional change in the workforce, consistent with the findings in Table 1 that show a decline in middle-skilled workers and an increase in low-skilled and high-skilled workers.

Next, the relationship between robot investments and changes in the strategic priorities of organizations was examined. These results are displayed in Table 4. The pattern of employment changes attributable to robot adoption—especially the decrease in managerial employment—may be related to firms' need to reduce labour costs. If true, these results may reflect a reverse causality where firms that focus on reducing the number of costly managers choose to adopt robots. As columns 1 and 2 show, the coefficient for robot investment is not statistically significant, providing no evidence that robot-purchasing firms are motivated by a desire to reduce labour costs. Columns 3 and 4 show a positive and significant coefficient for robot investment with respect to the strategic importance of improving product and service quality. Overall, the results suggest that robot investments are more likely to be motivated by a desire to improve the quality of production output, as opposed to a desire to improve efficiency through labour cost reductions. This suggests that the possibility of reverse causality where firms may choose to reduce managers and subsequently adopt robots is less likely. These results also corroborate evidence from the field—especially in manufacturing—according to which robots are often used to improve consistency and reduce production variance.

Table 4-1
Strategic priority regressions — Model specifications

	Model 1	Model 2	Model 3	Model 4
Regression type	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Matched
Dependent variable (strategic importance)	Reducing labor costs	Reducing labor costs	Improving product/ service quality	Improving product/ service quality

Note: WES: Worplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 4-2
Strategic priority regressions — Regression results

	Model 1	Model 2	Model 3	Model 4
ln(Total revenues)				
Coefficient	-0.014	0.118	0.098	0.180
Standard error	0.130	0.322	0.133	0.380
Multi-unit enterprise				
Coefficient	-0.197	0.192	-0.198	0.629 *
Standard error	0.121	0.347	0.173	0.374
Unionized				
Coefficient	-0.144	-0.743 ***	-0.336 *	0.093
Standard error	0.230	0.209	0.199	0.333
Outsourcing				
Coefficient	0.050	0.488	0.094	0.960
Standard error	0.178	0.488	0.169	0.590
ln(Robot capital stock)				
Coefficient	0.027	-0.001	0.108 ***	0.103 ***
Standard error	0.036	0.020	0.013	0.031
Year fixed effects	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes
Observations (number)	8,906	889	8,906	889
Adjusted R-squared	0.32	0.46	0.38	0.21

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)

Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

5.2 Changes in organizational practices and the nature of work

This section explores whether the allocation of decision-making authority to managers within the organization changes after robot adoption. If firms are simply downsizing managers to reduce slack, a change in decision-making authority for managers remaining within the firm is not necessarily expected. Downsizing may instead suggest that the remaining managers are doing more than before and, as a result, are granted increased decision-making authority. To explore this possibility, this study looks at how robot investments predict the allocation of decision-making authority over training activities and the choice of production technology. These results are shown in tables 5 and 6. These two decisions are particularly relevant, as they pertain to human capital management within the firm. Table 5 presents the results for the allocation of authority for training decisions, with the coefficient for robot investment being positive for non-managerial employees (columns 1 and 2) and negative for managerial employees (columns 3 and 4), with no significant relationship found for business owners and corporate headquarters (columns 5 and 6). The results provide evidence of a decentralization of responsibilities for training from managerial to non-managerial employees within the firm as a response to robot adoption. Table 6 shows results for the allocation of decision-making authority over the choice of production technology, with no significant relationship found for non-managerial employees (columns 1 and 2), a negative and significant relationship for managerial employees (columns 3 and 4), and a positive and significant relationship for business owners and corporate headquarters (columns 5 and 6).

In contrast with training activities, these results suggest that the choice of production technology becomes centralized upwards from managerial employees to business owners and corporate headquarters. Although the allocation of decision-making authority for all managerial tasks cannot be measured, these results suggest that the type of work managers are doing changes with robot adoption. The downsizing of managers represents not only a reduction in headcount, but also a change in their decision-making authority and the nature of tasks they perform. These results also suggest that robot adoption is also associated with fundamental changes in organizational design.

Table 5-1
Task allocation regressions, training decisions — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Regression type	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Matched	Full	Matched
Dependent variable (training decisions)	Non-managerial employees	Non-managerial employees	Managers	Managers	Business owners or corporate headquarters	Business owners or corporate headquarters

Note: WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 5-2
Task allocation regressions, training decisions — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ln(Total revenues)						
Coefficient	-0.003	-0.022	0.003	-0.017	0.027	0.307
Standard error	0.019	0.046	0.090	0.066	0.089	0.230
Multi-unit enterprise						
Coefficient	0.009	-0.094	-0.021	-0.234	0.110	0.755 *
Standard error	0.013	0.095	0.077	0.640	0.104	0.450
Unionized						
Coefficient	-0.041	0.014	-0.070	-0.027	-0.139	0.018
Standard error	0.139	0.015	0.212	0.025	0.173	0.101
Outsourcing						
Coefficient	0.011	0.121	-0.019	0.066	-0.058	-0.278
Standard error	0.028	0.074	0.072	0.300	0.081	0.195
ln(Robot capital stock)						
Coefficient	0.074 ***	0.077 ***	-0.077 ***	-0.080 ***	0.003	0.012
Standard error	0.011	0.012	0.011	0.012	0.003	0.009
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations (number)	6,173	632	6,173	632	6,173	632
Adjusted R-squared	0.29	0.84	0.33	0.72	0.39	0.75

* significantly different from reference category ($p < 0.05$)
*** significantly different from reference category ($p < 0.001$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 6-1
Task allocation regressions, choice of production technology — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Regression type	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer	WES employer	WES employer	WES employer
Sample	Full	Matched	Full	Matched	Full	Matched
Dependent variable (choice of production technology)	Non-managerial employees	Non-managerial employees	Managers	Managers	Business owners or corporate headquarters	Business owners or corporate headquarters

Note: WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 6-2
Task allocation regressions, choice of production technology — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ln(Total revenues)						
Coefficient	0.004	0.006	0.056	-0.131	-0.049	0.365
Standard error	0.008	0.033	0.072	0.100	0.075	0.262
Multi-unit enterprise						
Coefficient	-0.007	-0.010	0.038	-0.498	0.070	0.930 ***
Standard error	0.012	0.018	0.066	0.427	0.096	0.344
Unionized						
Coefficient	-0.000	0.009	0.231	0.868 ***	-0.527 ***	-0.878 ***
Standard error	0.004	0.009	0.189	0.092	0.181	0.070
Outsourcing						
Coefficient	-0.010	0.024	0.038	0.212	-0.003	-0.324 *
Standard error	0.019	0.024	0.075	0.250	0.077	0.179
ln(Robot capital stock)						
Coefficient	-0.000	0.002	-0.069 ***	-0.077 ***	0.075 ***	0.082 ***
Standard error	0.000	0.001	0.015	0.012	0.013	0.017
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations (number)	6,173	632	6,173	632	6,173	632
Adjusted R-squared	0.30	0.09	0.31	0.54	0.33	0.54

* significantly different from reference category ($p < 0.05$)
*** significantly different from reference category ($p < 0.001$)

Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

To further confirm these results at the organization level and consider how the nature of work may be changing with robot adoption at the individual employee level, a test was conducted to determine whether robot adoption at the organization level predicts changes in the span of control for managerial employees, the results of which are shown in Table 7, Column 1. The coefficient for robot investment was positive and statistically significant, suggesting that robot adoption predicts increases in the span of control for managers remaining within the organization. An increase in the span of control at the individual manager level is consistent with earlier organization-level findings of a reduction in managerial headcount and an increase in non-managerial employees.

Table 7-1
Span of control and work predictability regressions — Model specifications

	Model 1	Model 2
Regression type	Fixed effects	Fixed effects
Dataset	WES employee	WES employee
Dependent variable	Span of control	Work unpredctability

Note: WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 7-2
Span of control and work predictability regressions — Regression results

	Model 1	Model 2
ln(Total revenues)		
Coefficient	22.532 *	-0.112
Standard error	12.112	0.317
Multi-unit enterprise		
Coefficient	32.915	0.255
Standard error	29.069	0.270
Unionized		
Coefficient	-6.911	0.067
Standard error	4.560	0.231
Outsourcing		
Coefficient	-4.066	0.325
Standard error	5.147	0.229
ln(Robot capital stock)		
Coefficient	0.342 **	0.158 **
Standard error	0.132	0.066
Year fixed effects	Yes	Yes
Employee fixed effects	Yes	Yes
Observations (number)	11,719	10,969
Adjusted R-squared	0.15	0.59

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. All regressions using Workplace and Employee Survey data use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

As an additional test, the potential impact of robot investments on the routine nature of work for individual employees was examined. This study used a specific definition of routine—the degree to which workers can predict their schedule in advance, corresponding with the measure used. As shown in Table 7, Column 2, there is a positive relationship between robot investment and the unpredictability of work in advance. The results are consistent with the notion that, as robots automate a larger proportion of tasks within the organization and reduce variance in the production process, human workers are left to focus on work that is less predictable in nature.

5.3 Robots and performance measurement mechanism checks

Two separate tests using measures available in the WES employer survey were conducted to determine whether robot investments affect a firm's ability to measure performance, as proposed in the theoretical arguments of this study.

The first test examined whether robot investments increase the likelihood of improvements in performance measurement when organizational change occurs in the workplace. The WES employer survey asked whether any organizational changes occurred during the year, and organizational change was defined as a "change in the way in which work is organized within your workplace or between your workplace and others." If any organizational changes occurred, the survey subsequently asked respondents whether the impact of the organizational change that affected the most employees increased the "ability to measure performance" in the workplace. A dummy variable equal to 1 was created if the workplace reported having made an organizational change that increased the firm's ability to measure performance. To address sample selection concerns, a first-stage probit regression was estimated to predict the occurrence of organizational change, using the strategic priority of "reorganizing the work process" within the firm as an exogenous predictor, and including the Inverse Mills Ratio from this regression as an additional control variable. As shown in Table 8, Column 1, the coefficient for robot investment is positive and significant, suggesting that robots contribute to improved performance measurement when organizational changes are implemented.

The second test determined whether robot investments were positively related to the strategic priority of improving performance measurement within the firm. For the measure of strategic priority, the section of the WES employer survey that asked respondents to "please rate the following factors with respect to their relative importance in your workplace general business strategy," but now considering the factor of "improving measures of performance," was used. As the results in Table 8, columns 2 and 3, show, the coefficient for robot investment is positive and significant, suggesting that robot adoption and the strategic importance of improving measures of performance are positively related.

Table 8-1
Performance measurement regressions, Workplace and Employee Survey employer sample — Model specifications

	Model 1	Model 2	Model 3
Regression type	Fixed effects	Fixed effects	Fixed effects
Dataset	WES employer	WES employer	WES employer
Sample	Full	Full	Matched
Dependent variable	Increase in ability to measure performance	Strategic priority of improving measures of performance	Strategic priority of improving measures of performance

Note: WES: Workplace and Employee Survey.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

Table 8-2
Performance measurement regressions, Workplace and Employee Survey employer sample — Regression results

	Model 1	Model 2	Model 3
ln(Total revenues)			
Coefficient	0.034	0.090	-0.171
Standard error	0.047	0.141	0.258
Multi-unit enterprise			
Coefficient	0.027	0.167	0.356
Standard error	0.088	0.192	0.251
Unionized			
Coefficient	-0.028	0.039	-0.523 ***
Standard error	0.062	0.186	0.120
Outsourcing			
Coefficient	...	-0.011	0.702
Standard error	...	0.142	0.582
ln(Robot capital stock)			
Coefficient	0.022 **	0.076 ***	0.119 ***
Standard error	0.011	0.014	0.024
Inverse Mills ratio			
Coefficient	-0.140 **	...	...
Standard error	0.068	...	...
Organization fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations (number)	4,947	8,906	889
Adjusted R-squared	0.42	0.29	0.59

... not applicable
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. Inverse Mills ratio is from first stage probit regression predicting organizational change. All regressions use sampling weights.
Sources: Statistics Canada, Robots! (import data), and Workplace and Employee Survey.

5.4 Robustness checks

A series of additional robustness tests were conducted to test the results of this study. The positive relationship between robot investment and total employment was robust across different industries (appendix tables A2 to A4), suggesting that the results are not the result of industry-specific factors. Additional regressions (available upon request) controlled for IT investment as a possible omitted variable, investigated whether unobserved purchases from wholesalers and resellers within Canada (instead of direct import purchases) may affect the results, controlled for general improvements in firm performance as an alternative explanation for increases in total employment, controlled for import competition from China and the United States, and implemented an applied Heckman-style correction for the choice to adopt robots. The paper's main findings were robust to all of these additional controls.

6 Discussion and conclusion

This study uses novel data that capture investments in robotics for a population of businesses in a developed economy to provide the first firm-level evidence of the effect of robot adoption on employment and management, as well as the associated changes in organizational practices. The results suggest that robots do not affect employment within the firm uniformly. They lead to net increases in the headcount of non-managerial employees, but also decreases in the headcount of managerial employees. This is consistent with the notion that, by taking on a subset of responsibilities and activities in the production process of the firm, robots affect the demand for workers engaged in other activities within the firm. Employees whose skills have greater complementarity to robot investments are more likely to experience net gains in employment, depending on the degree to which their skills are complementary. This study found skill polarization of the non-managerial workforce, with decreases in middle-skilled employment and increases in low-skilled and high-skilled employment. This is consistent with previous findings on automation (Autor and Salomons 2018; Autor, Levy and Murnane 2003). Surprisingly, there was evidence of displacement of specific higher-skilled cognitive jobs (e.g., managers) that were previously less vulnerable to skill-biased technological change from earlier waves of technology. This reduction may be the result of both a decrease in the need for certain types of supervisory work from robot adoption and an indirect effect of the changing composition of non-managerial employees. Consistent with a decline in managerial employment and an increase in total employment, this study found that the span of control for managers also increased after robot adoption. There is also evidence that managerial work fundamentally changed after robot adoption, as the decision-making authority of managers was reduced. However, there is no evidence that job losses were caused by firms desiring to cut labour costs. In fact, there is evidence that firms adopt robots primarily to improve product and service quality.

In addition to changes in employment, the results of this study show that organizational practices change with robot adoption, as the allocation of decision-making authority for certain tasks shifts to different layers of the hierarchy and away from managers. Human resource-related decisions with respect to training were decentralized from managers to non-managerial employees, while the choice of production technology was centralized from managers to business owners and corporate headquarters. This is different from the effects of earlier generations of IT that tended to decentralize decision-making authority (Acemoglu et al. 2007). However, with robot adoption rapidly increasing in prevalence and capability, the allocation of decision-making authority and other complementary work practices will likely continue to evolve. Firms that can best match their capabilities and work practices to productive opportunities can benefit substantially from robot investments and develop potential competitive advantages. This finding highlights the need to understand the different types of complements to robots as a new technology.

Overall, the findings from organization-level data suggest that the effect of robots on labour is more nuanced than earlier research predicted and requires a deeper examination beyond the industry or region level to understand how robots are used to complement and substitute labour and how organizational practices need to evolve with the changing nature of work. While the present analysis suggests that robot adoption is associated with the use of different types of labour, the associated implication for wages is also an important question. The extent to which wages may change depends on the types of jobs that are created and eliminated. Initial evidence suggests that, although labour cost reduction is not the primary reason for which firms adopt robots, the reduction in managerial and middle-skilled employment and increase in low-skilled and high-skilled employment ultimately predict an ambiguous result for average wages. However, complementing the finding of a decline in demand for middle-skilled employment, Dauth, Findeisen, Südekum and Woessner 2018 used industry-level robot investments to examine their effect on employee wages and found that robot adoption leads to substantial wage decreases for middle-skilled workers.

Changes in employee types and skills as a result of robot adoption would also lead firms to implement complementary work practices to accommodate this skill change, similar to earlier generations of skill-biased technological change (Bresnahan, Brynjolfsson and Hitt 2002; Murnane, Levy and Autor 1999). To understand these effects, the collection of microdata, especially at the firm level, is crucial. In addition, better data on robot investment in different contexts are critical to understand whether the observed effects on employment and work practices can be generalized to other economies (Buffington, Miranda and Seamans 2018; Frank et al. 2019). While this study provides detailed firm-level evidence on robotics and shows that work practices have already evolved in response to robotic technology, future research could continue to examine how this technology affects different firms, occupations, industries and geographic regions (Felten, Raj and Seamans 2019). With rapid advances in robotics capabilities, understanding their implications is critical, as investments in robots are likely to have profound effects on both employment and organizations.

7 Appendix: The productivity and employment consequences of robots: Firm-level evidence

S1 Productivity

An additional test was conducted to determine whether investments in robotics lead to increases in firm productivity. As columns 2 to 4 in the table below show, the coefficient for robot capital stock is positive and significant, indicating that robots do in fact increase firm productivity.

Table A.1-1
Productivity regressions — Model specifications

	Model 1	Model 2	Model 3	Model 4
Regression type	Ordinary least squares	Ordinary least squares	Fixed effects	Levinsohn-Petrin
Dependent variable	ln(Total revenues)	ln(Total revenues)	ln(Total revenues)	ln(Total revenues)

Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.1-2
Productivity regressions — Regression results

	Model 1	Model 2	Model 3	Model 4
ln(Materials)				
Coefficient	0.411 ***	0.411 ***	0.235 ***	0.265 ***
Standard error	0.024	0.024	0.021	0.003
ln(Labor)				
Coefficient	0.445 ***	0.443 ***	0.310 ***	0.312 ***
Standard error	0.025	0.025	0.023	0.004
ln(Non-Robot capital stock)				
Coefficient	0.226 ***	0.224 ***	0.279 ***	0.220 ***
Standard error	0.041	0.041	0.019	0.005
ln(Robot capital stock)				
Coefficient	...	0.019 ***	0.007 ***	0.008 ***
Standard error	...	0.003	0.001	0.002
Industry fixed effects	Yes	Yes	No	...
Province fixed effects	Yes	Yes	No	...
Year fixed effects	Yes	Yes	Yes	...
Organization fixed effects	No	No	Yes	...
Observations (number)	929,162	929,162	929,162	929,162
Adjusted R-squared	0.87	0.87	0.97	...

... not applicable

*** significantly different from reference category ($p < 0.001$)

Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by industry. Standard errors for Levinsohn-Petrin estimation are bootstrapped with 100 repetitions.

Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

S2 Total employment regression results by industry

This section presents the results of the total employment specification for the NALMF sample (also including ordinary least squares) by industries. Overall, the results were consistent with the original baseline regressions, although the substantially smaller sample size and lower prevalence of robot adoption reduced statistical power in some cases.

Table A.2-1
Total employment by industry — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Regression type	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects
Industry	Automotive	Automotive	Petroleum and plastics	Petroleum and plastics	Minerals and metals	Minerals and metals	Machinery manufacturing	Machinery manufacturing
Dependent variable	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)

Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.2-2
Total employment by industry — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ln(Total assets)								
Coefficient	0.461 ***	0.148 ***	0.433 ***	0.205 ***	0.459 ***	0.257 ***	0.502 ***	0.301 ***
Standard error	0.026	0.040	0.010	0.029	0.008	0.019	0.010	0.030
Multi-unit enterprise								
Coefficient	0.395 ***	0.064	0.416 ***	0.109 ***	0.329 ***	0.075 ***	0.297 ***	0.121 ***
Standard error	0.079	0.044	0.035	0.026	0.029	0.020	0.039	0.033
ln(Robot capital stock)								
Coefficient	0.021 ***	0.024 ***	0.035 ***	0.009 ***	0.017 ***	0.012 ***	0.019 ***	0.007 **
Standard error	0.008	0.005	0.005	0.003	0.005	0.003	0.003	0.003
Industry fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Province fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations (number)	6,655	6,655	21,997	21,997	50,750	50,750	23,981	23,981
Adjusted R-squared	0.72	0.95	0.70	0.95	0.65	0.93	0.67	0.93

** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by firm.
Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.3-1
Total employment by industry — Model specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Regression type	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects
Industry	Computer and electronic manufacturing	Computer and electronic manufacturing	Other manufacturing	Other manufacturing	Healthcare	Healthcare	Scientific research services	Scientific research services
Dependent variable	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)

Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.3-2
Total employment by industry — Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ln(Total assets)								
Coefficient	0.445 ***	0.242 ***	0.415 ***	0.209 ***	0.201 ***	0.124 ***	0.355 ***	0.272 ***
Standard error	0.013	0.034	0.005	0.013	0.012	0.015	0.028	0.034
Multi-unit enterprise								
Coefficient	0.408 ***	0.151 ***	0.517 ***	0.118 ***	0.982 ***	0.158	0.317 **	0.087
Standard error	0.059	0.039	0.022	0.019	0.129	0.112	0.150	0.220
ln(Robot capital stock)								
Coefficient	0.026 ***	0.005	0.020 ***	0.002	0.061 ***	0.118 ***	0.028 **	0.018 *
Standard error	0.005	0.004	0.005	0.003	0.016	0.002	0.011	0.010
Industry fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Province fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Organization fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations (number)	13,371	13,371	103,673	103,673	12,165	12,165	1,829	1,829
Adjusted R-squared	0.67	0.93	0.63	0.93	0.41	0.92	0.53	0.93

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)
Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by firm.
Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.4-1
Total employment by industry — Model specifications

	Model 1	Model 2	Model 3	Model 4
Regression type	Ordinary least squares	Fixed effects	Ordinary least squares	Fixed effects
Industry	Administrative support, waste management services	Administrative support, waste management services	Other services	Other services
Dependent variable	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)

Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

Table A.4-2
Total employment by industry — Regression results

	Model 1	Model 2	Model 3	Model 4
ln(Total assets)				
Coefficient	0.284 ***	0.194 ***	0.328 ***	0.172 ***
Standard error	0.008	0.016	0.002	0.004
Multi-unit enterprise				
Coefficient	0.753 ***	0.095 **	0.527 ***	0.150 ***
Standard error	0.061	0.047	0.010	0.008
ln(Robot capital stock)				
Coefficient	0.027 *	0.018 **	0.027 ***	0.003
Standard error	0.014	0.007	0.006	0.005
Industry fixed effects	Yes	No	Yes	No
Province fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Organization fixed effects	No	Yes	No	Yes
Observations (number)	38,184	38,184	656,557	656,557
Adjusted R-squared	0.39	0.91	0.47	0.91

* significantly different from reference category ($p < 0.05$)
** significantly different from reference category ($p < 0.01$)
*** significantly different from reference category ($p < 0.001$)

Note: Robot stocks calculated based on 12-year useful life suggested by the International Federation of Robotics. Standard errors clustered by firm.
Sources: Statistics Canada, Robots! (import data), and National Accounts Longitudinal Microdata File.

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