The Employment Consequences of Robots: Firm-level Evidence

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Abstract

As a new general-purpose technology, robots have the potential to radically transform industries and affect employment. Preliminary empirical studies using industry and geographic region-level data have shown that robots differ from prior general-purpose technologies and predict substantial negative effects on employment. Using novel firm-level data, we show that investments in robotics are associated with increased employee turnover, but also an increase in total employment within the firm. Examining changes in labor composition, we find that manager headcount has decreased but non-managerial employee headcount has increased, suggesting that robots displace managerial work that in prior waves of technology adoption was considered more difficult to replace. However, we also find that firms are more likely to hire managers from outside the firm and invest in additional training, suggesting that firms require different employee skills as the nature of work changes with robot investment. We also provide additional evidence that robot investments are not generally motivated by the desire to reduce labor costs but are instead related to an increased focus on improving product and service quality. With respect to changes in the way work is organized within the firm, we find that robot adoption predicts organizational changes in ways that differ from prior technologies. While information technology has generally been found to decentralize decision-making authority within organizational hierarchies, we find that robots can either centralize or decentralize decision-making, depending on the task. Overall, our results suggest that the impact of robots on employment is more nuanced than prior studies have shown.

1 Introduction

We explore the employment consequences of robots within firms and how organizational and work practices are changing in response to robot adoption. As robotics and artificial intelligence (AI) are increasingly used by firms as the next engine of innovation and productivity growth (CEA 2016), their effect on labor, firm practices, and productivity has become a subject of growing importance. Anecdotal evidence in the popular press has documented extensively that AI and adaptable robotics can not only lead to gains in productivity, but also to consequences of increasing income inequality and reducing employment. Rapid advancements in vision, speech, natural language processing and prediction capabilities have shifted the comparative advantage from humans to machines for a growing list of tasks and occupations (Brynjolfsson and Mitchell 2017, Frey and Osborne 2017), potentially leaving human labor with substantially fewer activities that can add value (Brynjolfsson and McAfee 2014, Ford 2015). If this assessment is accurate, this shift would lead to severe negative consequences for employment as technology automates a large proportion of tasks currently done by labor (Acemoglu and Restrepo 2017, Dinlersoz and Wolf 2018, Graetz and Michaels 2015, Mann and Püttmann 2017).

However, it has also been argued that robots and AI are similar to past generations of general-purpose technologies (GPT) that ultimately increased labor demand. In this competing view, even as labor is displaced, the new jobs created will more than compensate for the jobs lost (Autor and Salomons 2017). Similar to the effects of prior generations of GPTs, these new jobs are likely to complement robots, suggesting a compositional change in labor within firms. Accordingly, different skills and organizational practices will also emerge to utilize the new capabilities that robots provide. As robots offer new capabilities that differ from prior IT investments (Brynjolfsson and Mitchell 2017), the emerging skill change and firm practices would also differ from those caused by IT investments and reflect those that are complementary to robots.

While recent theories have examined the conditions under which robot investments are expected to lead to productivity growth at the expense of labor (Acemoglu and Restrepo 2018), actual empirical evidence examining the effect of robots on employment has been limited, in part due to the lack of microdata measuring robot adoption at the firm level. Instead, empirical studies examining the effect of robots on labor have relied upon much coarser data at the industry or geographic region level (Graetz and Michaels 2015, Mann and Püttmann 2017). Although these studies have documented heterogeneous effects on labor, they largely predict a drastic decline in overall employment and labor share resulting from robot investments (Acemoglu and Restrepo 2017, Dinlersoz and Wolf 2018, Graetz and Michaels 2015, Mann and Püttmann 2017). However, analysis at the industry and geographic region level is insufficient to show the mechanisms through which firms are using robotics to substitute labor, and to demonstrate to what extent AI and robots can complement labor to generate new labor demand (Autor and Salomons 2018). Ultimately, firm-level analysis is necessary to examine the extent to which firms benefit from robotics, how they may substitute for or complement labor (Acemoglu and Restrepo 2017, Brynjolfsson et al. 2018), and what assets or capabilities firms need to derive greater value from robot investments.

In this study, we advance this nascent research stream by providing the first firm-level evidence of the effect of robots on labor and productivity using comprehensive data containing measures of robot investments, employment, and firm practices for businesses in the Canadian economy, spanning the years 2000-2015.[1] We find that firms' investments in robotics have increased over time, with the fastest growth being in more general-purpose robots adopted across an increasing range of industries.[2] However, contrary to the popular press and earlier studies at the industry and geographic region level, robot adoption does not predict employment declines, but is instead associated with increases in total employment. Our findings are consistent with prior research showing that the effects of GPTs have been to increase both employment and productivity. As additional evidence that robots are not adopted primarily as an effort to cut labor costs, we also find that robot adoption is not associated with an increase in the strategic importance of reducing labor costs for firms, but is instead associated with an increase in the strategic importance of improving product and service quality.

Labor composition has also changed. We find that robot adoption predicts the displacement of managers even though overall employment increases, with robot investments predicting both decreases in managerial hiring and increases in managerial turnover. By contrast, we observe an increase in both hiring and turnover of non-managerial employees. The displacement of managers over non-managerial employees differs from the effect of prior information technologies that generally displaced low- and middle-skilled workers (Autor et al. 2006, Autor et al. 2003, David and Dorn 2013, Dustmann et al. 2009, Murnane et al. 1999). Here, we find evidence that robots displace managerial positions that have higher cognitive requirements. These findings suggest a compositional change in labor in response to changes in the nature of work as a result of robot investment. Consistent with this view, we find that firms invest more in training employees to work with technologies. Similarly, we also find that robot investments are associated with a reduction of decision authority allocated to managers with respect to employee training and choice of production technology. Compared to previous findings showing that IT investments generally lead to decentralization of decision making, we find that the predicted outcome of robot adoption is both centralization and decentralization, depending on the task. For employee training,

[1] We use two main datasets for our empirical analysis spanning overlapping timeframes, described in more detail in the data section.

[2] Here, general-purpose robots are defined as robots other than those customized for automotive assembly.

decision authority is decentralized downwards to non-managerial employees while the choice of production technology is centralized upwards to business owners and corporate headquarters. These results show that not only has employment changed due to robots, but the change is related to complementary work practices that are critical to the understanding of how robots affect labor. While our analysis provides only initial firm-level evidence, our comprehensive set of outcomes—employment, labor composition, strategic priorities, training, and the allocation of decision rights—suggests that robots have a substantive effect on both employment and work practices in ways that differ from the effects of prior technologies.

Overall, our results show the importance of examining the effect of robot investment at the firm level and contribute to the important debate about the consequences of robot investments on labor.

2 Theoretical considerations

The adoption of GPTs is often associated with productivity gains in every sector of the economy (Bresnahan and Trajtenberg 1995). To maximize the value of GPTs, firms have substantially reorganized work activities and subsequently changed the nature of work and employee skill requirements (Autor et al. 2003, Bresnahan et al. 2002, Brynjolfsson et al. 2018). Robots and AI, being the most recent GPT (Brynjolfsson et al. 2018, Cockburn et al. 2018), have the potential to transform the economy (Agrawal et al. 2018, McAfee and Brynjolfsson 2017). The speed of this transformation is likely to be faster than earlier periods of automation because robots and AI can accelerate the automation process itself and lead to dramatic changes in productivity, labor, and how work is organized (Brynjolfsson and Mitchell 2017).

However, the effect of robots on employment remains an open question. Research examining the effect of AI and robots on labor is still nascent with only a few studies examining the substitutability of AI and robots on work (Acemoglu and Restrepo 2017, Arntz et al. 2016, Frey and Osborne 2017, Mann and Püttmann 2017, Manyika 2017). These preliminary studies have predicted dire consequences of labor displacement resulting from robot adoption. Surveying AI experts about the capabilities of AI and projecting their assessment on over 700 occupations, Frey and Osborne (2017) find that up to 47% of all jobs in the United States may be displaced. Using a task-based approach breaking each occupation into a set of concrete tasks, OECD researchers find that 70% of tasks performed by labor could be automated (Arntz et al. 2016). Other studies using the task-based approach have concluded that more than 50% of work tasks are vulnerable to automation (Manyika 2017). Using a measure of robot penetration at the industry level in the US, Acemoglu and Restrepo (2017) find that one robot can replace roughly six people. Graetz and Michaels (2015) also find that robot adoption is associated with a reduction in hours worked for low-skilled labor, using similar data on robot adoption for 17 countries.

The findings from these initial studies stand in stark contrast to earlier generations of technologies that have been found to increase employment in conjunction with productivity, ultimately leading to labor's share of productivity remaining constant. While preliminary empirical studies have documented that automation from robot investment can directly substitute labor, robots may also positively affect employment through 1) productivity increases from labor 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 labor; or 3) the creation of new tasks or increased demand for existing tasks that are complementary to robots (Acemoglu and Restrepo 2018, Brynjolfsson et al. 2018). However, these countervailing effects are difficult to observe using data at the industry and geographic region levels. Consequently, studies using these relatively coarse data to examine the effect of robots on productivity and labor have been unable to clearly examine the mechanisms through which firms are using robotics to substitute labor, and whether new types of jobs or increased demand for existing jobs are created that complement robot investment. 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 et al. 2002, Brynjolfsson and Hitt 1996), as the substantial heterogeneity in productivity growth across firms cannot be captured at the sector and industry level (Syverson 2004). For example, robots may incur productivity gains in some firms but losses in others within the same industry, but in aggregate show no productivity effect. Furthermore, more precise measurement of both IT and organizational capabilities at the firm level was critical to resolving the IT-productivity paradox that earlier studies discovered and to uncovering the factors explaining the heterogeneous effects of IT on firm outcomes (Brynjolfsson et al. 2002). With a firm-level measure of robot investments, we contribute to the literature by documenting the mechanisms through which robots can affect labor, which cannot be documented through industry or geographic region analyses.

2.1 Skills and organizational complements

Irrespective of whether robots increase or decrease overall employment, it is likely that the organization of work changes in some form as firms adopt robots. Similar to prior generations of skill-biased technical change, the demand and earnings for certain skills would increase while those for other skills may decrease. For example, with the rise of information technology (IT) in the late 1990s, the demand for skilled labor has gradually increased over time as routine tasks and simple decisions become automated. This led to an accompanying reduction in the demand for low and middle-wage routine occupations and an increase in demand for nonroutine and cognitively challenging tasks, such as managing employees and professional services. (Autor et al. 2006, Autor et al. 2003, Card and DiNardo 2002, Murnane et al. 1999). Although it has been argued that nonroutine and cognitively challenging tasks are difficult to automate (Autor et al.

2003, Murnane et al. 1999), the increasing sophistication of robots and AI is likely to automate tasks that were previously unaffected by automation.

With advances in vision, speech, and prediction, robotics has advanced beyond automating simple and routine tasks and become capable of performing more cognitively complex work as well as tasks involving manual dexterity. For example, machine vision has helped robots in the automotive industry to consistently install and weld parts onto car bodies with a high degree of precision, significantly reducing variance in the production process.[3] Robots have also become capable of automating large segments of complex warehousing logistics, effectively transporting objects without human intervention between locations, relieving humans of lifting and handling awkward, heavy objects and increasing efficiency by decreasing overall delivery time.[4] Collaborative robots are able to work with humans to enhance their capabilities, such as robotic arms that improve human manual dexterity while reducing stress on muscles and tendons. In the medical and pharmaceutical industries, robots have been used to handle and prepare materials, follow complex protocols to analyze samples in potentially hazardous settings, and deliver medications to patients without human intervention. As these technologies become more pervasive and organizations learn how to utilize them, labor composition, managerial roles and employment, and the allocation of decision authority are all likely to be substantially affected (Bresnahan et al. 2002).

Accordingly, we expect labor and skill composition will change with robot adoption, as has been the case with prior waves of skill-biased technical change. With robots performing an increasing range of tasks, the accompanying change in labor may also require different ways of organizing work. An extensive literature has documented the importance of having complementary work practices and human capital to fully exploit the capabilities that new technologies can offer (Aral et al. 2012, Bresnahan et al. 2002, Tambe et al. 2012). For example, with employees becoming more skilled in doing complex non-routine tasks, decision rights may become more decentralized (Acemoglu et al. 2007). They can also centralize to management since using robots through computer algorithms may be easier than ensuring humans follow work rules precisely (Brynjolfsson et al. 2008). Other work practices would also evolve such as more technical training so workers are updated with knowledge of how to use the latest technologies (Bresnahan et al. 2002). Here, we explore the work practices and decision authority allocations that have emerged with robot adoption and provide a first examination of the effect of robots on employment at the firm level.

3 Data and Measures

3.1 Data

[3] https://blog.robotiq.com/bid/69722/Top-5-Robotic-Applications-in-the-Automotive-Industry
[4] https://www.nytimes.com/2017/09/10/technology/amazon-robots-workers.html

To measure robot investment at the firm level, we use data capturing the purchases of robots imported by Canadian firms provided by the Canadian Border Services Agency (CBSA) from 1996 to 2017. Global production of robotics hardware is highly concentrated in relatively few countries including Japan, Germany, the United States and increasingly China. By contrast, Canada does not produce a meaningful quantity of robotics hardware domestically and consequently must import robots from foreign producers, allowing us to exploit 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 classifies industrial robots separately from other types of technologies, machinery, and equipment.[5] The classification details several different types of robots as distinct HS codes, which we group into two consistent categories across the time period of our data: 1) robots for automotive assembly lines and 2) all other types of robots.[6] 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. While in principle misclassification by importing firms or customs agents may occur if robot purchases are misidentified, over 90 percent of the total value of imported robots captured in our data is directly attributable to publicly known robot producers (listed as the exporting firm) or to purchasing firms that were clearly identified as using robots.[7] To further validate our measure of robot investment, we also benchmark our measure to data reported by the Robotics Industry Association (RIA), and find both measures are comparable, showing similar trends over time (see detailed discussion in Appendix section S1).

We merge our robot investment data with two datasets maintained by Statistics Canada containing 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 tax filing data from 2000-2015; and 2) the Workplace and Employee Survey (WES), which contains comprehensive information on employment and firm management practices, for the years 2001-2006. The survey is a random stratified sample in a panel structure, representative of the population of businesses in the Canadian economy in each year.[8]

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[5] Industrial robots are a separate classification at the ten digit HS code level recorded by the CBSA.
[6] Our measure of total robot investment is the sum of these two categories of robots. The HS code structure for robots changes over the time period of our data, but can be clearly grouped consistently in this manner over the entire period.
[7] Verification was done manually by searching the name of the importing firm in the public domain for evidence of robot usage.
[8] An important strength of the WES is that responding to the survey was mandatory under Canadian law, which resulted in regular response rates of approximately 90 percent, mitigating concerns of non-response bias in our analysis.

We make several adjustments to both our NALMF and WES samples to more precisely capture those firms of sufficient size that purchased robots with the intention of implementing them as an end user for production. Here, we only include firms with at least ten employees, and removed those firms in the finance and insurance (NAICS code 52) and real estate rental and leasing sectors (NAICS code 53), as firms in these sectors were found to be primarily involved in leasing robots to other firms.[9] We also removed firms in service industries that were engaged in programming imported robots for the purpose of reselling them to other firms (NAICS codes 5413, 5414, 5415, 5416), and firms in the wholesale trade sector (NAICS code 41). In our final data used for analysis, our NALMF sample contains 168,729 firms in total for the years 2000-2015, and our WES sample contains 3,981 businesses in total for the years 2001-2006. Descriptive statistics and correlation tables for both our NALMF and WES samples are shown in Appendix section S12.

3.2 Measures

Robot investment. Using our data capturing imports of robotics hardware, we create a measure of robot capital stock by adding all robot purchases by each firm recorded in each year. To adjust our robot capital stock measure for economic depreciation, we assume a useful life of 12 years based upon stated guidance given by the International Federation of Robotics (IFR).

Employee count. To measure the total number of employees within the firm, we use the total count of employees provided in the NALMF data for each firm-year, recorded from payroll deduction remittance forms submitted by all Canadian firms to the Canada Revenue Agency (CRA). Total numbers of managerial and non-managerial employees are recorded as responses in each year of the WES survey.[10]

Hiring and turnover. Using data capturing employee hiring and departures in the WES survey, we construct measures of both managerial and non-managerial hiring activity and turnover. To measure the rate of managerial hiring, we divide the number of new managerial hires within a given year by the average number of managers during the period, and we similarly calculate the hiring rate of non-managerial employees. Managerial turnover is calculated as the total count of managers who leave the organization in each year divided by the average number of managers during the period. Non-managerial turnover is calculated in a similar manner.

[9] These sectors comprised only a negligible percentage of total robot imports into Canada.

[10] The survey provides a variety of examples of what is included in the definition of managers: "Examples: president of a single location company; retail store manager; plant manager; senior partners in business services firms; production superintendent; as well as vice-presidents, assistant directors, junior partners and assistant administrators whose responsibilities cover more than one specific domain, department heads or managers (engineering, accounting, R&D, personnel, computing, marketing, sales, etc.); heads or managers of specific product lines; junior partners or assistant administrators with responsibilities for a specific domain; and assistant directors in small locations (without an internal department structure)."

Strategic importance of cost reductions and quality improvements. To measure the strategic importance of cost reductions and quality improvements to the firm, we exploit a section of the WES survey which asks 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. Respondents are asked to choose the importance of each factor on a Likert scale with possible responses being (1) Not applicable, (2) Not important, (3) Slightly important, (4) Important, (5) Very important, and (6) Crucial. Here, we consider the factors of "reducing labour costs," "reducing other operating costs" aside from labor, and "improving product/service quality" separately for analysis. For our measure of strategic priority of each factor, we redefine on the Likert scale values of (1) to be equal to (2), as changes between (1) and (2) do not clearly capture the changes in strategic priority that we aim to measure.[11]

Decision authority for training and choice of production technology. The WES data contain detailed information regarding decision-making authority for tasks across different layers of the organizational hierarchy, drawn from survey questions similar to those used by Bresnahan et al. (2002) and Bloom et al. (2013) measuring worker autonomy. The survey asks, "who normally makes decisions with respect to the following activities?" Here, we consider the activities of "training" and "choice of production technology" 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 of 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, we create three dummy variables, each equal to one if: 1) non-managerial employees were assigned decision authority over the task, 2) work supervisors or senior managers were assigned authority over the task, to capture managerial employees, or 3) business owners or corporate headquarters were assigned authority over the task.

Training. In a separate section of the WES survey, respondents are asked to report whether the firm provides training for employees across a variety of types. Specifically, the survey defines training as "includ[ing] all types of training intended to develop your employees' skills and/or knowledge," either through "classroom job-related training" or "on-the-job training." With respect to specific types of training, the survey asks, "did this workplace pay for or provide any of the following types of training?" Here, we consider a range of possible types of training: 1) computer hardware, 2) professional, 3) on other office and non-office equipment, 4) team-building, leadership, communication, 5) group decision-making or problem-solving, 6) orientation for new employees, and 7) apprenticeship.

[11] This modification does not change the sign or significance of our results from using each original variable. Simply dropping all values of (1) also produces results of identical sign and significance level.

Managers recruited from outside the firm. To measure whether firms implement a systematic workplace practice of external hiring for managerial positions, the WES asks how vacant managerial positions are usually filled. Here, we create a dummy variable equal to one if managerial positions are reported as usually being filled "from outside the company" as opposed to within the firm, with the added condition that at least one manager is hired in the same year if the practice changed from the prior year.[12]

Controls. A number of control variables are also included in our analysis. In all our specifications, we include organization fixed effects to address concerns of unobserved heterogeneity across firms and year fixed effects to control for aggregate shocks and trends. We control for organization size, measured by logged total assets in our NALMF sample and logged total revenues in our WES sample. We also include a dummy variable control for businesses that are part of a multi-establishment firm in both samples. In our WES sample analysis, a dummy variable is used to control for businesses that have an organized union.[13]

4 Patterns and trends in robot adoption

Figure 2 shows aggregate robot capital stock in Canada for each year from 1996-2017, with robots for automotive assembly and all other types of robots displayed as two distinct categories.[14] Overall, investment has been steadily increasing since the late 1990s, with a substantial decline in investment growth corresponding roughly to the timeframe of the Great Recession for automotive assembly robots.[15] Since 2008, investment in automotive assembly robots has continued to decline, while investment in non-automotive robots has increased at an accelerating rate. The divergence in investment between the two types of robots is consistent with anecdotal evidence that the types of robots being adopted by firms has evolved over time, away from highly customized robots for automotive production to more general-purpose robots that can be used by businesses across a wider range of economic sectors.

5 Results and robustness checks

5.1 Results

Results for our baseline tests of the relationship between investments in robotics and employment are presented in Table 1. Columns 1 through 7 provide OLS estimates with organization fixed effects using

[12] The condition of requiring at least one manager to be hired was added to capture not only a change in work practices, but evidence of actual hiring. Removing this additional condition and using only the measure of external managerial hiring as a work practice does not change the sign or significance level of our results.
[13] This variable was not available in the NALMF data.
[14] We note the graphs in this section use all available robot import data to show aggregate distribution and trends, not our NALMF or WES regression samples.
[15] We note that the Great Recession did not begin at the same time in Canada and the United States. The United States entered the Great Recession in December 2007, while Canada did not enter a recession until October 2008, which ended in July 2009.

each of our employee count, hiring, and turnover measures as dependent variables. As Column 1 shows, the coefficient for our measure of robot investment is positive and statistically significant, suggesting that robot investments by firms predict a net increase in employment, as opposed to a decline. Columns 2 and 3 investigate this in greater detail by separately considering the effects on manager headcount and non-managerial employee headcount. Here, the coefficient for robot investment is negative and significant for managers, but positive and significant for non-managerial employees. As the contrast between both columns show, robot investments predict a decrease in the number of managers within the firm, but an increase in the number of non-managerial employees, suggesting that effects on employment are not uniform across all types of employees within the firm. Managers in particular may be more likely to experience negative employment effects from robots within the firm. Columns 4 through 7 examine whether these results are explained by changes in hiring or turnover for both managerial and non-managerial employees. As shown in Columns 4 and 6, investments in robotics predict both a decrease in hiring of managers (negative and significant coefficient), as well as an increase in managerial turnover (positive and significant coefficient), suggesting that both contribute to the change in managerial headcount. By contrast, in Columns 5 and 7, the coefficient for robot investment is positive and significant, suggesting that investments in robotics increase both non-managerial hiring as well as non-managerial turnover. While both hiring and turnover increase, the net effect of the two (Column 3) ultimately predicts a net gain in total employment for non-managerial employees. However, we also note that while overall managerial employment may be negatively affected, robot adoption also predicts a change in work practices to hiring managers from outside the firm (Column 8).

We next examine how robot investments may be related to changes in the strategic priorities of firms, with results displayed in Table 2. As Column 1 shows, the coefficient for robot investment is not statistically significant, providing no evidence that purchases of robots by firms are motivated by a desire to reduce labor costs. In Column 2, the coefficient for robot investment is negative and significant, again providing no evidence that the use of robots is driven by an increase in the strategic importance of reducing other operating (non-labor) costs, and suggesting instead that implementing such cost reductions becomes less important to the firm when investments in robotics are made. In Column 3, we find a positive and significant coefficient for robot investment with respect to the strategic importance of improving product/service quality. Overall, the results suggest that robot investments are more likely to be motivated by improving the quality of firm output, as opposed to efficiency gains from labor or other operating cost reductions. This also corroborates evidence in the field, especially in manufacturing, that suggests robots are often used to reduce production variance.[16]

[16] https://www.robots.com/faq/why-should-my-company-use-industrial-robots

To complement our findings with respect to employment and firm strategic priorities, we also explore how the roles of managerial and non-managerial employees may also be changing as a consequence of robot adoption. Specifically, we examine how robot investments predict the allocation of decision authority over training activities and the choice of production technology, with results shown in Table 3. Columns 1 through 3 show results for the allocation of authority for training decisions, with the coefficient for robot investment being positive for non-managerial employees and negative for managerial employees, with no significant relationship found for business owners/corporate headquarters. The results provide evidence of decentralization of responsibilities for training from managerial to non-managerial employees within the firm as a response to robot adoption. Columns 4 through 6 show results for the allocation of decision authority over the choice of production technology, with no significant relationship found for non-managerial employees, a negative and significant relationship for managerial employees, and a positive and significant relationship for business owners/corporate headquarters. In contrast with training activities, the results suggest the choice of production technology becomes centralized upwards from managerial employees to business owners/corporate headquarters.

As an additional step, we exploit data on different types of training from the WES survey to examine the nature of training that firms may be investing in due to robot adoption, with results shown in Table 4. As shown in Columns 1 and 2, the coefficients for robot investment are positive and significant for both training in computer hardware as well as professional training, providing evidence that robot investments predict greater investment for both types of training. While the WES does not explicitly define computer hardware or professional training, we include results for a variety of other types of training (Columns 3 through 7), which are distinct responses in the survey. For these other types of training, we find evidence of a negative and significant relationship between robot investment and training for other office and non-office equipment, and no evidence of a relationship for other types of training. Taken together, the results provide evidence that firms invest in some type of training for computer technology as well as for professional roles, which is distinct from the use of other equipment, leadership skills, group decision-making, orientation for new employees, or apprenticeship.

5.2 Robustness checks

Here, we consider several alternative explanations for our results. A primary concern is that because firms choose whether to invest in robots, robot-adopting firms in our sample may be systematically different from firms that do not invest, potentially biasing our estimates. We test the robustness of our results to this issue in two ways. First, we estimate our main regressions using a matched sample created using Coarsened Exact Matching (CEM) (Iacus et al. 2012).[17] Second, we implement an applied Heckman correction method

[17] A more detailed description of our matching procedure is provided in Appendix section S4.

to account for unobservable differences between firms that adopted robots and those that did not in our WES sample (Heckman 1976, Shaver 1998).[18] Using this method, we begin by estimating a probit regression predicting robot adoption with the same independent variables as in our original employment regressions (excluding robot investment), and include as an additional exogenous predictor whether firms report that a lack of information about technologies hinders their ability to adopt them. Residuals from this first stage regression can be interpreted as a firm's likelihood of adopting robots that is unexplained by the covariates, which we include in our employment regressions as a control variable in the form of an inverse Mills ratio. We find similar results for both robustness tests that address selection concerns (see Appendix sections S4 and S8).[19]

Another possible explanation for our results is that employment may simply be expanding due to improved firm performance, which may be correlated with robot investment. To address this concern, we include an additional control for total revenues in our NALMF sample. For our WES sample, since we already control for total revenues, we add a dummy variable equal to one if firms report productivity levels above their main competitors. For both samples, we find similar results with the inclusion of these additional controls (see Appendix section S7). We also note that general changes in performance are unlikely to explain our contrast in results between managers and non-managerial employees, since such effects typically predict similar consequences for all types of employees (Kletzer 1998).

Finally, we examine whether our employment results may be driven by overall investments in IT as opposed to robots. Here we control for IT capital stock in both our NALMF and WES samples. In our NALMF sample, we use a measure of IT capital stock constructed by Statistics Canada that exploits all IT capital investment captured from tax filing records. In the WES sample, we construct an IT capital stock measure based upon reported investments in "computer hardware/software" asked by the survey. We find similar results after including these additional controls (see Appendix section S6).[20]

6 Discussion and conclusion

Utilizing novel data capturing investments in robotics for a population of businesses in a developed economy, we provide the first firm-level evidence of the effect of robot adoption on employment. The results suggest that robots do not affect employment within the firm uniformly, leading to net increases in the headcount of non-managerial employees, but also decreases in the headcount of managerial employees,

[18] Further explanation is provided in Appendix section S8.
[19] We also instrument for robot adoption as an additional robustness check (see Appendix section S8), and find directionally consistent results.
[20] However, we note that because our measures of overall IT capital stock are relatively coarse (using very general category definitions) and may not precisely capture investments in non-robotics AI technologies, measurement error of non-robotics AI investment could potentially affect our results to some degree if correlated with robot investment.

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. Surprisingly, we find evidence of displacement of specific higher cognitive-skilled jobs such as managers that were previously less vulnerable to skill-biased technical change from earlier waves of technology. However, we find no evidence that these job losses are caused by firms desiring to cut labor costs of workers with higher wage premiums, as we find that firms primarily adopt robots to improve product and service quality.

Two possible explanations may account for the negative effect on managerial employment. First, as the capabilities of robotics have advanced substantially over time, automation may extend to managerial work itself such as monitoring and quality assurance, which can directly reduce the demand for managers (Leavitt and Whisler 1958). Second, the nature of managerial work may be the changing, which may indirectly affect managerial employment as the management of workers doing non-routine, cognitively challenging tasks is likely to differ substantively from managing workers doing routine manual tasks (MacDuffie 1997, Parker and Slaughter 1988). Supervisors of routine work may be primarily occupied with ensuring that employees arrive on time, monitoring their work procedures and output, and training them (Helper and Henderson 2014, Taylor 1977). However, when routine work is done by robots, employees are left with less routine and more cognitively complex work. These employees often possess expertise in dealing with problems outside of routine operations, including designing new products and production processes, and can often resolve production problems better than their managers (Helper et al. 2000, Kenny and Florida 1993). As a consequence, managing these employees may entail less monitoring and issuing of direct commands and more advising and empowerment of employees to solve problems (Malone 2003, Mintzberg 1973, Mintzberg 2013). Accordingly, managers may supervise more employees than before, ultimately reducing their headcount (Malone 2003, Malone 2004). While both the direct and indirect effects could contribute to the decline in managerial employment that we have observed, the indirect effect is likely to dominate the direct effect during the time period of our data, given that advances in AI in automating managerial work are still relatively new (Moulds 2018). Over time, as robotics and AI continue to advance rapidly, the direct effect from automating managerial work could further reduce managerial employment, and the nature of managerial work would continue to evolve.

In addition to changes in employment, we also observe that organizational practices change with robot adoption as the allocation of decision authority for certain tasks shifts to different layers of the hierarchy, away from managers. Human resource-related decisions with respect to training are decentralized from managers to non-managerial employees, while the choice of production technology is centralized from managers to business owners and corporate headquarters. This differs from effects of earlier generations of

IT that tended to decentralize decision authority (Acemoglu et al. 2007). However, with robot adoption rapidly increasing in prevalence and capability due to AI advances, we expect that the allocation of decision authority and other complementary work practices are likely to continue to evolve. Those firms that can best match their capabilities and work practices to productive opportunities can benefit substantially from robot investments and develop potential competitive advantages, highlighting the need to understand the different types of complements to robots as a new technology.

Overall, our findings using firm-level data suggest the effect of robots on labor is more nuanced than earlier work predicted and requires a deeper examination beyond the level of industry or region to understand how they are used to complement and substitute labor. While our analysis suggests that robot adoption is associated with using different types of labor, it is also important to examine the associated implication on wages. Our initial evidence suggests that although labor cost reduction is not the primary reason for why firms adopt robots, the reduction in managerial labor that is typically highly compensated compared to non-managerial employees suggests that the average wage is likely to change and possibly decrease as a result of robot adoption. The extent to which wages may change depends on the type of jobs that are created. Similarly, the change in employee types and skills as a result of robot adoption would also lead firms to implement complementary work practices to accommodate the skill change, similar to earlier generations of skill-biased technical change (Bresnahan et al. 2002, Murnane et al. 1999). To understand these effects, the collection of microdata, especially at the firm level, is crucial to examine the implications of robots on employment and wages. Additionally, better data about robot investment and AI more generally across different contexts are critical to understanding whether the effects we observe on employment and work practices can be generalized (Buffington et al. 2018, Frank et al. 2019). While we provide the first firm-level evidence on robotics that we are aware of and show that work practices have already evolved in response to robot technologies, future research should continue to examine how robotics and AI technologies in general affect different firms, occupations, industries, and geographical regions (Felten et al. 2018). Understanding their implications is critical as investments in robots and AI are likely to have profound effects on both employment and organizations.

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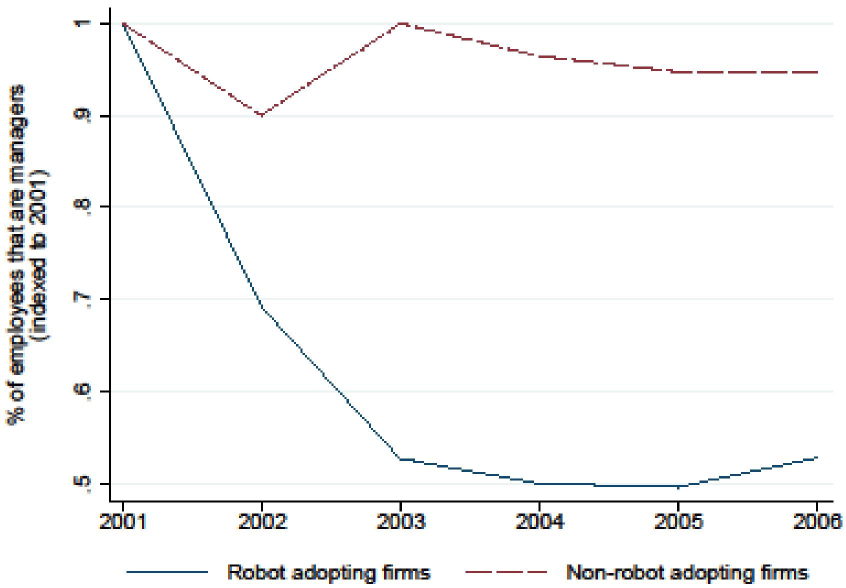
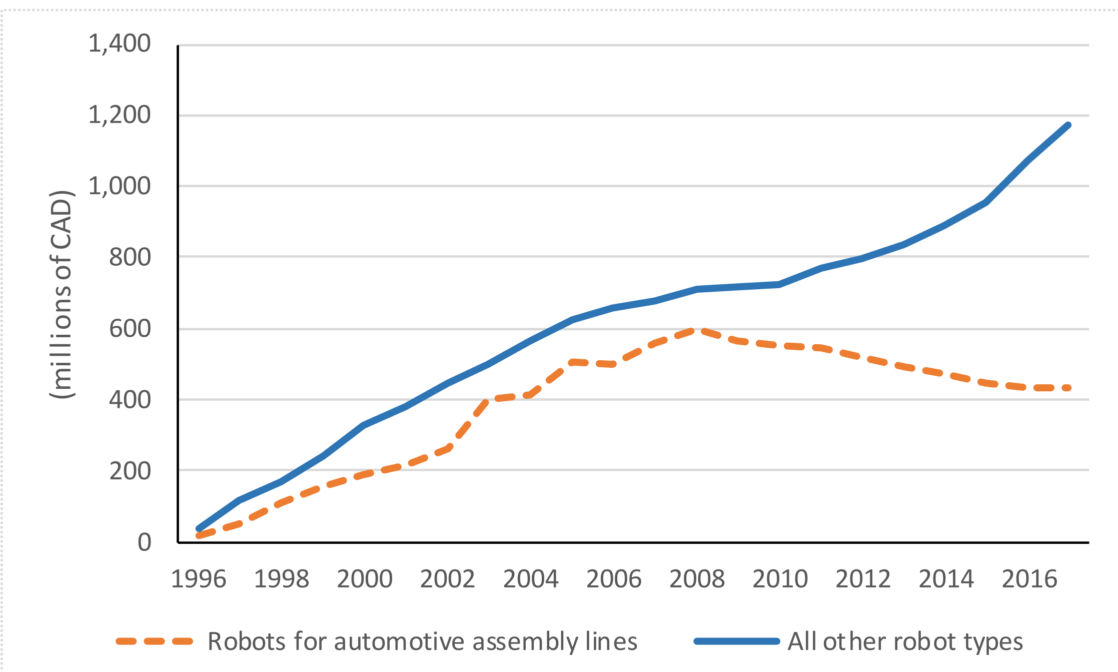
Figure 1. Average percentage of employees at the firm that are managers



Note: For each series, values are normalized by dividing by the value in 2001.

Figure 2. Aggregate robot stock in Canada by robot type, 1996-2017



Note: Robot stock is depreciated using a 12-year useful life assumption, following guidance from the International Federation of Robotics (IFR).

Table 1. Employment regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	NALMF	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	ln(Total employees)	ln(Total managers)	ln(Total non-mgr. employees)	Mgr. Hiring Rate	Nonmgr. Hiring Rate	Mgr. Turnover	Nonmgr. Turnover	Outside mgr. recruitment
ln(Total assets)	0.191***							
	(0.013)							
ln(Total revenues)		0.084***	0.243***	0.005	-0.046	-0.005	-0.049	-0.036
		(0.032)	(0.053)	(0.012)	(0.060)	(0.038)	(0.061)	(0.034)
Multi-unit enterprise	0.139***	0.032	0.046	0.034	0.012	-0.036	-0.034	-0.024
	(0.014)	(0.096)	(0.049)	(0.025)	(0.047)	(0.086)	(0.067)	(0.073)
Unionized		0.168	0.026	0.048	-0.059	-0.081	-0.063*	0.065
		(0.108)	(0.033)	(0.032)	(0.049)	(0.091)	(0.037)	(0.074)
ln(Robot capital stock)	0.007***	-0.080***	0.005**	-0.007***	0.013***	0.044***	0.012***	0.024***
	(0.002)	(0.011)	(0.002)	(0.002)	(0.003)	(0.007)	(0.003)	(0.006)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	929,162	17,449	17,449	17,449	17,449	17,449	17,449	16,522
Adj R-squared	0.92	0.69	0.88	0.19	0.58	0.04	0.30	0.39

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 2. Strategic priority regressions

	(1)	(2)	(3)
	FE	FE	FE
Dependent variable (strategic importance):	Reducing labor costs	Reducing other operating costs	Improving product/service quality
ln(Total revenues)	-0.011	0.049	0.105
	(0.132)	(0.130)	(0.136)
Multi-unit enterprise	-0.199	0.178	-0.201
	(0.121)	(0.176)	(0.173)
Unionized	-0.144	-0.527**	-0.335*
	(0.230)	(0.260)	(0.199)
ln(Robot capital stock)	0.027	-0.117***	0.107***
	(0.036)	(0.013)	(0.013)
Year fixed effects	Y	Y	Y
Organization fixed effects	Y	Y	Y
Observations	8,906	8,906	8,906
Adj R-squared	0.32	0.34	0.38

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Task allocation regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dependent variable:	Training decisions			Choice of Production Technology		
	Non-managerial employees	Managers	Business owners or Corp HQ	Non-managerial employees	Managers	Business owners or Corp HQ
ln(Total revenues)	-0.001	0.000	0.019	0.002	0.061	-0.049
	(0.018)	(0.084)	(0.084)	(0.007)	(0.067)	(0.070)
Multi-unit enterprise	0.010	-0.022	0.107	-0.008	0.039	0.069
	(0.013)	(0.077)	(0.102)	(0.012)	(0.065)	(0.095)
Unionized	-0.041	-0.071	-0.141	-0.001	0.232	-0.527***
	(0.139)	(0.212)	(0.174)	(0.004)	(0.190)	(0.182)
ln(Robot capital stock)	0.074***	-0.077***	0.004	-0.000	-0.069***	0.075***
	(0.011)	(0.011)	(0.003)	(0.000)	(0.015)	(0.013)
Year fixed effects	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y
Observations	6,173	6,173	6,173	6,173	6,173	6,173
Adj R-squared	0.29	0.33	0.39	0.30	0.31	0.33

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Training regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Dependent variable (type of training):	Computer hardware	Professional	Other office and non-office equipment	Team-building, leadership, comm.	Group decision-making or problem-solving	Orientation	Apprentice-ship
ln(Total revenues)	0.042	0.065	0.027	0.052	0.032	0.059	0.018
	(0.032)	(0.044)	(0.031)	(0.036)	(0.029)	(0.050)	(0.037)
Multi-unit enterprise	-0.003	-0.076	0.031	0.164*	0.065	-0.069	0.036
	(0.034)	(0.054)	(0.033)	(0.094)	(0.044)	(0.075)	(0.065)
Unionized	0.014	-0.014	-0.002	-0.150*	0.028	-0.060	-0.014
	(0.055)	(0.063)	(0.066)	(0.077)	(0.034)	(0.058)	(0.039)
ln(Robot capital stock)	0.020***	0.034***	-0.034***	0.003	-0.000	-0.002	0.000
	(0.003)	(0.005)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	17,449	17,449	17,449	17,449	17,449	17,449	17,449
Adj R-squared	0.38	0.47	0.34	0.45	0.38	0.47	0.55

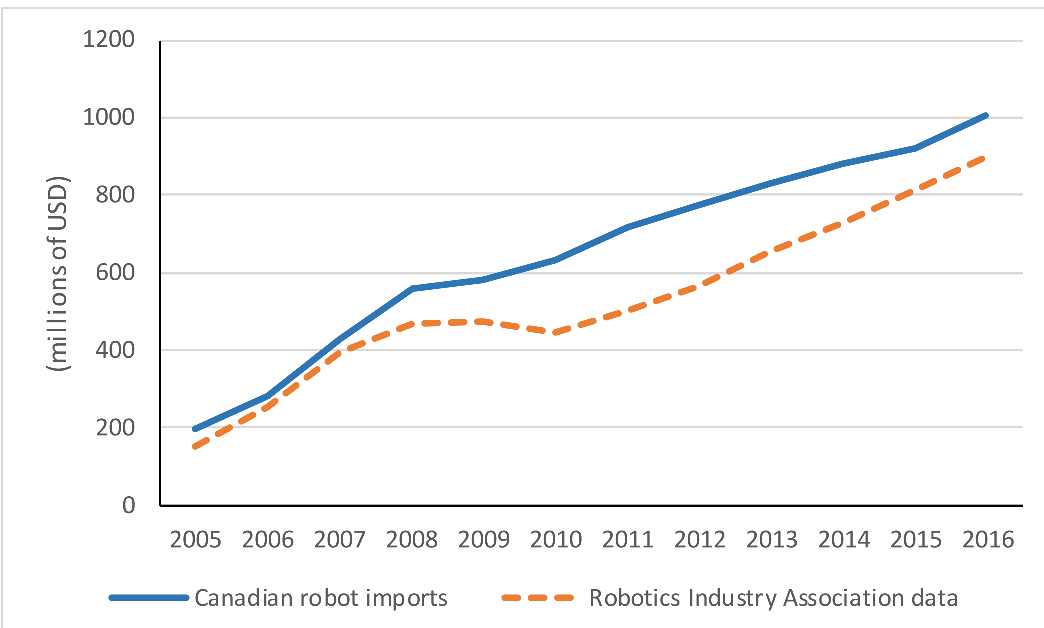
Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Appendix: The Employment Consequences of Robots: Firm-level Evidence

S1 Comparison to Robotic Industries Associaton (RIA) data

Below is a graphical comparison of the value of robot stock calculated from imports into Canada compared to the total value of robot stock calculated from data provided by the Robotic Industries Association (RIA) for the years 2005-2016.[1] We note that imports of robots into Canada should generally be a more comprehensive measure of total robot purchases, since all purchases of robots from abroad are in principle captured by the Canadian Border Services Agency (CBSA). By contrast, the RIA relies upon self-reported information provided by its members, who are a subset of all purchasers within Canada and all sellers of robots to Canada, which is likely to include transactions of the largest buyers and sellers of robots. However, both follow a similar pattern regarding overall robot investment.

Figure A1. Comparison of Canadian robot imports to Robotic Industries Associaton (RIA) data



Note: Robot stock is depreciated using a 12 year useful life assumption, following guidance from the International Federation of Robotics (IFR).

[1] The RIA reports values in US dollars, so for comparability we present the import data in US dollars here.

However, for the years 2009 and 2010, there are significant inconsistencies between shipment data reported for North America by the RIA and International Federation of Robotics (IFR), the two main industry associations that report robot purchases for North America.[234] Although the IFR regularly uses data provided by the RIA and possesses its data for earlier years, we note that the IFR only reports country-level data for North America beginning in 2011, after the 2009-2010 period. If we remove these years and separately graph the comparison from 2005-2008 and 2011-2016, the value of robot stock is much more similar from the two data sources, as shown in Figures A2 and A3 below.

Figure A2. Comparison of Canadian robot imports to Robotic Industries Associaton (RIA) data, 2005-2008

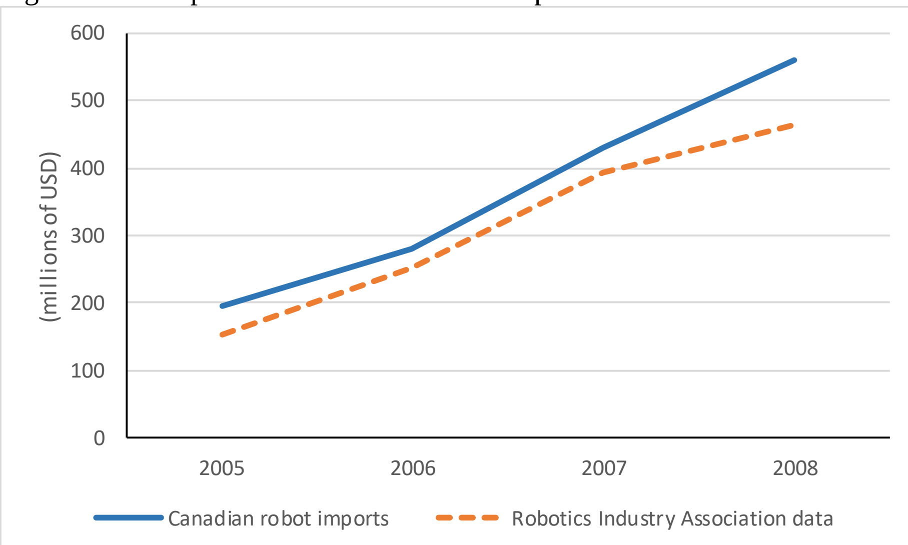
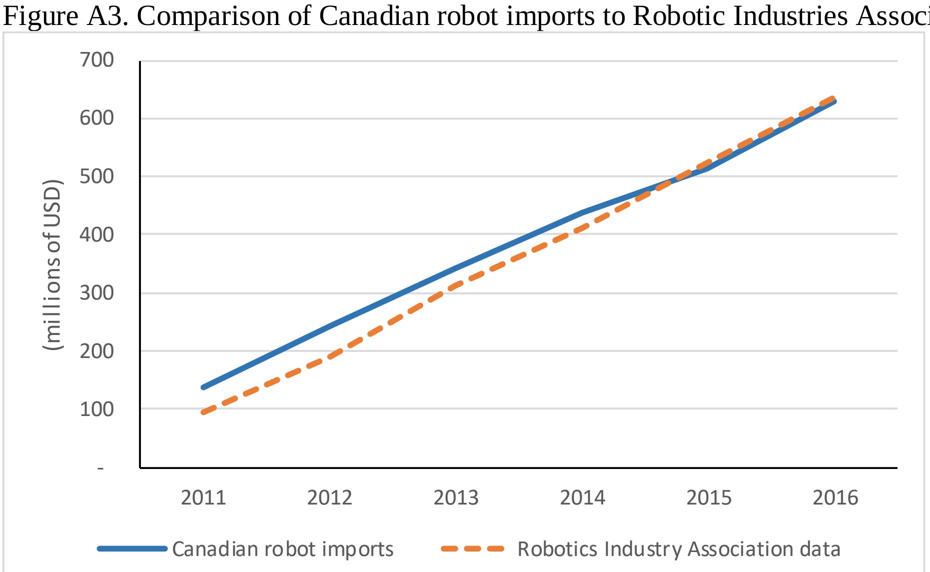


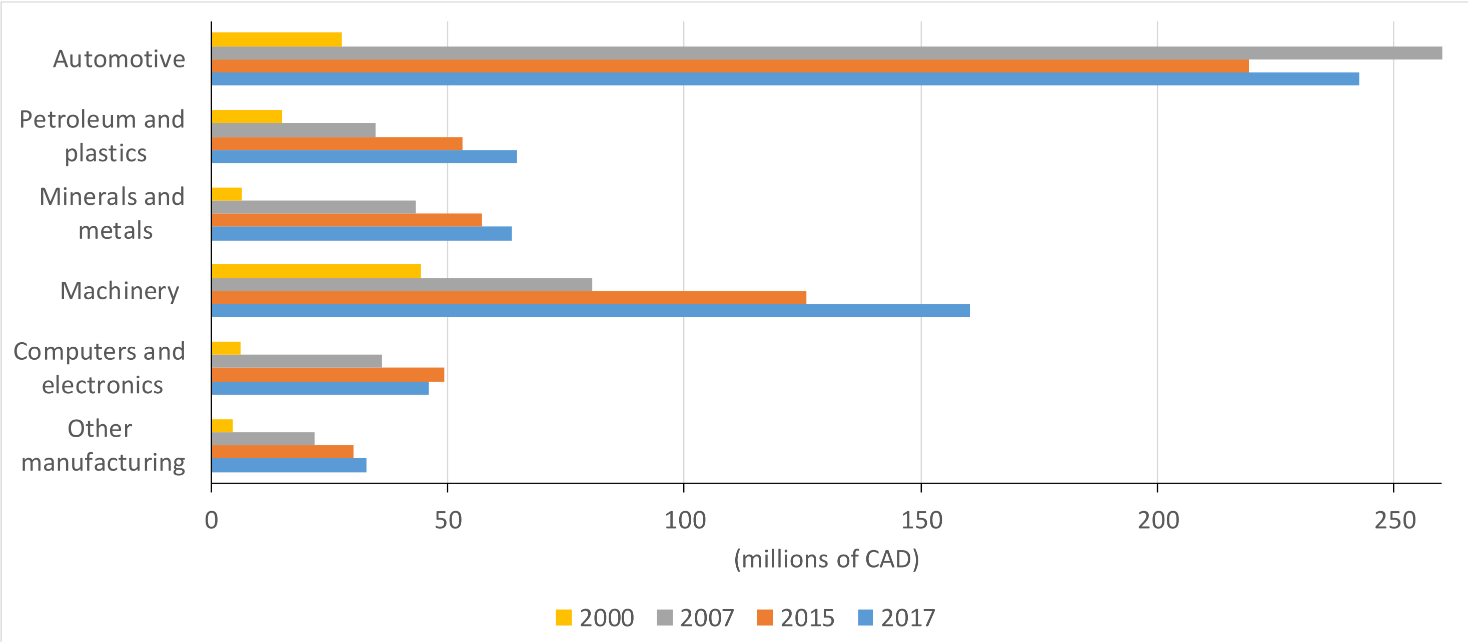
Figure A3. Comparison of Canadian robot imports to Robotic Industries Associaton (RIA) data, 2011-2016



[2] For the years 2005-2008 and 2011-2015, the IFR reports consistently greater shipments in each year, being an average of 26% higher with a standard deviation of 7%. The consistently higher numbers are to be expected, since the IFR draws upon more data sources to augment data it regularly receives from the RIA. However, shipments reported by the IFR were 19% lower in 2009 and 459% higher in 2010.
[3] The RIA is the industry association for North America; the IFR is the global industry association.
[4] The IFR does not report total values of robot purchases for Canada, so cannot be used for comparison with our main measure of robot investment.

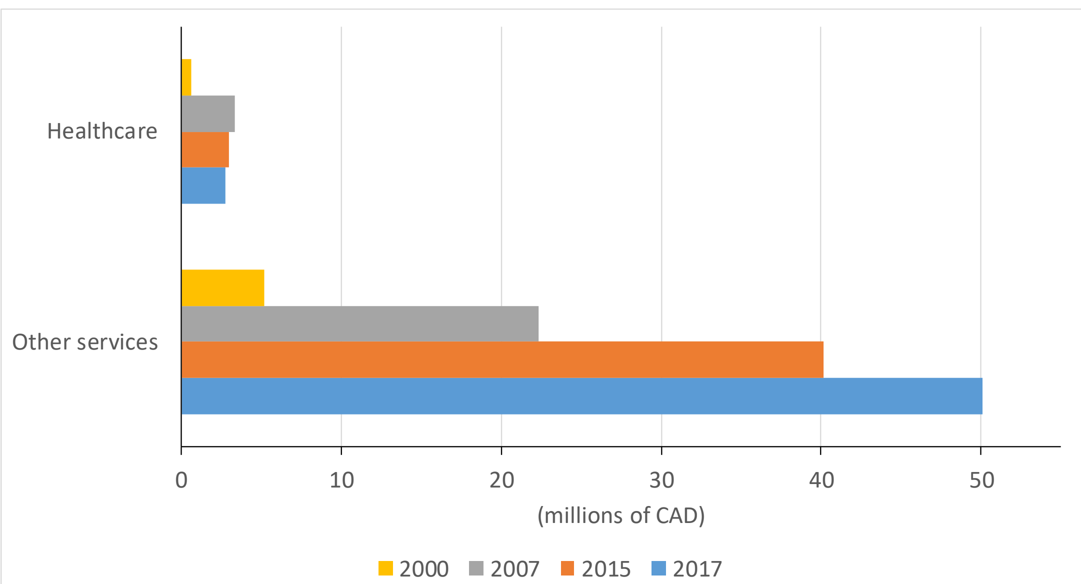
S2 Robot investment by industry

Figure A4. Total robot stock attributable by manufacturing sector, 2000-2017



Note: Automotive sector includes NAICS codes 3361, 3362, 3363. Petroleum and plastics includes 324, 325, and 326. Minerals and metals includes 327, 331, and 332. Machinery includes 333. Computers and electronics includes 334 and 335. Other manufacturing includes all other NAICS codes in the manufacturing sector.

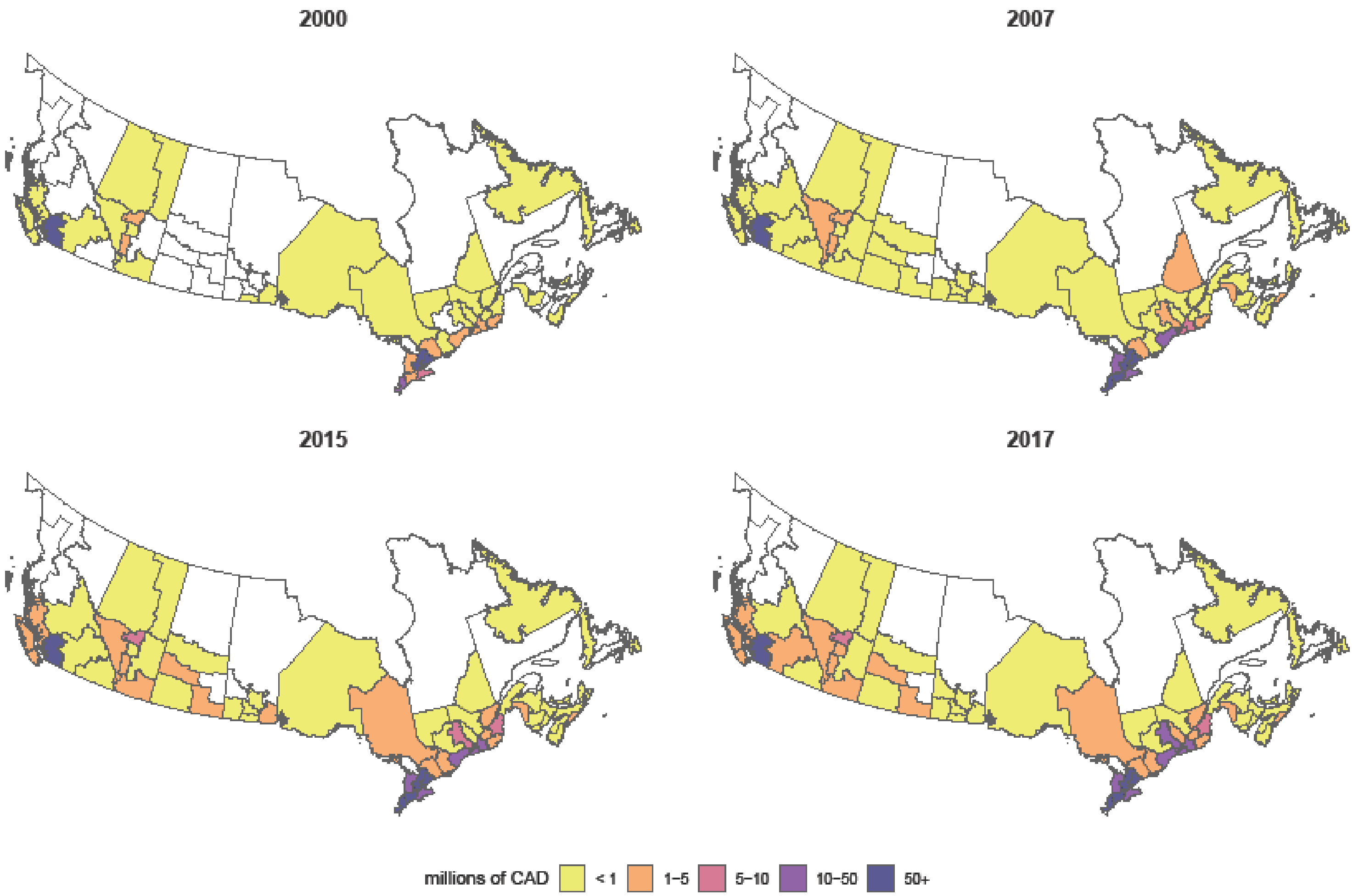
Figure A5. Total robot stock attributable by services sector, 2000-2017



Note: Healthcare includes NAICS code 62. Other services includes all other NAICS codes outside the manufacturing sector, healthcare, and wholesale trade.

S3 Robot investment by geographic region

Figure A6. Total robot stock attributable by economic region[5]: Canada



[5] Economic regions are groupings of census divisons created by Statistics Canada as a standard geographic unit for analysis of regional economic activity.

Figure A7. Total robot stock attributable by economic region: Toronto, Montreal, and surrounding areas

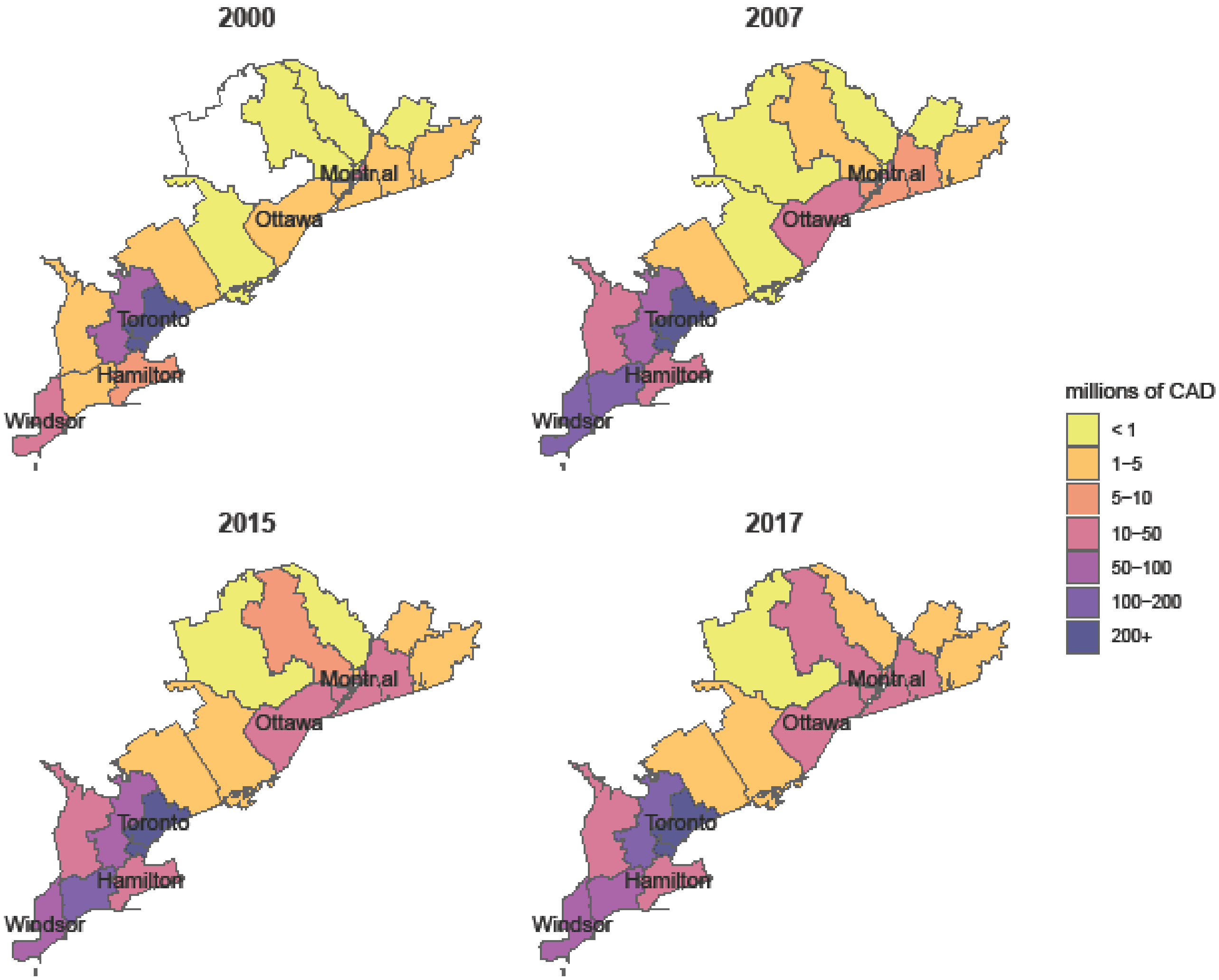
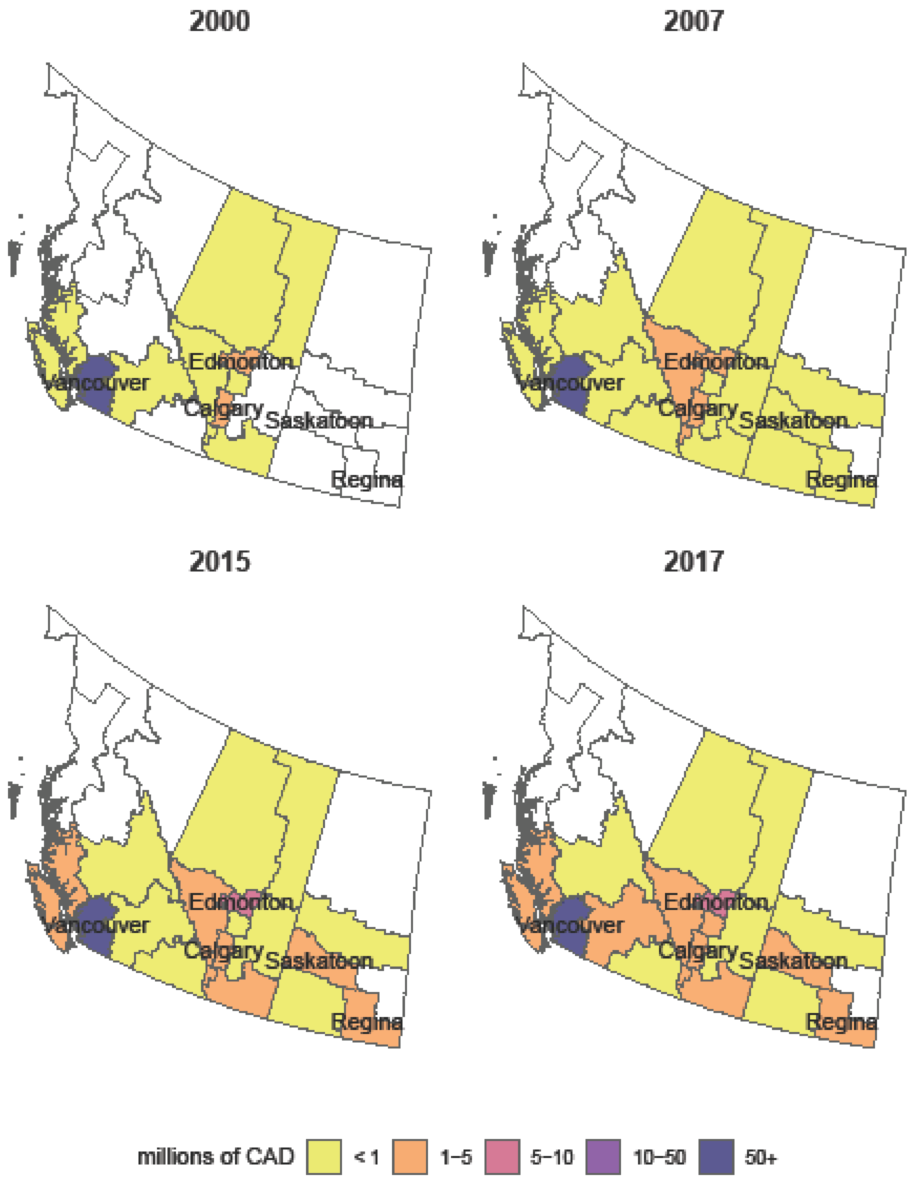


Figure A8. Total robot stock attributable by economic region: British Columbia, Alberta, and Saskatchewan



S4 Matched sample analysis

To address concerns of selection bias in robot adoption that may affect our coefficient estimates, we estimate our main regressions using a matched sample created using Coarsened Exact Matching (CEM) (Iacus et al. 2012). For our NALMF sample, we match firms in our sample that adopt robots to non-robot adopting firms by industry (measured by 4 digit NAICS code), year, province, whether the firm is part of a multi-unit enterprise, total assets, firm age, average annual earnings of the firm's employees, and capital stock. Matching is done exactly by industry, year, province, and multi-unit status, with coarsening allowed for the other variables. For our WES sample, matching is done exactly by industry, year, and province, with coarsening allowed for total revenues, age of the organization, average annual employee earnings, and capital stock.[6,7] As shown below in Table A9, overall we find similar results, with the effect of robot investment on total employment in the NALMF sample (Column 1) increasing substantially compared to our original estimates (0.007 to 0.015), and the considerably smaller sample size reducing statistical power in some cases but showing similar point estimates. Tables A10-A12 also show similar results.

Table A9. Employment regressions, matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	NALMF	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	ln(Total employees)	ln(Total managers)	ln(Total non-mgr. employees)	Mgr. Hiring Rate	Nonmgr. Hiring Rate	Mgr. Turnover	Nonmgr. Turnover	Outside mgr. recruitment
ln(Total assets)	0.215***							
	(0.037)							
ln(Total revenues)		0.013	0.367***	0.022	0.047**	0.027	0.199***	0.028
		(0.166)	(0.087)	(0.013)	(0.020)	(0.064)	(0.059)	(0.058)
Multi-unit enterprise	0.144***	0.313	0.002	-0.083	0.190	0.142	-0.172	-0.114*
	(0.022)	(0.430)	(0.044)	(0.054)	(0.137)	(0.148)	(0.169)	(0.068)
Unionized		0.594	-0.151***	-0.017	-0.067*	-0.320	1.013**	0.004
		(0.475)	(0.050)	(0.020)	(0.039)	(0.196)	(0.432)	(0.270)
ln(Robot capital stock)	0.015**	-0.072***	0.004*	-0.008***	0.012*	0.066**	0.017*	0.040***
	(0.006)	(0.015)	(0.002)	(0.002)	(0.007)	(0.027)	(0.009)	(0.013)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	41,399	1,742	1,742	1,742	1,742	1,742	1,742	1,652
Adj R-squared	0.94	0.76	0.94	0.13	0.18	0.09	0.19	0.29

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[6] In the WES data, the three Atlantic provinces of Newfoundland, New Brunswick, and Nova Scotia were combined by Statistics Canada into a single geographic region.
[7] Capital stock data for the WES sample was provided by the Capital and Investment Program (CIP), a dataset maintained by Statistics Canada.

Table A10. Strategic priority regressions, matched sample

	(1)	(2)	(3)
	FE	FE	FE
Dependent variable (strategic importance):	Reducing labor costs	Reducing other operating costs	Improving product/service quality
ln(Total revenues)	0.136	-0.561	0.203
	(0.189)	(0.358)	(0.389)
Multi-unit enterprise	0.230	0.202	0.713
	(0.265)	(0.568)	(0.465)
Unionized	-0.753	-0.731***	0.065
	(0.637)	(0.204)	(0.324)
ln(Robot capital stock)	0.003	-0.163***	0.108***
	(0.043)	(0.017)	(0.031)
Year fixed effects	Y	Y	Y
Organization fixed effects	Y	Y	Y
Observations	887	887	887
Adj R-squared	0.45	0.48	0.20

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table A11. Task allocation regressions, matched sample

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dependent variable:	Training decisions			Choice of Production Technology		
	Non-managerial employees	Managers	Business owners or Corp HQ	Non-managerial employees	Managers	Business owners or Corp HQ
ln(Total revenues)	-0.018	-0.007	0.284	0.007	-0.139	0.364
	(0.042)	(0.057)	(0.229)	(0.032)	(0.104)	(0.254)
Multi-unit enterprise	-0.031	-0.199	0.610*	0.002	-0.392	0.765***
	(0.090)	(0.600)	(0.359)	(0.015)	(0.368)	(0.284)
Unionized	0.014	-0.025	0.015	0.009	0.859***	-0.870***
	(0.014)	(0.024)	(0.101)	(0.009)	(0.090)	(0.070)
ln(Robot capital stock)	0.076***	-0.080***	0.012	0.002	-0.079***	0.085***
	(0.013)	(0.012)	(0.009)	(0.001)	(0.012)	(0.017)
Year fixed effects	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y
Observations	630	630	630	630	630	630
Adj R-squared	0.84	0.73	0.75	0.07	0.51	0.51

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table A12. Training regressions, matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Dependent variable (type of training):	Computer hardware	Professional	Other office and non-office equipment	Team-building, leadership, comm.	Group decision-making or problem-solving	Orientation	Apprentice-ship
ln(Total revenues)	0.118**	0.147*	0.046	0.121	0.124	-0.101	0.078
	(0.054)	(0.081)	(0.076)	(0.089)	(0.079)	(0.141)	(0.074)
Multi-unit enterprise	-0.033	0.099	0.105	0.066	0.156	-0.140***	-0.078
	(0.035)	(0.163)	(0.127)	(0.146)	(0.145)	(0.046)	(0.164)
Unionized	0.073*	0.079*	-0.311**	-0.217**	0.011	-0.194	0.024
	(0.044)	(0.046)	(0.152)	(0.086)	(0.021)	(0.223)	(0.037)
ln(Robot capital stock)	0.019***	0.023***	-0.054***	0.003	0.007	-0.018	0.005
	(0.006)	(0.005)	(0.010)	(0.007)	(0.008)	(0.011)	(0.005)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	1,742	1,742	1,742	1,742	1,742	1,742	1,742
Adj R-squared	0.43	0.45	0.37	0.41	0.39	0.47	0.59

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

S5 Addressing robots purchased from wholesalers and other resellers

In addition to end-using firms that purchase robots from abroad, wholesalers and value-added resellers within Canada also import robots with the intention to resell them to other firms. For these transactions, wholesalers and resellers are listed as the importing firm (identified by their NAICS code), but the import data do not capture the identity of the firm purchasing robots from these resellers.[8] In the context of our data, the robot investments of these firms would be understated, potentially biasing our coefficient estimates.

To address this concern, we exploit data on trade shipments between firms within Canada captured in the Surface Transportation File (STF), a dataset maintained by Statistics Canada. The data captures all shipments by truck and rail carriers between businesses within Canada during the years 2004-2012, recorded at the zip code level. Zip codes are also recorded in the NALMF data, allowing us to merge the two datasets.[9] To explore whether robot purchases from wholesalers and other resellers within Canada may be affecting our results, we identify the zip code of all reselling firms in our sample that imported robots, and remove all firms located in zip codes that receive shipments from the zip code of the resellers. This effectively removes potential purchasing firms from resellers in our data, although they cannot be precisely identified. The results below are for our baseline employment regression for our NALMF sample using only the years 2004-2012 (Columns 1 and 2), and comparing to the sample with these potential purchasers from robot wholesalers removed (Columns 3 and 4). As the results show, we obtain similar findings.[10]

Table A13. Potential purchasers from robot wholesalers removed

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Dataset:	NALMF	NALMF	NALMF	NALMF
	Full sample 2004-2012	Full sample 2004-2012	Wholesaler recipient zipcodes	Wholesaler recipient zipcodes
Dependent variable:	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)
ln(Total assets)	0.376***	0.189***	0.375***	0.189***
	(0.014)	(0.013)	(0.014)	(0.013)
Multi-unit enterprise	0.487***	0.113***	0.489***	0.114***
	(0.030)	(0.019)	(0.030)	(0.019)
ln(Robot capital stock)	0.031***	0.004*	0.031***	0.004*
	(0.004)	(0.002)	(0.004)	(0.002)
Industry fixed effects	Y	N	Y	N
Region fixed effects	Y	N	Y	N
Year fixed effects	Y	Y	Y	Y
Organization fixed effects	N	Y	N	Y
Observations	564,365	564,365	554,496	554,496
Adj R-squared	0.55	0.94	0.55	0.94

Standard errors in parentheses, clustered by industry. *** p<0.01, ** p<0.05, * p<0.1

[8] The following NAICS codes identify wholesalers and value-added resellers: 41, 5413, 5414, 5415, and 5416.
[9] The WES data does not contain zip codes.
[10] Robot capital stock coefficient in Columns 2 and 4 has a p-value of 6%

S6 Controlling for IT investment

To address the concern that our employment results may be driven by overall investments in IT as opposed to robot investment, here we include an additional control variable for IT capital stock in both our NALMF and WES samples. In our NALMF sample, we use a measure of IT capital stock constructed by Statistics Canada that exploits all IT capital investment captured from tax filing records. In the WES sample, we construct an IT capital stock measure based upon reported investments in "computer hardware/software" asked by the survey.[11] As shown below in Columns 1 through 8, we obtain similar results.

Table A14. Employment regressions IT capital stock control variable added for NALMF and WES samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	NALMF	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	ln(Total employees)	ln(Total managers)	ln(Total non-mgr. employees)	Mgr. Hiring Rate	Nonmgr. Hiring Rate	Mgr. Turnover	Nonmgr. Turnover	Outside mgr. recruitment
ln(Total assets)	0.196***							
	(0.011)							
ln(Total revenues)		0.083***	0.243***	0.005	-0.045	-0.004	-0.050	-0.038
		(0.032)	(0.052)	(0.012)	(0.060)	(0.038)	(0.061)	(0.034)
Multi-unit enterprise	0.128***	0.033	0.046	0.034	0.012	-0.037	-0.033	-0.024
	(0.012)	(0.095)	(0.049)	(0.025)	(0.047)	(0.086)	(0.066)	(0.072)
Unionized		0.166	0.026	0.048	-0.058	-0.080	-0.065*	0.063
		(0.107)	(0.033)	(0.032)	(0.048)	(0.090)	(0.037)	(0.074)
ln(Robot capital stock)	0.007***	-0.080***	0.004**	-0.007***	0.013***	0.044***	0.012***	0.025***
	(0.002)	(0.011)	(0.002)	(0.002)	(0.003)	(0.007)	(0.003)	(0.006)
ln(IT capital stock)	0.009***	0.002	0.002*	0.001	0.003*	-0.001	0.002*	0.004
	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	901,123	17,442	17,442	17,442	17,442	17,442	17,442	16,519
Adj R-squared	0.92	0.69	0.88	0.19	0.58	0.04	0.30	0.39

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[11] We use a useful life assumption of 5 years for IT investment, following Baldwin et al. (2015).

S7 Controlling for general improvements in firm performance

An alternative explanation for our results is that firms that are generally expanding employment due to improved performance may be more likely to adopt robots, potentially introducting omitted variable bias in our estimates. To address this concern, we include an additional control for total revenues in our NALMF sample. For our WES sample, since we already control for total revenues, we add a dummy variable equal to one if firms report productivity levels above their main competitors to capture relative as well as absolute performance.[12] As shown below in Columns 1 through 8, we find similar results after including these additional controls.

Table A15. Employment regressions selection control variable added for WES sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	NALMF	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	ln(Total employees)	ln(Total managers)	ln(Total non-mgr. employees)	Mgr. Hiring Rate	Nonmgr. Hiring Rate	Mgr. Turnover	Nonmgr. Turnover	Outside mgr. recruitment
ln(Total assets)	0.052***							
	(0.007)							
ln(Total revenues)	0.393***	0.084***	0.242***	0.005	-0.046	-0.005	-0.048	-0.036
	(0.019)	(0.032)	(0.053)	(0.012)	(0.060)	(0.038)	(0.061)	(0.034)
Multi-unit enterprise	0.092***	0.032	0.045	0.034	0.012	-0.036	-0.032	-0.024
	(0.010)	(0.096)	(0.049)	(0.025)	(0.047)	(0.084)	(0.066)	(0.073)
Unionized		0.167	0.028	0.049	-0.058	-0.083	-0.065*	0.066
		(0.108)	(0.031)	(0.032)	(0.049)	(0.090)	(0.035)	(0.072)
ln(Robot capital stock)	0.004***	-0.080***	0.006**	-0.007***	0.014***	0.043***	0.011***	0.025***
	(0.001)	(0.011)	(0.002)	(0.002)	(0.003)	(0.006)	(0.003)	(0.006)
Productivity above main competitors		-0.007	0.044	0.003	0.010	-0.027	-0.054**	0.031
		(0.028)	(0.029)	(0.007)	(0.019)	(0.026)	(0.027)	(0.032)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	929,162	17,449	17,449	17,449	17,449	17,449	17,449	16,522
Adj R-squared	0.93	0.69	0.88	0.19	0.58	0.04	0.30	0.39

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[12] The survey specifically asks "compared to your main competitors, how would you rate your workplace performance?" with "productivity" listed as a performance measure.

S8 Additional selection robustness checks

In addition to the matching exercise presented earlier, we implement an applied Heckman correction method to account for unobservable differences between firms that adopted robots and those that did not (Heckman 1976, Shaver 1998). Using this method, we begin by estimating a probit regression predicting robot adoption with the same independent variables as in our original employment regressions (excluding robot investment), and include as an additional exogenous predictor whether firms report that a lack of information about technologies hinders their ability to adopt them. Specifically, the survey asks whether factors "impede the implementation of new technology in your workplace" with "lack of information on technologies" as a possible response. Residuals from this first stage regression (shown below in Column 1) can be interpreted as a firm's likelihood of adopting robots that is unexplained by the covariates, which we include in our employment regressions as a control variable in the form of an inverse Mills ratio. As shown in Columns 2 through 8, we obtain similar results. For our NALMF sample, we also instrument for robot adoption by multiplying the percentage of workers in each 4-digit NAICS code in occupations with high "manual dexterity" and relatively low "verbal ability" in 2000 by the inverse of the median price per robot in Canada for each year.[13] As robot prices decrease over time, those industries with more workers similar to the capabilities of robots (who possess these attributes) are presumably more likely to adopt them. In this additional test, we find directionally consistent results.

Table A16. Employment regressions with selection control variable added for WES sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	WES	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	Robot adoption	ln(Total managers)	ln(Total non-mgr. employees)	Mgr. Hiring Rate	Nonmgr. Hiring Rate	Mgr. Turnover	Nonmgr. Turnover	Outside mgr. recruitment
ln(Total revenues)	-0.028	0.083***	0.242***	0.005	-0.048	-0.005	-0.050	-0.037
	(0.051)	(0.032)	(0.052)	(0.012)	(0.060)	(0.038)	(0.061)	(0.034)
Multi-unit enterprise	-0.076	0.030	0.046	0.034	0.007	-0.037	-0.036	-0.028
	(0.267)	(0.096)	(0.049)	(0.025)	(0.047)	(0.086)	(0.067)	(0.072)
Unionized	0.342	0.185*	0.028	0.048	-0.021	-0.079	-0.046	0.092
	(0.306)	(0.109)	(0.034)	(0.033)	(0.058)	(0.090)	(0.045)	(0.077)
ln(Robot capital stock)		-0.080***	0.005**	-0.007***	0.013***	0.044***	0.012***	0.024***
		(0.011)	(0.002)	(0.002)	(0.003)	(0.007)	(0.003)	(0.006)
Lack of information on tech.	-0.865***							
	(0.275)							
Probit inverse mills ratio		0.049	0.006	-0.001	0.107	0.007	0.046	0.075*
		(0.046)	(0.020)	(0.009)	(0.076)	(0.047)	(0.054)	(0.040)
Industry fixed effects	Y	N	N	N	N	N	N	N
Region fixed effects	Y	N	N	N	N	N	N	N
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	N	Y	Y	Y	Y	Y	Y	Y
Observations	17,449	17,449	17,449	17,449	17,449	17,449	17,449	17,449
pseudo-R-squared	0.18							
log likelihood	-8,896							
Adj R-squared		0.69	0.88	0.19	0.58	0.04	0.30	0.39

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[13] We use data and measures from the Labour Force Survey (LFS) and Career Handbook 2003, maintained by Statistics Canada and Employment and Social Development Canada respectively.

S9 Regression results by industry

Here, we show the results of our main employment specification for our NALMF sample (also including OLS) by industries in our data, using the same industry definitions as in section S2. Overall, we find results consistent with our original baseline regressions, although the substantially smaller sample size and/or lower prevalence of robot adoption reduces statistical power in some cases for our firm fixed effect specifications.

Table A17. Employment regressions by industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
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)
ln(Total assets)	0.461***	0.148***	0.433***	0.205***	0.459***	0.257***	0.502***	0.301***
	(0.026)	(0.040)	(0.010)	(0.029)	(0.008)	(0.019)	(0.010)	(0.030)
Multi-unit enterprise	0.395***	0.064	0.416***	0.109***	0.329***	0.075***	0.297***	0.121***
	(0.079)	(0.044)	(0.035)	(0.026)	(0.029)	(0.020)	(0.039)	(0.033)
ln(Robot capital stock)	0.021***	0.024***	0.035***	0.009***	0.017***	0.012***	0.019***	0.007**
	(0.008)	(0.005)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Industry fixed effects	Y	N	Y	N	Y	N	Y	N
Region fixed effects	Y	N	Y	N	Y	N	Y	N
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	N	Y	N	Y	N	Y	N	Y
Observations	6,655	6,655	21,997	21,997	50,750	50,750	23,981	23,981
Adj R-squared	0.72	0.95	0.70	0.95	0.65	0.93	0.67	0.93

Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Table A18. Employment regressions by industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Industry:	Computer and electronic manufacturing	Computer and electronic manufacturing	Other manufacturing	Other manufacturing	Healthcare	Healthcare	Other services	Other 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)
ln(Total assets)	0.445***	0.242***	0.415***	0.209***	0.201***	0.124***	0.325***	0.174***
	(0.013)	(0.034)	(0.005)	(0.013)	(0.012)	(0.015)	(0.002)	(0.004)
Multi-unit enterprise	0.408***	0.151***	0.517***	0.118***	0.982***	0.158	0.538***	0.148***
	(0.059)	(0.039)	(0.022)	(0.019)	(0.129)	(0.112)	(0.010)	(0.008)
ln(Robot capital stock)	0.026***	0.005	0.020***	0.002	0.061***	0.118***	0.026***	0.008*
	(0.005)	(0.004)	(0.005)	(0.003)	(0.016)	(0.002)	(0.005)	(0.004)
Industry fixed effects	Y	N	Y	N	Y	N	Y	N
Region fixed effects	Y	N	Y	N	Y	N	Y	N
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	N	Y	N	Y	N	Y	N	Y
Observations	13,371	13,371	103,673	103,673	12,165	12,165	696,570	696,570
Adj R-squared	0.67	0.93	0.63	0.93	0.41	0.92	0.47	0.91

Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

S10 Standard errors clustered by geographic region

While the relatively small number of provinces in Canada decreases the reliability of standard errors (Cameron and Miller 2015), for robustness we show results for our key regressions here with standard errors clustered by province.[14][15] As Tables A19 and A20 show, we find similar results.

Table A19. Employment, strategic priority, and training regressions clustered by province

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Dataset:	NALMF	WES	WES	WES	WES	WES	WES	WES
Dependent variable:	ln(Total employees)	ln(Total managers)	ln(Total non-mgr. employees)	Reducing labor costs	Reducing other operating costs	Improving product/service quality	Computer hardware training	Professional training
ln(Total assets)	0.191***							
	(0.008)							
ln(Total revenues)		0.084**	0.243***	-0.011	0.049	0.105	0.042	0.065**
		(0.029)	(0.028)	(0.141)	(0.075)	(0.131)	(0.028)	(0.031)
Multi-unit enterprise	0.139***	0.032	0.046	-0.199*	0.178	-0.201	-0.003	-0.076*
	(0.010)	(0.097)	(0.060)	(0.108)	(0.144)	(0.140)	(0.035)	(0.046)
Unionized		0.168	0.026	-0.144	-0.527*	-0.335**	0.014	-0.014
		(0.168)	(0.028)	(0.253)	(0.279)	(0.124)	(0.041)	(0.051)
ln(Robot capital stock)	0.007***	-0.080**	0.005**	0.027	-0.117**	0.107***	0.020**	0.034**
	(0.002)	(0.028)	(0.002)	(0.050)	(0.043)	(0.021)	(0.010)	(0.014)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	929,162	17,449	17,449	8,906	8,906	8,906	17,449	17,449
Adj R-squared	0.92	0.69	0.88	0.32	0.34	0.38	0.38	0.47

Standard errors in parentheses, clustered by province. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[14] In the WES data, the three Atlantic provinces of Newfoundland, New Brunswick, and Nova Scotia were combined by Statistics Canada into a single geographic region.
[15] For brevity, we refer to both provinces and territories here simply as provinces.

Table A20. Task allocation regressions clustered by province

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dependent variable:	Training decisions			Choice of Production Technology		
	Non-managerial employees	Managers	Business owners or Corp HQ	Non-managerial employees	Managers	Business owners or Corp HQ
ln(Total revenues)	-0.001	0.000	0.019	0.002	0.061	-0.049
	(0.018)	(0.028)	(0.022)	(0.004)	(0.038)	(0.051)
Multi-unit enterprise	0.010	-0.022	0.107	-0.008	0.039	0.069
	(0.020)	(0.079)	(0.117)	(0.011)	(0.092)	(0.121)
Unionized	-0.041	-0.071	-0.141	-0.001	0.232	-0.527*
	(0.146)	(0.240)	(0.177)	(0.005)	(0.193)	(0.219)
ln(Robot capital stock)	0.074***	-0.077***	0.004	-0.000	-0.069***	0.075***
	(0.011)	(0.008)	(0.003)	(0.000)	(0.013)	(0.011)
Year fixed effects	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y
Observations	6,173	6,173	6,173	6,173	6,173	6,173
Adj R-squared	0.29	0.33	0.39	0.30	0.31	0.33

Standard errors in parentheses, clustered by province. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

S11 Productivity

As an additional test, we examine whether investments in robotics lead to increases in firm productivity.[16] As Columns 2 through 4 in the table below show, the coefficient for robot capital stock is positive and significant, providing evidence that robots do in fact increase firm productivity.

Table A21. Productivity regressions

	(1)	(2)	(3)	(4)
Dependent variable: ln(Total revenues)	OLS	OLS	FE	Levinsohn-Petrin
ln(Materials)	0.411***	0.411***	0.235***	0.265***
	(0.024)	(0.024)	(0.021)	(0.003)
ln(Labor)	0.445***	0.443***	0.310***	0.312***
	(0.025)	(0.025)	(0.023)	(0.004)
ln(Non-Robot capital stock)	0.226***	0.224***	0.279***	0.220***
	(0.041)	(0.041)	(0.019)	(0.005)
ln(Robot capital stock)		0.019***	0.007***	0.008***
		(0.003)	(0.001)	(0.002)
Industry fixed effects	Y	Y	N	
Region fixed effects	Y	Y	N	
Year fixed effects	Y	Y	Y	
Organization fixed effects	N	N	Y	
Observations	929,162	929,162	929,162	929,162
Adj R-squared	0.87	0.87	0.97	

Standard errors in parentheses, clustered by industry. Standard errors for Levinsohn-Petrin estimation are bootstrapped with 100 repetitions. *** p<0.01, ** p<0.05, * p<0.1

[16] Logged materials, labor, and capital stock were calculated using measures of each variable provided in the NALMF data.

S12 Descriptive statistics and correlation tables

Table A22. Descriptive statistics, NALMF sample

	Variable	Mean	σ	1	2	3	4
1.	ln(Total employees)	3.23	0.76	1.00			
2.	ln(Total assets)	14.13	1.55	0.62	1.00		
3.	Multi-unit enterprise	0.05	0.22	0.36	0.30	1.00	
4.	ln(Robot capital stock)	0.07	0.89	0.16	0.15	0.08	1.00
	N = 929,162						

Table A23. Descriptive statistics, WES sample

	Variable	Mean	σ	1	2	3	4	5	6	7	8	9	10
1.	ln(Total managers)	1.32	0.77	1.00									
2.	ln(Total non-mgr. employees)	3.08	0.87	0.42	1.00								
3.	Mgr. Hiring Rate	0.20	0.31	0.10	0.13	1.00							
4.	Nonmgr. Hiring Rate	0.22	0.59	0.07	-0.02	0.17	1.00						
5.	Mgr. Turnover	0.15	0.26	-0.30	0.06	0.21	0.03	1.00					
6.	Nonmgr. Turnover	0.17	0.31	0.15	-0.14	0.20	0.54	-0.01	1.00				
7.	ln(Robot capital stock)	0.02	0.46	0.01	0.03	0.02	-0.003	0.02	-0.01	1.00			
8.	ln(Total revenues)	14.67	1.29	0.50	0.68	0.07	-0.02	0.01	-0.05	0.02	1.00		
9.	Multi-unit enterprise	0.08	0.28	0.21	0.35	0.02	-0.03	0.01	-0.01	0.003	0.33	1.00	
10.	Unionized	0.19	0.39	0.15	0.26	0.05	-0.01	0.08	-0.04	0.02	0.26	0.21	1.00
	N = 17,449												

Note: To prevent the harmful disclosure of any organization-specific information, Statistics Canada does not allow minimum and maximum values for variables to be reported.

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