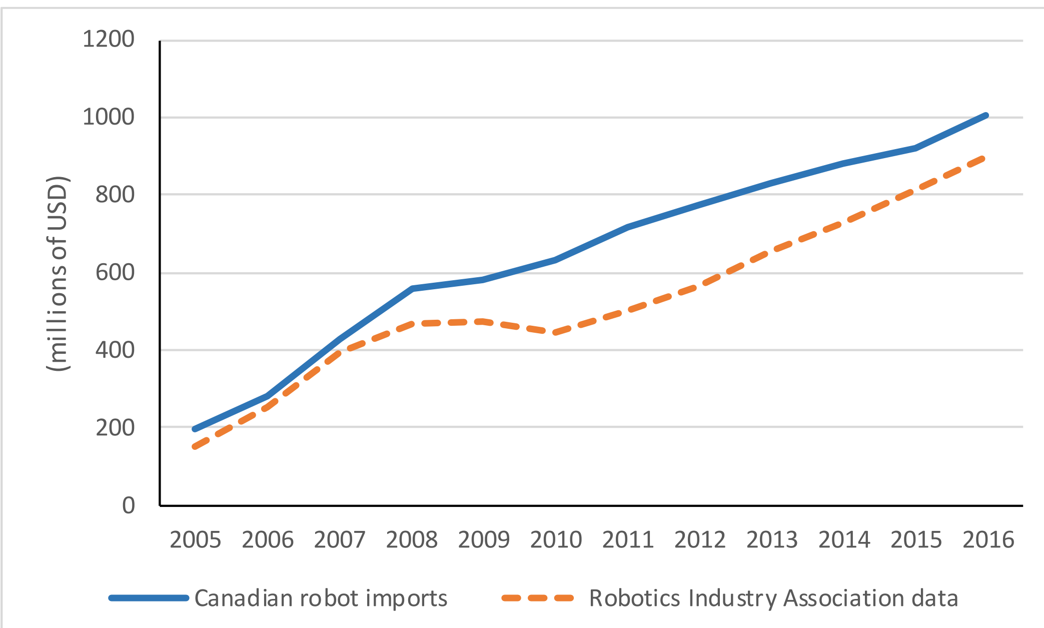
Appendix: The Employment Consequences of Robots: Firm-level Evidence

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

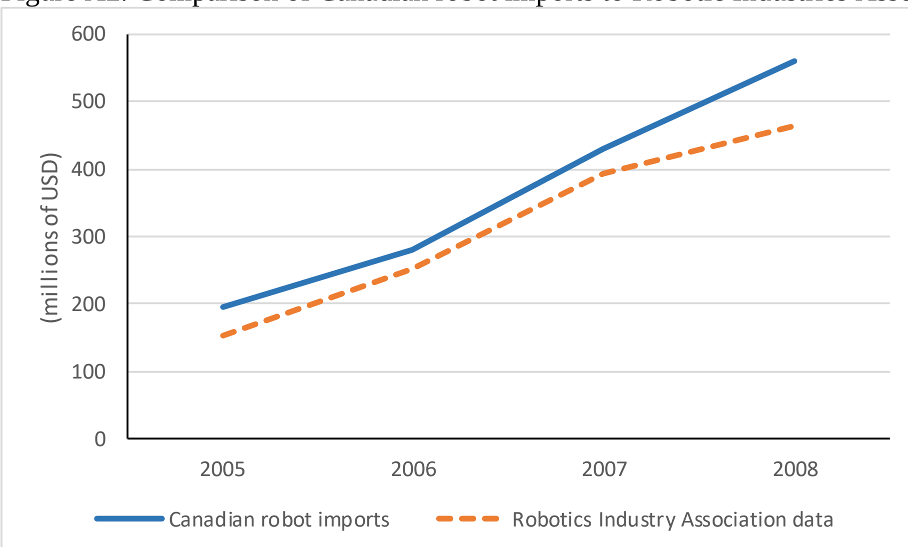
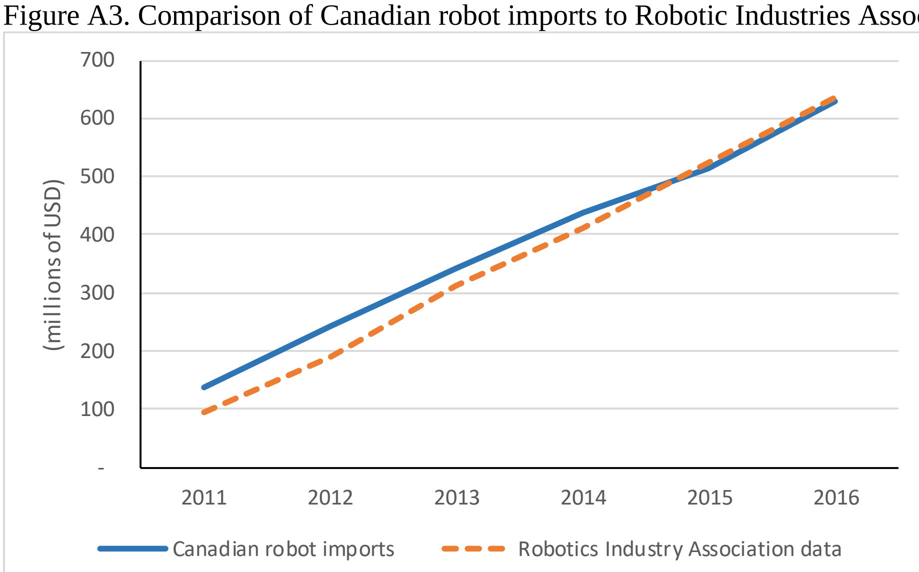


Figure A3. Comparison of Canadian robot imports to Robotic Industries Associaton (RIA) data, 2011-2016



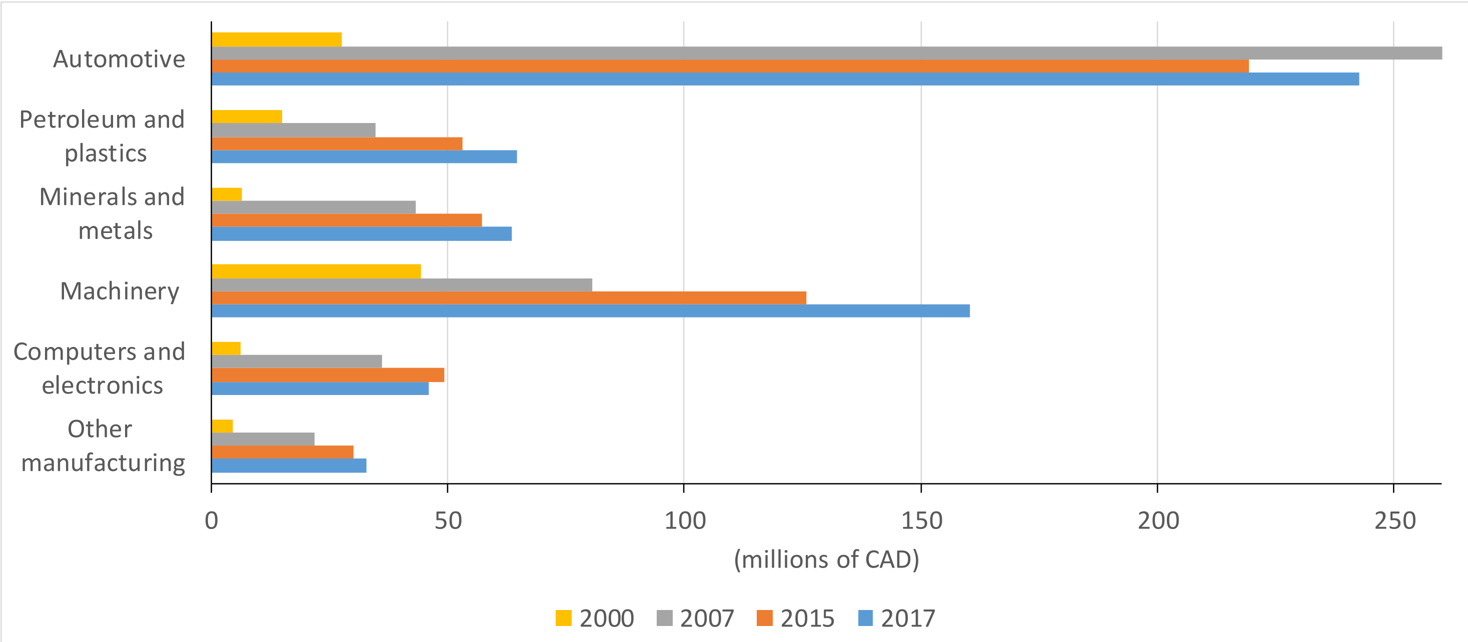
[2] For the years 2005-2008 and 2011-2015, the IFR reports consistently greater shipments in each year, being an average of 26% higher with a standard deviation of 7%. The consistently higher numbers are to be expected, since the IFR draws upon more data sources to augment data it regularly receives 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.

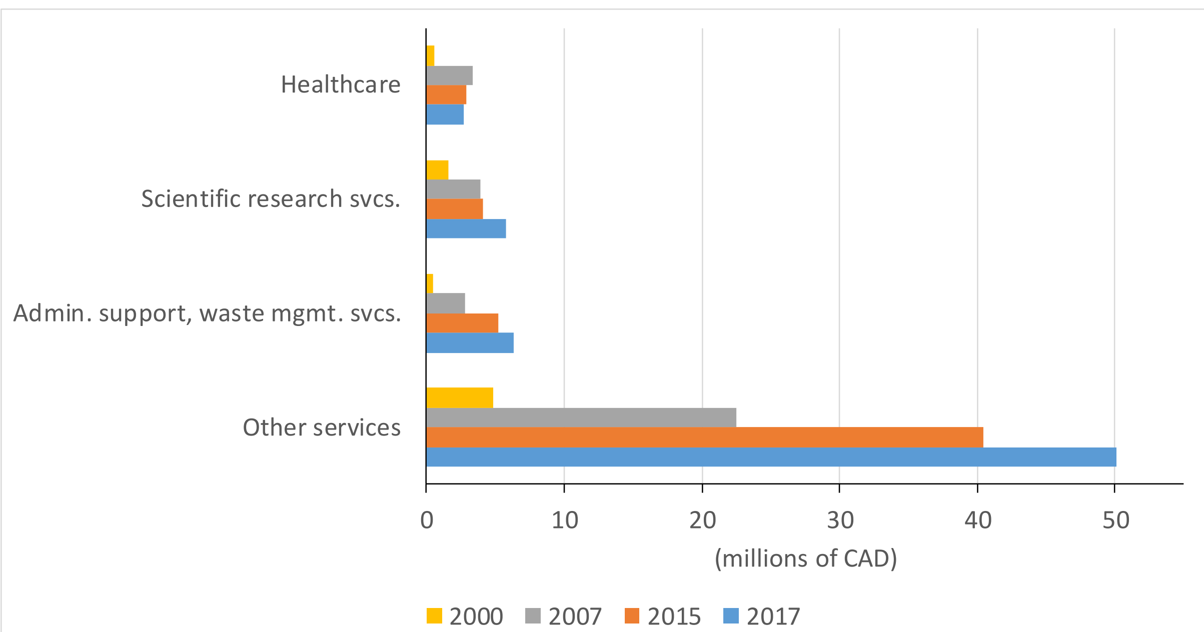
S2 Robot investment by industry

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.

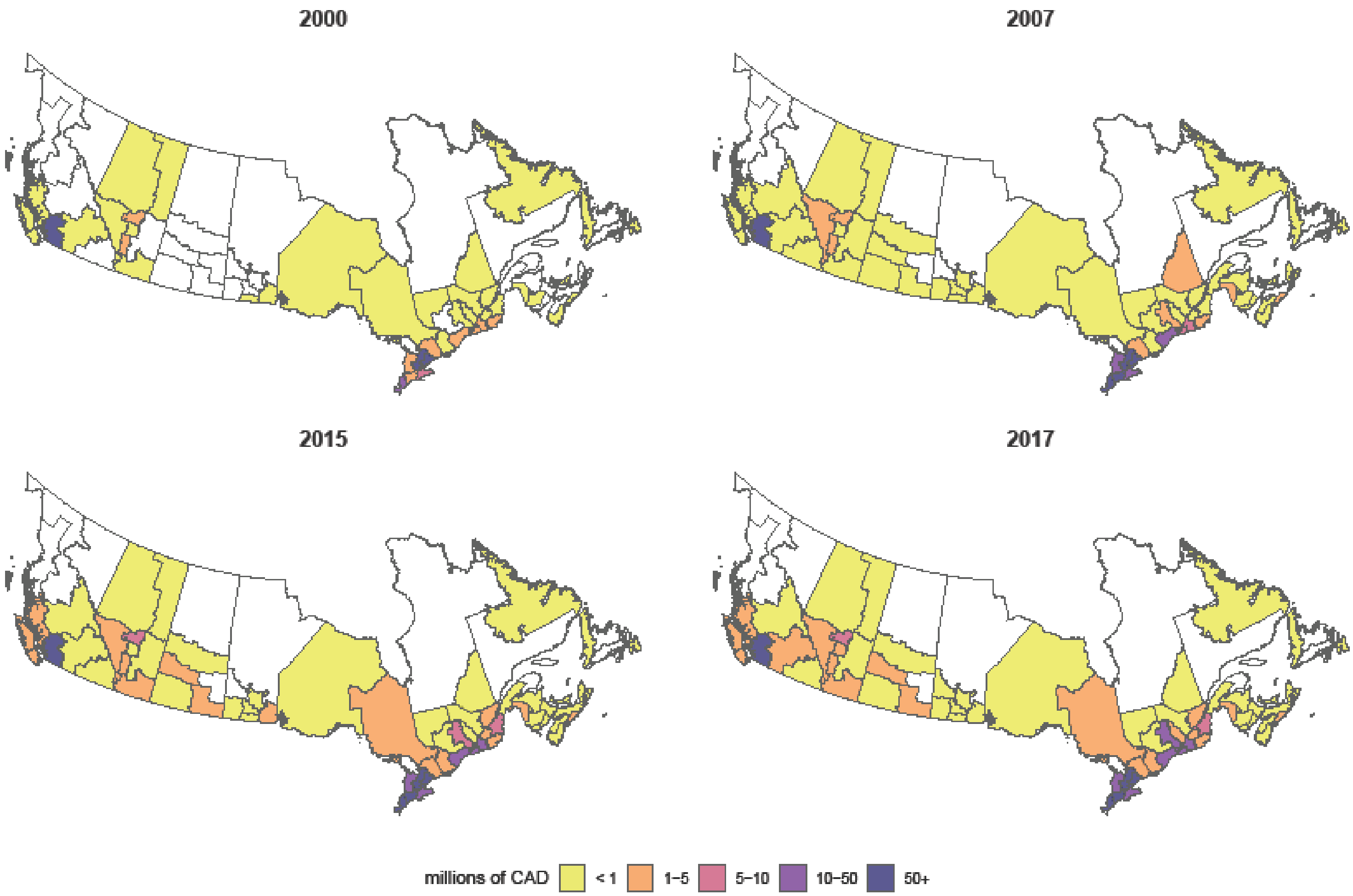
Figure A5. Total robot stock attributable by services sector, 2000-2017



Note: Healthcare includes NAICS code 62. Scientific research services includes 5417. Administrative support and waste management and remediation services includes 56. Other services includes all other NAICS codes outside the manufacturing sector, healthcare, scientific research services, administrative support and waste management and remediation services, 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

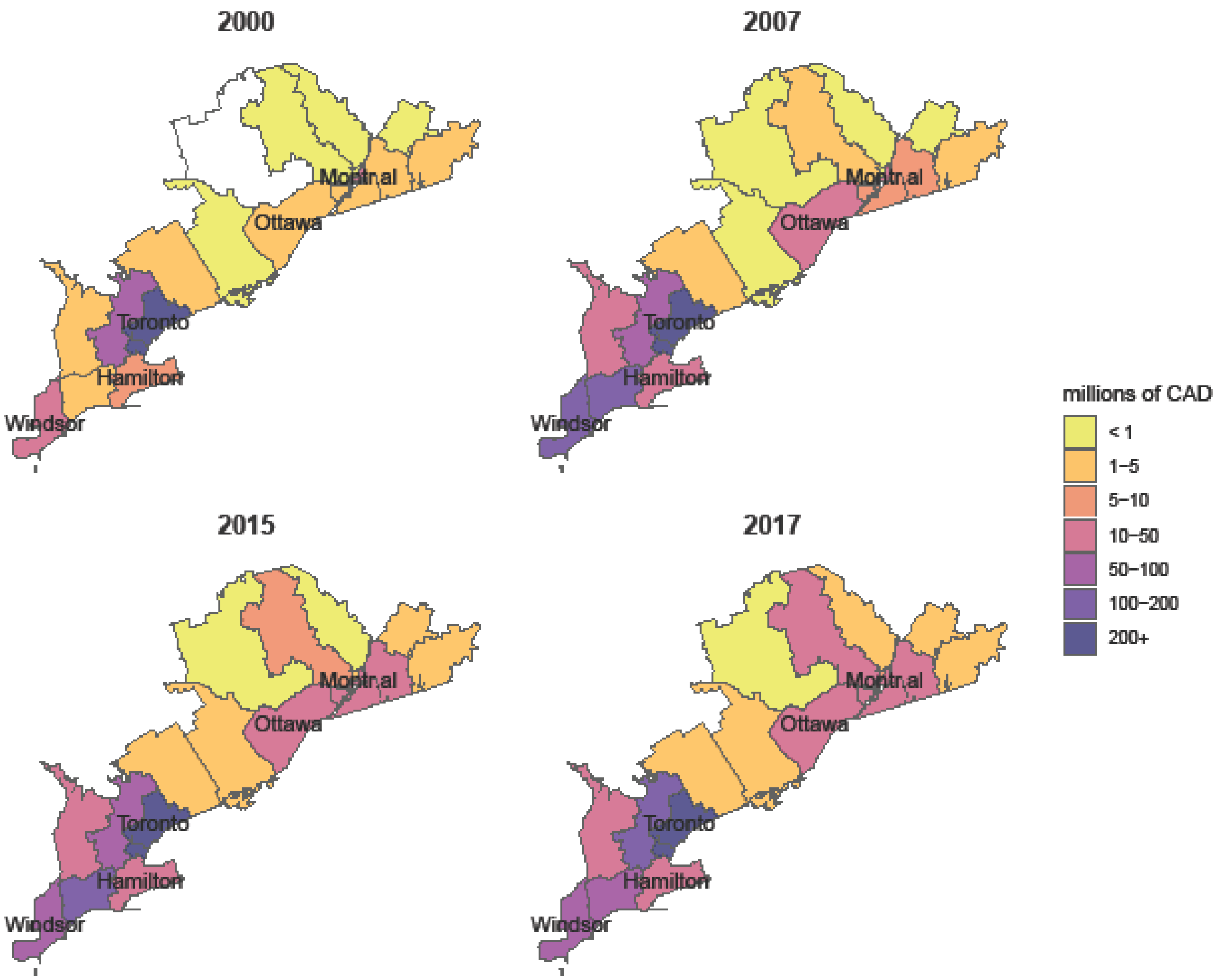
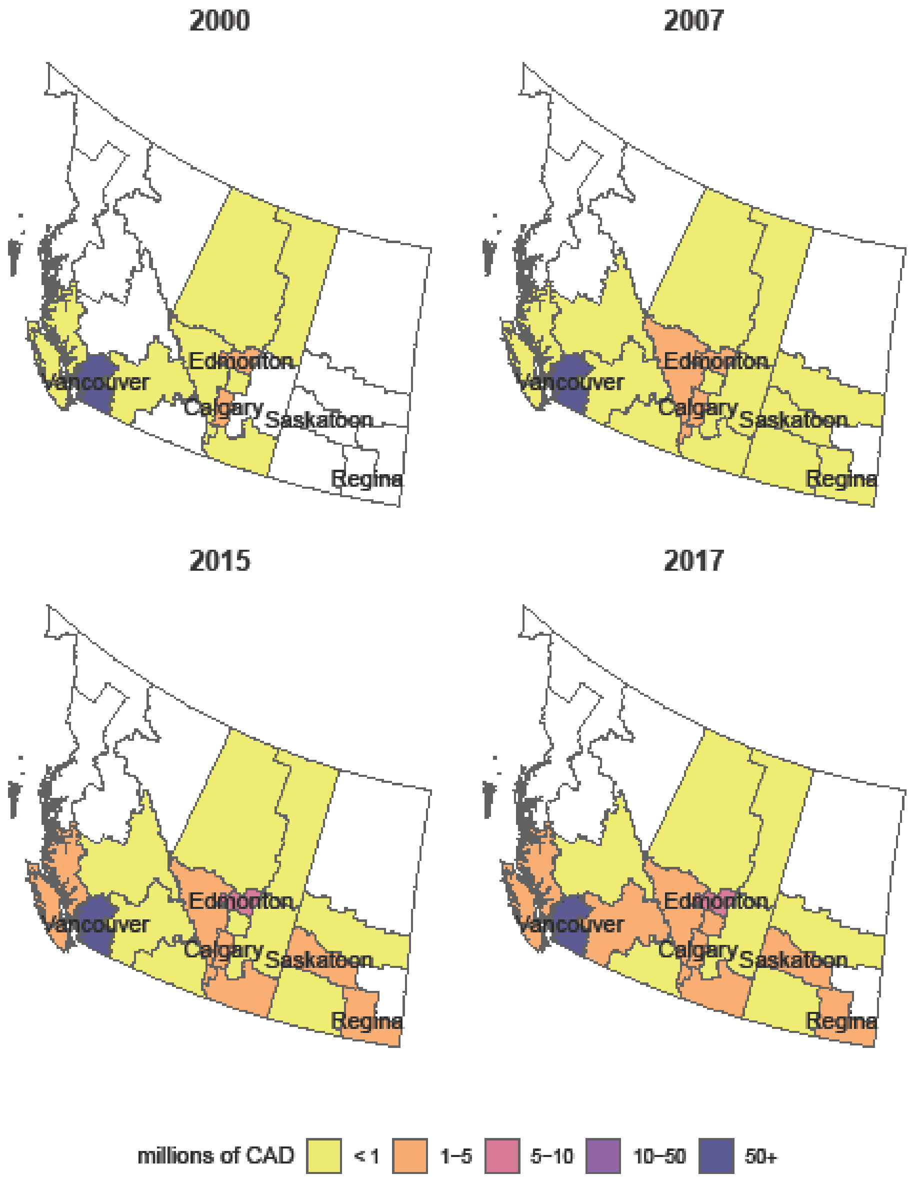


Figure A8. Total robot stock attributable by economic region: British Columbia, Alberta, and Saskatchewan



S4 Total employment regression results by industry

Here, we show the results of our total 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.

Table A9. Total 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
Province 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 A10. Total 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	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)
ln(Total assets)	0.445***	0.242***	0.415***	0.209***	0.201***	0.124***	0.355***	0.272***
	(0.013)	(0.034)	(0.005)	(0.013)	(0.012)	(0.015)	(0.028)	(0.034)
Multi-unit enterprise	0.408***	0.151***	0.517***	0.118***	0.982***	0.158	0.317**	0.087
	(0.059)	(0.039)	(0.022)	(0.019)	(0.129)	(0.112)	(0.150)	(0.220)
ln(Robot capital stock)	0.026***	0.005	0.020***	0.002	0.061***	0.118***	0.028**	0.018*
	(0.005)	(0.004)	(0.005)	(0.003)	(0.016)	(0.002)	(0.011)	(0.010)
Industry fixed effects	Y	N	Y	N	Y	N	Y	N
Province 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	1,829	1,829
Adj R-squared	0.67	0.93	0.63	0.93	0.41	0.92	0.53	0.93

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

Table A11. Total employment regressions by industry

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Industry:	Admin. support, waste mgmt. svcs.	Admin. support, waste mgmt. svcs.	Other services	Other services
Dependent variable:	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)
ln(Total assets)	0.284***	0.194***	0.328***	0.172***
	(0.008)	(0.016)	(0.002)	(0.004)
Multi-unit enterprise	0.753***	0.095**	0.527***	0.150***
	(0.061)	(0.047)	(0.010)	(0.008)
ln(Robot capital stock)	0.027*	0.018**	0.027***	0.003
	(0.014)	(0.007)	(0.006)	(0.005)
Industry fixed effects	Y	N	Y	N
Province fixed effects	Y	N	Y	N
Year fixed effects	Y	Y	Y	Y
Organization fixed effects	N	Y	N	Y
Observations	38,184	38,184	656,557	656,557
Adj R-squared	0.39	0.91	0.47	0.91

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

S5 Controlling for IT investment

To address the concern that our 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.[6] As shown in the following tables, we obtain similar results.

Table A12. Employment regressions, IT control variable added

	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Dataset:	NALMF	WES Employer	WES Employer	WES Employer	WES Employer
Dependent variable:	ln(Total employees)	ln(Total middle-skilled)	ln(Total low-skilled production)	ln(Total high-skilled)	ln(Total managers)
ln(Total assets)	0.196***				
	(0.011)				
ln(Total revenues)		0.151	0.119	0.038	0.083**
		(0.103)	(0.084)	(0.071)	(0.033)
Multi-unit enterprise	0.128***	-0.079	-0.233*	0.091	0.033
	(0.012)	(0.096)	(0.133)	(0.062)	(0.095)
Unionized		0.394***	0.196	-0.222**	0.166
		(0.115)	(0.162)	(0.095)	(0.107)
Outsourcing		0.003	0.045	0.168**	-0.001
		(0.084)	(0.105)	(0.067)	(0.059)
ln(Robot capital stock)	0.007***	-0.086***	0.062***	0.017**	-0.080***
	(0.002)	(0.014)	(0.021)	(0.007)	(0.011)
ln(IT capital stock)	0.009***	-0.007	0.006	0.004	0.002
	(0.000)	(0.006)	(0.009)	(0.006)	(0.003)
Year fixed effects	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y
Observations	901,123	17,442	17,442	17,442	17,442
Adj R-squared	0.92	0.70	0.72	0.59	0.69

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

Table A13. Strategic priority regressions, IT control variable added

	(1)	(2)
	FE	FE
Dataset:	WES Employer	WES Employer
Dependent variable (strategic importance):	Reducing labor costs	Improving product/service quality
ln(Total revenues)	-0.020	0.099
	(0.129)	(0.134)
Multi-unit enterprise	-0.184	-0.199
	(0.124)	(0.173)
Unionized	-0.155	-0.335*
	(0.230)	(0.201)
Outsourcing	0.038	0.096
	(0.175)	(0.170)
ln(Robot capital stock)	0.029	0.107***
	(0.037)	(0.014)
ln(IT capital stock)	0.010	-0.001
	(0.011)	(0.013)
Year fixed effects	Y	Y
Organization fixed effects	Y	Y
Observations	8,903	8,903
Adj R-squared	0.32	0.38

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 A14. Task allocation regressions, IT control variable added

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dataset:	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer
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)	-0.003	0.004	0.027	0.004	0.056	-0.049
	(0.019)	(0.090)	(0.089)	(0.009)	(0.072)	(0.075)
Multi-unit enterprise	0.003	-0.017	0.108	-0.007	0.037	0.069
	(0.018)	(0.077)	(0.104)	(0.012)	(0.067)	(0.096)
Unionized	-0.048	-0.066	-0.141	0.000	0.230	-0.528***
	(0.131)	(0.210)	(0.177)	(0.004)	(0.191)	(0.186)
Outsourcing	0.020	-0.025	-0.055	-0.011	0.039	-0.001
	(0.028)	(0.074)	(0.081)	(0.019)	(0.075)	(0.077)
ln(Robot capital stock)	0.073***	-0.077***	0.003	-0.000	-0.069***	0.075***
	(0.012)	(0.011)	(0.003)	(0.000)	(0.015)	(0.014)
ln(IT capital stock)	-0.007*	0.004	-0.002	0.001**	-0.001	-0.001
	(0.004)	(0.006)	(0.006)	(0.000)	(0.006)	(0.007)
Year fixed effects	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y
Observations	6,171	6,171	6,171	6,171	6,171	6,171
Adj R-squared	0.30	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 A15. Span of control and work predictability regressions, IT control variable added

	(1)	(2)
	FE	FE
Dataset:	WES Employee	WES Employee
Dependent variable:	Span of control	Work Unpredctability
ln(Total employees)	22.601*	-0.111
	(11.971)	(0.320)
Multi-unit enterprise	32.936	0.255
	(29.062)	(0.270)
Union member	-6.934	0.066
	(4.580)	(0.232)
Outsourcing	-4.030	0.329
	(5.245)	(0.227)
ln(Robot capital stock)	0.338***	0.158**
	(0.129)	(0.066)
ln(IT capital stock)	0.117	-0.004
	(0.425)	(0.015)
Year fixed effects	Y	Y
Employee fixed effects	Y	Y
Observations	11,717	10,968
Adj R-squared	0.15	0.59

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 A16. Performance measurement regressions, IT control variable added

	(1)	(2)
	FE	FE
Dataset:	WES Employer	WES Employer
Dependent variable:	Increase in ability to measure performance	Strategic priority of improving measures of performance
ln(Total revenues)	0.022	0.092
	(0.048)	(0.141)
Multi-unit enterprise	0.040	0.163
	(0.089)	(0.196)
Unionized	-0.011	0.042
	(0.061)	(0.194)
Outsourcing		-0.008
		(0.142)
ln(Robot capital stock)	0.022**	0.075***
	(0.011)	(0.016)
Inverse Mills ratio	-0.141**	
	(0.068)	
ln(IT capital stock)	0.007	-0.003
	(0.005)	(0.022)
Organization fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	4,945	8,903
Adj R-squared	0.42	0.29

Standard errors in parentheses, clustered by industry. Inverse Mills ratio is from first stage probit regression predicting organizational change. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

S6 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.[7] 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.[8] 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.[9]

Table A17. 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 dropped	Wholesaler recipient zipcodes dropped
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
Province 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

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

S7 Controlling for general improvements in firm performance

An alternative explanation for our finding of increases in total employment 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 additional controls for total sales lagged one, two, and three years. As shown below in comparing Columns 1 and 2 (OLS and FE specifications) with Columns 3 and 4, we find similar results after including these additional controls. 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).

Table A18. Total employment, lagged sales controls included

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Dataset:	NALMF	NALMF	NALMF	NALMF
Dependent variable:	ln(Total employees)	ln(Total employees)	ln(Total employees)	ln(Total employees)
ln(Total assets)	0.309***	0.191***	0.052***	0.095***
	(0.012)	(0.013)	(0.017)	(0.019)
Multi-unit enterprise	0.372***	0.139***	0.240***	0.076***
	(0.028)	(0.014)	(0.031)	(0.013)
ln(Robot capital stock)	0.013***	0.007***	0.013***	0.003***
	(0.003)	(0.002)	(0.003)	(0.001)
ln(Total sales), lagged			0.510***	0.351***
			(0.035)	(0.027)
ln(Total sales), 2 years lagged			-0.006	-0.010
			(0.009)	(0.007)
ln(Total sales), 3 years lagged			0.027*	0.031***
			(0.015)	(0.005)
Industry fixed effects	Y	N	Y	N
Province fixed effects	Y	N	Y	N
Year fixed effects	Y	Y	Y	Y
Organization fixed effects	N	Y	N	Y
Observations	929,162	929,162	459,398	459,398
Adj R-squared	0.48	0.92	0.71	0.95

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

S8 Additional selection robustness checks

Here, we implement an applied Heckman correction method to account for unobservable differences between firms that adopted robots and those that did not in our WES sample (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 government regulations hinder their ability to adopt them. Specifically, the survey asks whether factors "impede the implementation of new technology in your workplace" with "government standards and regulations" 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. We also estimate a dummy variable for robot adoption instead of our continuous measure.[10] As shown in the following tables, we obtain similar results.[11]

Table A19. Employment regressions with selection control variable added

	(1)	(2)	(3)	(4)	(5)
	Probit	FE	FE	FE	FE
Dataset:	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer
Dependent variable:	Robot adoption	ln(Total middle-skilled)	ln(Total low skilled production)	ln(Total high skilled)	ln(Total managers)
ln(Total revenues)	-0.018	0.145	0.119	0.041	0.080**
	(0.043)	(0.103)	(0.086)	(0.071)	(0.032)
Multi-unit enterprise	-0.087	-0.084	-0.241*	0.095	0.020
	(0.268)	(0.096)	(0.132)	(0.063)	(0.095)
Unionized	0.365	0.419***	0.221	-0.237**	0.217*
	(0.321)	(0.114)	(0.181)	(0.111)	(0.112)
Outsourcing	-0.252	-0.021	0.033	0.183***	-0.033
	(0.355)	(0.086)	(0.106)	(0.070)	(0.058)
Robot adoption dummy		-0.099***	0.073***	0.015**	-0.084***
		(0.012)	(0.015)	(0.007)	(0.008)
Govt. regulations impeding tech adoption	-0.864***				
	(0.334)				
Probit inverse mills ratio		0.097	0.079	-0.062	0.135
		(0.097)	(0.131)	(0.103)	(0.144)
Industry fixed effects	Y	N	N	N	N
Province fixed effects	Y	N	N	N	N
Year fixed effects	Y	Y	Y	Y	Y
Organization fixed effects	N	Y	Y	Y	Y
Observations	17,449	17,449	17,449	17,449	17,449
pseudo-R-squared	0.19				
log likelihood	-8,856				
Adj R-squared		0.70	0.72	0.59	0.69

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

[10] Using our continuous measure does not change the sign or statistical significance of our results.
[11] We also added the inverse mills ratio as a control to our span of control, work unpredictability, and performance measurement regression test and found similar and statistically significant results.

Table A20. Strategic priority regressions with selection control variable added

	(1)	(2)
	FE	FE
Dataset:	WES Employer	WES Employer
Dependent variable (strategic importance):	Reducing labor costs	Improving product/service quality
ln(Total revenues)	-0.016	0.095
	(0.130)	(0.134)
Multi-unit enterprise	-0.206*	-0.223
	(0.123)	(0.174)
Unionized	-0.098	-0.199
	(0.232)	(0.202)
Outsourcing	0.023	0.017
	(0.187)	(0.158)
Robot adoption dummy	0.377	1.168***
	(0.375)	(0.128)
Probit inverse mills ratio	0.157	0.458
	(0.223)	(0.377)
Year fixed effects	Y	Y
Organization fixed effects	Y	Y
Observations	8,906	8,906
Adj R-squared	0.32	0.38

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 A21. Task allocation regressions with selection control variable added

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dataset:	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer
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	0.001	0.030	0.004	0.055	-0.046
	(0.018)	(0.090)	(0.089)	(0.008)	(0.071)	(0.074)
Multi-unit enterprise	0.013	-0.026	0.114	-0.006	0.035	0.076
	(0.013)	(0.079)	(0.106)	(0.012)	(0.066)	(0.097)
Unionized	-0.059	-0.043	-0.167	-0.007	0.243	-0.560***
	(0.141)	(0.216)	(0.179)	(0.007)	(0.191)	(0.191)
Outsourcing	0.018	-0.031	-0.046	-0.008	0.033	0.012
	(0.030)	(0.072)	(0.077)	(0.019)	(0.075)	(0.074)
Robot adoption dummy	0.082***	-0.086***	0.003	-0.000	-0.075***	0.081***
	(0.009)	(0.008)	(0.003)	(0.000)	(0.014)	(0.013)
Probit inverse mills ratio	-0.055	0.081	-0.084	-0.018	0.035	-0.100
	(0.059)	(0.103)	(0.083)	(0.018)	(0.069)	(0.089)
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

S9 Imports from the US and China

Here, we repeat our baseline analyses controlling for imports from the US and China (Autor, Dorn, and Hanson, 2013). We acquired data on total imports from each respective country into Canada by industry (4 digit NAICS code) and year for the Canadian manufacturing sector, which was provided to us by Statistics Canada. Using this data, we include the total value of imports in each industry-year from the US and China as separate control variables across our main regressions. As the following tables show, we find similar results.

Table A22. Employment regressions with US and Chinese import controls

	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Dataset:	NALMF	WES Employer	WES Employer	WES Employer	WES Employer
Dependent variable:	ln(Total employees)	ln(Total middle-skilled)	ln(Total low skilled production)	ln(Total high skilled)	ln(Total managers)
ln(Total assets)	0.236***				
	(0.012)				
ln(Total revenues)		0.162	0.277***	0.099**	0.123***
		(0.117)	(0.093)	(0.045)	(0.046)
Multi-unit enterprise	0.113***	-0.014	-0.118	0.057	0.050
	(0.013)	(0.102)	(0.152)	(0.075)	(0.118)
Unionized		0.108	0.286**	-0.306***	-0.226*
		(0.169)	(0.123)	(0.094)	(0.129)
Outsourcing		0.272**	-0.127	0.151**	0.008
		(0.113)	(0.138)	(0.071)	(0.049)
ln(Robot capital stock)	0.008***	-0.071***	0.069***	0.016**	-0.067***
	(0.002)	(0.013)	(0.013)	(0.007)	(0.007)
US imports	0.002***	0.005	0.009	-0.001	-0.004*
	(0.001)	(0.006)	(0.008)	(0.003)	(0.002)
Chinese imports	0.003	-0.041	0.031	0.002	0.009
	(0.003)	(0.034)	(0.040)	(0.045)	(0.016)
Year fixed effects	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y
Observations	242,646	7,171	7,171	7,171	7,171
Adj R-squared	0.93	0.73	0.77	0.69	0.73

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 A23. Strategic priority regressions with US and Chinese import controls

	(1)	(2)
	FE	FE
Dataset:	WES Employer	WES Employer
Dependent variable (strategic importance):	Reducing labor costs	Improving product/service quality
ln(Total revenues)	-0.072	0.129
	(0.079)	(0.139)
Multi-unit enterprise	-0.205	0.038
	(0.128)	(0.149)
Unionized	0.063	0.247
	(0.161)	(0.155)
Outsourcing	0.102	0.102
	(0.161)	(0.231)
ln(Robot capital stock)	0.015	0.088***
	(0.026)	(0.010)
US imports	-0.007	0.005
	(0.011)	(0.005)
Chinese imports	-0.013	0.014
	(0.040)	(0.081)
Year fixed effects	Y	Y
Organization fixed effects	Y	Y
Observations	3,628	3,628
Adj R-squared	0.30	0.34

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 A24. Task allocation regressions with US and Chinese import controls

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Dataset:	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer	WES Employer
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)	-0.051	0.029	-0.058	0.020	0.105	-0.226***
	(0.041)	(0.077)	(0.049)	(0.024)	(0.073)	(0.070)
Multi-unit enterprise	0.023	-0.051	0.041	-0.006	0.025	0.083
	(0.020)	(0.097)	(0.027)	(0.014)	(0.075)	(0.111)
Unionized	-0.052	0.115	-0.194**	-0.001	0.122	-0.275**
	(0.042)	(0.093)	(0.094)	(0.005)	(0.103)	(0.107)
Outsourcing	0.097	0.048	-0.092	0.012	0.026	-0.143
	(0.060)	(0.112)	(0.094)	(0.049)	(0.066)	(0.127)
ln(Robot capital stock)	0.080***	-0.084***	0.005	0.000	-0.079***	0.082***
	(0.006)	(0.006)	(0.003)	(0.001)	(0.004)	(0.005)
US imports	0.011***	-0.007	-0.003	0.000	-0.006	0.008
	(0.004)	(0.007)	(0.004)	(0.000)	(0.007)	(0.006)
Chinese imports	0.031*	-0.015	-0.017	-0.004	-0.005	-0.026
	(0.019)	(0.031)	(0.022)	(0.005)	(0.019)	(0.025)
Year fixed effects	Y	Y	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y	Y	Y
Observations	2,492	2,492	2,492	2,492	2,492	2,492
Adj R-squared	0.32	0.44	0.46	0.33	0.44	0.48

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

Table A25. Span of control and work predictability regressions with US and Chinese import controls

	(1)	(2)
	FE	FE
Dataset:	WES Employee	WES Employee
Dependent variable:	Span of control	Work Unpredctability
ln(Total employees)	5.741*	-0.077
	(3.009)	(0.315)
Multi-unit enterprise	31.845	0.332
	(20.434)	(0.296)
Union member	-2.717	0.229
	(7.148)	(0.294)
Outsourcing	-4.606*	0.310
	(2.417)	(0.411)
ln(Robot capital stock)	0.243**	0.233***
	(0.106)	(0.039)
US imports	0.649	-0.055
	(0.730)	(0.050)
Chinese imports	-0.224	-0.231
	(1.385)	(0.558)
Year fixed effects	Y	Y
Employee fixed effects	Y	Y
Observations	5,209	4,585
Adj R-squared	0.78	0.58

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 A26. Performance measurement regressions with US and Chinese import controls

	(1)	(2)
	FE	FE
Dataset:	WES Employer	WES Employer
Dependent variable:	Increase in ability to measure performance	Strategic priority of improving measures of performance
ln(Total revenues)	-0.049	-0.132
	(0.112)	(0.118)
Multi-unit enterprise	0.026	0.159
	(0.102)	(0.177)
Unionized	-0.164	-0.032
	(0.117)	(0.165)
Outsourcing		-0.223
		(0.162)
ln(Robot capital stock)	0.033*	0.078***
	(0.020)	(0.013)
Inverse Mills ratio	-0.058	
	(0.086)	
US imports	-0.009*	-0.014***
	(0.005)	(0.005)
Chinese imports	0.080**	-0.030
	(0.036)	(0.045)
Organization fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	2,314	3,628
Adj R-squared	0.18	0.25

Standard errors in parentheses, clustered by industry. Inverse Mills ratio is from first stage probit regression predicting organizational change. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

S10 Selection on unobservables bias bounding exercise

Here, we examine the sensitivity of our managerial and middle-skilled employment results to possible selection on unobservables bias, using the method developed by Oster (2019). The method exploits observable controls which are likely to be correlated with unobservable factors which may bias the coefficient of interest, and compares the R-squared and coefficient of interest when the observable controls are excluded and included in separate specifications. Oster (2019) derives a simple test parameter δ and suggests that an absolute value of δ greater than 1 implies a sufficient degree of confidence in the direction of the coefficient estimate.[12] In the following table, Columns 1 and 3 show our managerial and middle-skilled employment specifications without the relevant controls, and Columns 2 and 4 show the results with controls added, along with the estimated δ parameter.[13]

Table A27. Managerial and middle-skilled employment, Oster bounding exercise

	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
Dataset:	WES Employer	WES Employer	WES Employer	WES Employer
Dependent variable:	ln(Total managers)	ln(Total managers)	ln(Total middle-skilled)	ln(Total middle-skilled)
ln(Total revenues)	0.079**	0.138***	0.137	0.179**
	(0.031)	(0.035)	(0.103)	(0.089)
Multi-unit enterprise	-0.074***	-0.076***	-0.073***	-0.070***
	(0.009)	(0.008)	(0.011)	(0.012)
Unionized		-0.246**		0.392***
		(0.102)		(0.129)
Outsourcing		0.004		0.029
		(0.052)		(0.087)
ln(Robot capital stock)	-0.074***	-0.076***	-0.073***	-0.070***
	(0.009)	(0.008)	(0.011)	(0.012)
ln(IT capital stock)		0.001		-0.005
		(0.003)		(0.005)
Organizational change		0.019		0.083
		(0.047)		(0.119)
ln(Total non-mgr. employees)		-0.260***		
		(0.036)		
ln(Total low skilled production emp.)				-0.214***
				(0.042)
ln(Total high skilled)				-0.196***
				(0.068)
Organizational change		0.019		0.083
		(0.047)		(0.119)
Year fixed effects	Y	Y	Y	Y
Organization fixed effects	Y	Y	Y	Y
Observations	17,442	17,442	17,442	17,442
Adj R-squared	0.69	0.71	0.70	0.73
Oster's Delta		-3.03		2.34

Standard errors in parentheses, clustered by industry. Adjusted R-squared is overall R-squared. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

[12] Negative values of δ imply that if the observables are positively correlated with our robot investment variable, the unobservables must be negatively (instead of positively) correlated with robot adoption to obtain our coefficient estimate.
[13] The organizational change is a dummy control variable comes from a separate section of the WES survey, where the survey asks In a separate section of the WES, respondents are asked whether their workplace experienced any organizational changes during the year, where organizational change is defined as "a change in the way in which work is organized within your workplace."

S11 Average employee wage

Here, we examine whether robot investments are associated with the average wage within the firm. As shown in Column 1 in the table below, we find no evidence of a relationship. In Column 2, we find only weak evidence (significance at the 10% level) of a positive relationship between robot investment and the average wage. Overall, the results do not show compelling evidence of a relationship between robot adoption and the average wage inside the firm. Given our earlier findings of increases in both low and high-skilled workers (as well as the decrease in managers), the results presented here suggest the net effect of these workforce composition changes on the average wage within the firm may be relatively negligible.

Table A28. Average employee wage within the firm

	(1)	(2)
	OLS	FE
Dataset:	NALMF	NALMF
Dependent variable:	Average wage	Average wage
ln(Total assets)	4,088.1***	2,068.1***
	(282.3)	(199.8)
Multi-unit enterprise	-1,093.5**	-280.4
	(449.7)	(274.8)
ln(Robot capital stock)	-66.7	73.9*
	(89.4)	(38.6)
Industry fixed effects	Y	N
Province fixed effects	Y	N
Year fixed effects	Y	Y
Organization fixed effects	N	Y
Observations	929,162	929,162
Adj R-squared	0.48	0.90

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

S12 First stage and selection regressions

First stage results for our 2SLS estimation for total employment as well our probit estimation of endogenous choice of organizational change are presented below.

Table A29. First stage of total employment 2SLS regression, first stage probit predicting choice of organizational change

	(1)	(2)
	OLS	Probit
Dataset:	NALMF	WES Employer
Dependent variable:	ln(Robot capital stock)	Organizational change
ln(Total assets)	0.084***	
	(0.016)	
ln(Total revenues)		0.180***
		(0.045)
Multi-unit enterprise	0.140***	0.209
	(0.030)	(0.185)
Pct. of workers in each industry in high manual, low verbal occupations in 1995 x inverse median price per robot in Canada	1.111***	
	(0.178)	
Unionized		0.040
		(0.128)
Outsourcing		0.095
		(0.195)
ln(Robot capital stock)		-0.028
		(0.024)
Strategic priority of workplace reorg.		0.150***
		(0.052)
Industry fixed effects	Y	Y
Province fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	865,759	8,622
Adj R-squared	0.07	
pseudo-R-squared		0.22
log likelihood		-217,150

Standard errors in parentheses, clustered by industry. F-statistic of excluded instrument in Column 1 is 38.94. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

S13 Productivity

As an additional test, we examine whether investments in robotics lead to increases in firm productivity.[14] 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 A30. Productivity regressions

Dependent variable: ln(Total revenues)	(1) OLS	(2) OLS	(3) FE	(4) 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

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

S14 Descriptive statistics and correlation tables

Table A31. Descriptive statistics, NALMF sample

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

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.

Table A32. Descriptive statistics, WES employment sample

	Variable	Mean	σ	1	2	3	4	5	6	7	8	9	10	11	12	13	14
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.	ln(Total mgr. hires)	0.44	0.68	0.60	0.16	1.00											
4.	ln(Total non-mgr. hires)	2.56	1.11	0.29	0.62	0.27	1.00										
5.	ln(Total mgr. departures)	0.34	0.63	0.04	0.27	-0.06	0.24	1.00									
6.	ln(Total non-mgr. departures)	2.35	1.14	0.36	0.53	0.38	0.75	0.20	1.00								
7.	ln(Total middle-skilled)	0.98	1.19	0.26	0.35	0.08	0.12	0.09	0.09	1.00							
8.	ln(Total low-skilled production)	1.23	1.40	0.22	0.45	0.07	0.22	0.10	0.21	0.04	1.00						
9.	ln(Total high-skilled)	0.37	0.79	0.20	0.29	0.13	0.15	0.11	0.15	0.16	-0.03	1.00					
10.	ln(Robot capital stock)	0.02	0.45	0.01	0.03	0.01	0.02	0.03	0.02	0.04	0.02	0.04	1.00				
11.	ln(Total revenues)	14.66	1.30	0.50	0.68	0.22	0.35	0.20	0.37	0.40	0.36	0.28	0.02	1.00			
12.	Multi-unit enterprise	0.08	0.27	0.21	0.35	0.11	0.20	0.10	0.24	0.11	0.14	0.12	0.003	0.33	1.00		
13.	Unionized	0.19	0.39	0.15	0.26	0.13	0.10	0.13	0.14	0.25	0.18	0.03	0.02	0.26	0.21	1.00	
14.	Outsourcing	0.30	0.46	0.08	0.05	0.07	0.05	0.03	0.07	0.09	0.08	0.07	0.002	0.12	0.06	0.07	1.00
	N = 17,449																

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