BANK OF CANADA
BANQUE DU CANADA

Staff working paper / Document de travail du personnel—2026-34

Last updated: September 18, 2026

Automation and Inequality: How Robots Shift Income Between Workers and Owners

Gabriela Galassi
Canadian Economic Analysis Department
Bank of Canada
GGalassi@bank-banque-canada.ca

Gaelan MacKenzie
International Economic Analysis Department
Bank of Canada
GMacKenzie@bank-banque-canada.ca

DOI: https://doi.org/10.34989/swp-2026-34 | ISSN 1701-9397

Automation and Inequality: How Robots Shift Income Between Workers and Owners*

Gabriela Galassi† Gaelan MacKenzie‡

August 2026

Abstract

We estimate the direct effects of robot adoption on the within-firm distribution of income between non-owner workers and individual owners in Canadian private manufacturing corporations. We link firm-level data on industrial robot imports to matched owner-worker-firm data that identify owners of private corporations, their employment income, and firms' dividend payments to owners and retained earnings. Robot adoption is associated with sizable increases in firm revenues, value added, and non-owner employment and payroll. Unlike several studies of robot adoption in other settings, we find little evidence that adoption reduces adopters' conventionally measured labor share of value added; if anything, the non-owner labor share increases slightly, while the total owner income share does not rise. Owners nevertheless benefit from adoption, but primarily through increases in employment income. These results underscore the importance of distinguishing owner employment income from ordinary worker payroll for measuring how firm-level technology shocks affect workers, owners, and the distribution of income within firms.

JEL Codes: J23, J31, D33, O33, D22

*We thank our discussants Eva O. Arceo-Gómez, Mark Hellsten, and Rob Seamans for their detailed comments, and Tatjana Dahlhaus, Hartmut Egger, Simon Galle, John Haltiwanger, Lu Han, Stéphanie Houle, Yuko Imura, Myeongwan Kim, Katja Mann, and Ben Tomlin for constructive feedback. We thank conference and seminar participants at the Workshop on the Impact of Automation on Labor Markets, the 2025 BIS CCA Research Conference on "Labour Markets", the Bank of Canada, Statistics Canada, the 2026 Econometric Society North American Summer Meeting, and the NBER SI 2026 Conference on Research in Income and Wealth. Results in this paper have been screened by Statistics Canada to ensure that no confidential information has been released. The views expressed herein are solely those of the authors and do not reflect those of the Bank of Canada nor Statistics Canada.

†Canadian Economic Analysis Department, Bank of Canada

‡International Economic Analysis Department, Bank of Canada

1 Introduction

Rapidly increasing adoption of automation technologies raises hopes for dramatic improvements in aggregate welfare through productivity gains. However, this trend also sparks concerns over adverse impacts on the employment and earnings of workers whose skills are more easily replaced by these technologies and the share of income earned by workers relative to capital owners.[1] This broad transformation could exacerbate economic inequality. Given the potential benefits of automation, it is important to understand how the rewards of increased adoption will be distributed throughout the economy. While evidence for the impacts of emerging technologies like artificial intelligence remains limited, a growing body of work has looked to older, more established automation technologies for evidence of distributional effects.

Prior work has explored the impacts of automation on workers. This paper examines an additional dimension through which automation may influence the distribution of income: its impact on the earnings of workers and business owners. We evaluate how firm-level outcomes for workers and owners in the Canadian manufacturing sector respond to the adoption of industrial robots, an automation technology whose use throughout the global economy continues to expand, and assess the implications of these responses for income inequality. We focus on the impacts on adopting firms.

To do this, we use Canadian firm-level data on robot adoption linked with a panel of matched individual-firm-level data for the period between 2002–2018. Since Canada has historically been a negligible producer of robots, adoption is measured using data on the value of imports of industrial robots. The matched individual-firm-level data, which is based on administrative tax records, includes annual employment income individuals receive from each firm and financial flows from firms' income statements. A distinguishing feature of the Canadian data is the information it contains on the direct and indirect ownership shares of the individual owners of privately held corporations that are derived from corporate income tax returns.[2] Because owners have multiple options for extracting income from their businesses, including through dividend payments and employment income, the identification of individual owners enables us to net out payments to owners from the compensation of workers in a private firm's total payroll and construct a firm-level measure of employment that counts individuals who are not owners of the firm.[3]

[1]See, for example, Acemoglu and Restrepo (2018, 2019, 2022) and Moll et al. (2022).

[2]Private corporations account for the vast majority of incorporated businesses in Canada, though they tend to be smaller and are less likely to have imported robots than publicly traded corporations.

[3]Canada does not allow for legal forms of incorporation that permit business income to pass through to owners. Wolfson et al. (2016) describes the factors influencing the decision of owners of private corporations in Canada to take income out of the firm as either dividends or employment income.

This additional information has substantial consequences for the measurement of distributional outcomes. Among private corporations in manufacturing, most firms pay out no dividends, and owners tend to take income out of their businesses in the form of employment income. Therefore, distinguishing between employment income paid to workers and owners is crucial for measuring outcomes such as the shares of surplus each group earns and evaluating the extent to which ordinary workers benefit from automation relative to owners.

We examine the direct effects of robot adoption on adopting private corporations using fixed-effect panel regressions and event-study specifications that exploit variation in the timing of adoption across firms. The estimates compare within-firm changes around adoption to contemporaneous changes among other firms in the panel, including never-adopters, future adopters prior to adoption, and firms that have already adopted. Firm fixed effects absorb permanent differences across firms, while industry-year and location-year fixed effects account for sectoral and local shocks. We further control for observable factors related to selection into robot adoption. The event studies allow us to examine the timing of effects and assess whether outcomes evolve differentially before adoption.

We estimate effects for four groups of outcomes that we use to compare the effects in our empirical setting with results found in other contexts and demonstrate the consequences of accounting for owners with employment income on firm-level outcomes.

The first group includes measures of firm scale including their revenues, value added, employment, payroll, and total owner income. Across these outcomes, we find evidence consistent with the literature that robot adoption is associated with large increases in a firm's scale.[4] For example, robot adopters increase their value added and number of non-owner workers by 57% on average following adoption. However, the effect on employment would be understated by 11% when including owners paying themselves employment income in the count of workers.

Second, we evaluate the impacts of robot adoption on per-worker payroll, value added and revenues and find that robot adoption increases average payroll but has no discernible impact on the other two measures. Moreover, we show that per-worker value added and revenue instead increase following robot adoption if we do not adjust the measure of employment to net out individual owners who pay themselves employment income.

Our third group of outcomes speaks directly to the impact of robot adoption on the within-firm shift in the distribution of income across workers and owners. We find that the non-owner labor share of value added increases by 1.4 percentage points following robot

[4] This evidence includes results in Acemoglu et al. (2020) for France, Dixon et al. (2021) for Canada, Humlum (2021) for Denmark, Koch et al. (2021) for Spain, Acemoglu et al. (2023) for the Netherlands, and Benmelech and Zator (2025) for Germany.

adoption, which stands in contrast to results from other settings, while the owner income share of value added declines by 1.7 percentage points.[5] That the owner income share declines does not imply that owners do not benefit from robot adoption. We find that the response of the level of total owner income (dividends, owner employment income, and retained earnings) is positive, though only marginally statistically significant, while that of the income owners extract from the firm (dividends and owner employment income) is positive and statistically significant. As with our findings for firm scale and per-worker outcomes, the treatment of owners' employment income has a large impact on the impacts on the labor and owner shares; when it is reallocated from total owner income to payroll, we cannot reject that there is no effect of robot adoption on the conventionally measured labor share and residual owner share. Furthermore, our results imply that robot adoption is associated with a larger increase in employment income paid to workers than to owners.

Existing theories suggest several channels through which automation can shift total earnings away from workers and toward owners or residual claimants in adopting firms: task displacement (Acemoglu and Restrepo, 2018, 2019), weakened worker bargaining power (Leduc and Liu, 2024), rent dissipation (Acemoglu and Restrepo, 2024), and markup increases as adopters expand (Firooz et al., 2025; Hubmer and Restrepo, 2026). Taken together, the pattern of results for these first three groups of outcomes is difficult to reconcile with any of these forces being the dominant channel in our setting. Instead, our results are consistent with robots being more complementary to workers and adoption leading firms to an expansion of firm scale that outweighs any automation of tasks performed by workers. Our pattern of results complements those of Hirvonen et al. (2025), who find that investment in advanced machinery in small- and medium-sized manufacturing firms leads to an expansion of firm scale that is not accompanied by an increase in value added per worker or a decline in the labor share of revenues (though they do not consider effects on firm-level non-owner worker outcomes).

The last set of outcomes characterizes the impact of robot adoption on the source composition of owners' income, which, because of the novelty of our data, has no precedent in the automation literature. We find that robot adoption primarily affects the income that owners take out from their businesses by increasing their total employment income and we cannot reject that there is no impact on firms' dividend payments to owners.

This result has important implications for the interpretation of the impacts of economic

[5]Other firm-level estimates from France (Acemoglu et al., 2020) and the Netherlands (Acemoglu et al., 2023) find negative impacts of robot adoption on the labor share of value added, while (Aghion et al., 2025) find negative effects of investment in a more general set of automation technologies on firms' labor shares in France. These papers do not separate out employment income received by owners in the measurement of the labor share.

shocks on the labor share of value added when the measurement of the labor share includes the employment income owners pay themselves, as is typically the case. While the increase in owners' employment income following robot adoption could reflect an increase in the quantity or returns to human capital they supply, the absence of a dividend response suggests that part of the increase could also reflect salary-like extraction of residual claims to profits. Thus, more caution is warranted in interpreting the incidence of shocks for workers and owners when owners' employment income cannot be identified: conventional payroll measures can partly mask owner incidence, while conventional profit measures can understate it.

Our paper contributes to the empirical literature on the effects of automation technologies by using data on firm owners to evaluate a new margin of the distributional impacts of automation. Existing studies have analyzed the impacts on different groups of workers, on workers at adopters relative to non-adopters, and on the labor share of value added measured inclusive of the employment income of owners.[6] By adding owners' employment income to other sources of owner income, we estimate the differential within-firm impact of robot adoption on workers and owners by providing a measure of the impact of robot adoption on the share of firm surplus earned by non-owner workers that is appropriate for worker-owner incidence.

In addition, our paper builds directly on the literature on the producer-level effects of automation by characterizing the impact of the treatment of owners who receive employment income for the effects on a wide range of outcomes.[7] We show that removing such owners from measures of payroll and employment can lead to large quantitative differences in the estimated effects of robot adoption on firm scale, value added per worker, and the labor share of value added.

Our main result is that adoption of robots by private corporations in Canada is more beneficial for non-owner workers at adopting firms than estimates in other settings would suggest, as adoption is associated with increases in employment and payroll per worker while the labor share of value added does not decline. Our analysis also suggests that treating owners with employment income as ordinary workers would lead to an understatement of these positive impacts of adoption on workers.

[6] See Graetz and Michaels (2018); Acemoglu and Restrepo (2020); Acemoglu et al. (2020); Dauth et al. (2021); Koch et al. (2021); Humlum (2021); Domini et al. (2022); Acemoglu et al. (2023); Bonfiglioli et al. (2024); Aghion et al. (2025); Bessen et al. (2025); Hirvonen et al. (2025) and Barth et al. (2026) for impacts on worker groups, Acemoglu et al. (2020); Bessen et al. (2020); Koch et al. (2021); Acemoglu et al. (2023); Bonfiglioli et al. (2024); Aghion et al. (2025) and Bisio et al. (2025) for impacts on employment at adopters relative to non-adopters, and Acemoglu et al. (2020, 2023) and Bonfiglioli et al. (2024) for the labor share of value added.

[7] In addition to the firm-level studies cited above, this includes the plant-level analysis in Dinlersoz and Wolf (2024).

We also contribute to the literature on the importance of accounting for the different sources of income earned by private business owners for distributional outcomes. Most papers in this literature have examined the impacts of market-level policies such as minimum wages (Drucker et al., 2021; Rao and Risch, 2026), corporate income taxes (Risch, 2024; Kennedy et al., 2026), or pandemic-era subsidies (Splinter et al., 2026). Closest to our work is Wang and Young (2026), who evaluate the distributional impacts of firm-level export demand and value added shocks in private corporations. While they focus on the incidence of these shocks across the income distribution, we estimate the impacts on the within-firm distribution of income across workers and owners. As in their analysis, we find that identifying owner employment income is critical for measuring the impact of firm-level shocks on owners' total income.

The rest of this paper continues as follows. In Section 2 we describe the data, variables, and sample selection used in our analysis. Section 3 outlines the empirical methods we use to evaluate the impacts of robot adoption. We present our results in Section 4. Section 5 concludes.

2 Data

We estimate the impacts of robot adoption on Canadian firms, their workers, and their owners using multiple data sources provided by Statistics Canada. Owners of firms can include corporations, partnerships, trusts, and individuals. We denote the relationship between an individual who works for or owns a firm as an affiliation between the individual and the firm. Firm- and affiliation-level data are taken from the Canadian Employer-Employee Dynamics Database (CEEDD), which links information from a variety of administrative records. Data on firm-level robot adoption are constructed using import transactions of industrial robots that are identified from detailed product-level customs data.

2.1 Firm-Level Data

Our analysis uses data from the CEEDD for the 2001-2018 period. Firm-level data are primarily sourced from one component of the CEEDD, the National Accounts Longitudinal Microdata File (NALMF), which includes information for any firm that files a corporate income tax return, a payroll tax deduction remittance, or maintains a sales tax account with the Canada Revenue Agency. We focus on incorporated businesses that are required to file a T2 Corporation Income Tax Return once each fiscal year.[8] This tax return includes information on the location of the firm's headquarters, the primary industry from which the firm derives its revenues, and the firm's consolidated income statement and balance sheet that contain financial data on their assets, revenues, expenses, net income, dividends, and retained earnings.

Firms are classified into industries according to the North American Industry Classification System (NAICS). Although firms report NAICS codes at the six-digit level in their corporate income tax returns, these codes are provided at the four-digit level in the NALMF. Reported industry codes are based on the different NAICS vintages that change periodically, so we crosswalk all four-digit NAICS codes to the 2007 NAICS vintage using concordance tables provided by Statistics Canada.[9] We focus our analysis on firms in industries in the manufacturing and related sectors for which robot adoption is relatively prevalent during our sample period (either because adoption rates are particularly high or because a large number of firms have adopted robots). Like Acemoglu et al. (2023), we define a broad manufacturing sector that includes (narrow) manufacturing; mining, quarrying, and oil and gas extraction; utilities; construction; transportation and warehousing; professional, scientific, and technical services; and management of companies and enterprises.[10]

To delineate the geographic areas within which firms are located in a consistent framework suitable for regional analysis, we use the head office locations of firms at the level of aggregation of a Statistical Area Classification (SAC) that are taken from the NALMF. The SAC groups municipalities into census metropolitan areas, census agglomerations, or rural and small-town areas based on their population size and commuting patterns. We use the mode of the SAC of the observed headquarters location over time for each firm and assign the earliest observed modal SAC to a firm in cases where it has multiple modes.

2.1.1 Robot-Adoption Data

Data on robot adoption rely on the methodology developed in Dixon (2020) and Dixon et al. (2021), which constructs a firm–year panel of robot adoption information using comprehensive Canadian product-level data on imports of industrial robots collected by the Canada Border Services Agency. Industrial robots are identified through detailed Harmonized System (HS) codes that are comparable with classifications defined by the International Federation of

[8]In 2002, incorporated businesses accounted for approximately 90% of total Canadian business sector GDP (Rispoli, 2009).

[9]We impute missing values of a firm's four-digit NAICS codes after applying the crosswalk whenever the firm's non-missing NAICS codes in the nearest three years to the year with the missing code (searching up to three years before or after that year) are identical.

[10]This broad manufacturing sector includes the following 2-digit NAICS codes: 21, 22, 23, 31, 32, 33, 48, 49, 54, and 55.

Robotics (IFR).[11] Import values and quantities are aggregated to the firm–year level to form the measures of robot adoption used in our analysis. As firm-level coverage of robot imports is significantly limited before 2002, we use robot imports during the 2002–2018 period to measure robot adoption and restrict our empirical analysis to this period.

2.2 Affiliation-Level Data

A distinguishing feature of the CEEDD is that it provides details on both ownership and employment affiliations between individuals and firms. Owners of firms are identified from the Schedule 50 form that some privately-held corporations include as part of their corporate income tax return and which we refer to as the T2S50. Private corporations are required to submit the T2S50 if any of their shareholders owns 10% or more of the common and/or preferred shares of the corporation, and they must report the identity and the percentage of common and preferred shares held by any such shareholder. We label owners listed on a T2S50 as the direct owners of the corporation.

Because corporate ownership may be structured such that a corporation is itself directly owned by another corporation (or in one of many other potentially complex arrangements), an individual can hold shares in a corporation both directly and indirectly. Statistics Canada processes the T2S50 forms for all corporate tax units to arrive at a total chained imputed ownership share for each individual owner of each tax unit.[12] For the small minority of corporations with multiple tax units filing a T2S50, we compute firm-level ownership shares for each individual owner as a weighted sum of their ownership shares across tax units where the weights are the shares of each tax unit in the total assets of the firm that are taken from the balance sheets included in their T2 Corporation Income Tax Returns.

Throughout our analysis, we classify an individual as an owner of a firm if they are ever observed to have a non-zero imputed ownership share in the firm over the entire period from 2001–2018. This convention mitigates potential concerns that changes in an individual's ownership status reflects changes in their shareholdings above or below the 10% T2S50 reporting threshold described above.[13]

[11] Dixon (2020) validates the use of these import data to measure the value of robots in Canada by aggregating across firms and comparing these amounts with the total value of shipments of robots reported by the IFR (after transforming both measures into annual stocks). Canadian firms are not themselves meaningful producers of industrial robots.

[12] In their implementation of this chained ownership imputation, common and preferred shares are given equal weights within each tax unit.

[13] Bena et al. (2024) find that for private corporations in the CEEDD for the 2010–2017 period, ownership is highly stable on a year-to-year basis with new owners and exiting owners accounting for just 3.7% and 4% of firm-owner-year observations, respectively. The average year-to-year change in an owner's share is just 0.2 percentage points.

Employment relationships between individuals and firms are identified from annual T4 Statements of Remuneration Paid, which are forms issued by firms to each of their workers. These forms include the province of employment of the worker, their total employment income, and any dues paid by the employee for their membership in a trade union when those dues are deducted by the employer.[14] Total employment income includes wages, salaries, commissions, bonuses, taxable benefits, and the value of security options received by a worker.

Given our classification of ownership affiliations described above, we hereafter use the term worker to refer to an affiliation between a firm and an individual who is never observed to be an owner of that firm.

2.3 Variable Construction and Sample Selection

This section clarifies how we map the data described above into variables used in our analysis and the restrictions we impose to arrive at our baseline sample. For all financial flows, we deflate the variables in each year using the Consumer Price Index provided by Statistics Canada so that all values are measured in 2002 Canadian Dollars.

Our firm-level analysis evaluates the effects of robot adoption on four groups of outcomes: firm scale, per-worker outcomes, the allocation of firm-level surplus to owners and workers, and the source composition of owners' income.

Building on earlier studies of the firm-level effects of robot adoption, we identify the first year a firm imports robots over the 2002–2018 period as our principal measure of adoption.[15] To supplement this discrete measure of adoption, we follow Dixon et al. (2021) and construct a continuous measure of the firm-level stock of robots using the cumulative value of robot imports subject to compound depreciation over a 12 year useful-life period.

We measure firm scale and per-worker outcomes along multiple dimensions. We count the number of workers with non-zero employment income affiliated with a firm in each year as our measure of employment and define the firm's payroll as the total employment income of those workers. Total revenues are taken directly from the NALMF. Total owner income is defined as the sum of dividends, the change in the value of retained earnings (which we refer to as retained earnings for brevity), and any employment income received by individuals identified as owners of the firm.[16] We calculate firm-level value added as the sum of before-tax net

[14] Employment income and union dues included on a T4 statement correspond to amounts paid for work conducted in a calendar year

[15] Most other studies using robot imports data to identify robot adoption events focus on countries in the European Union (EU) for which reporting of imports from other EU countries is subject to minimum reporting requirements on total firm-level import value. Unlike these studies, our robot imports data is reported from data collected from virtually all import transactions.

[16] Dividends declared by the firm include dividend payments to shareholders as well as premiums paid on the redemption of shares by the firm. The change in the value of retained earnings is calculated as the

income, payroll paid to workers, employment income of owners, and depreciation as captured by the capital cost allowance reported by the firm. We set value added to be missing for any firm-year observation for which it is negative. Measures in our second group of outcomes include payroll per worker, revenues per worker, and value added per worker.

Other important outcome variables for our analysis include those that characterize how the total surplus of the firm is allocated to the incomes of owners and workers. These include the labor share of value added, calculated as payroll divided by value added, and the corresponding owner share of value added, which uses total owner income instead of payroll. We set each of these shares to be missing whenever they are larger than one.

The final set of results examine how robot adoption affects the different sources of owners' income by contrasting effects on total owner income with effects on dividends, owner employment income, and owner payout (which we define as the sum of dividends and owner employment income). In addition, we examine effects on dividends and owner payout as a share of total income paid out by the firm (i.e., owner payout plus worker payroll).

We restrict our analysis sample to the set of firm's in the broad manufacturing sector defined above and drop any observations from our analysis if either employment or revenues are missing or zero. To emphasize the relative impact of robot adoption on workers and owners and highlight the insights that can be drawn from our matched individual-firm-level data that allows for the identification of individual owners, we use as our baseline sample the set of firm-year observations for which at least one individual owner is observed to have a non-zero imputed ownership share in the year and label this as the T2S50-firm sample. We contrast results for T2S50 firms with the sample of observations that do not impose this restriction (which we denote as the all-firm sample).

2.4 Descriptive Statistics

Our data for all firms in the broad manufacturing sector form an unbalanced 17-year panel covering 690,130 distinct firms, of which 1,445 import robots at some point between 2002–2018 (0.210%).[17] When restricted to our baseline sample of T2S50 firms with ownership share information, the number of firms falls to 406,710, of which 865 are robot importers (0.213%).

Figure 1 reports the prevalence of robot adoption over time in the broad manufacturing sector. In Panel A, we plot the ratio of firms that import robots in each year from 2002 to 2018 relative to the number of firms in the sample for both the T2S50-firm and all-firm samples. The rate of robot adoption fluctuates over time but shows an overall upward trend, especially following the Great Recession. For T2S50 firms, the rate of robot adoption nearly

difference between the end-of-period and start-of-period stocks of retained earnings reported by firms.

[17] All firm and observation counts are rounded in accordance with Statistics Canada confidentiality rules.

doubled from roughly 0.041% in 2002 to 0.079% in 2018. This increasing trend is also present in the sample of firm-year observations with at least 10 employees (see Figure A1).

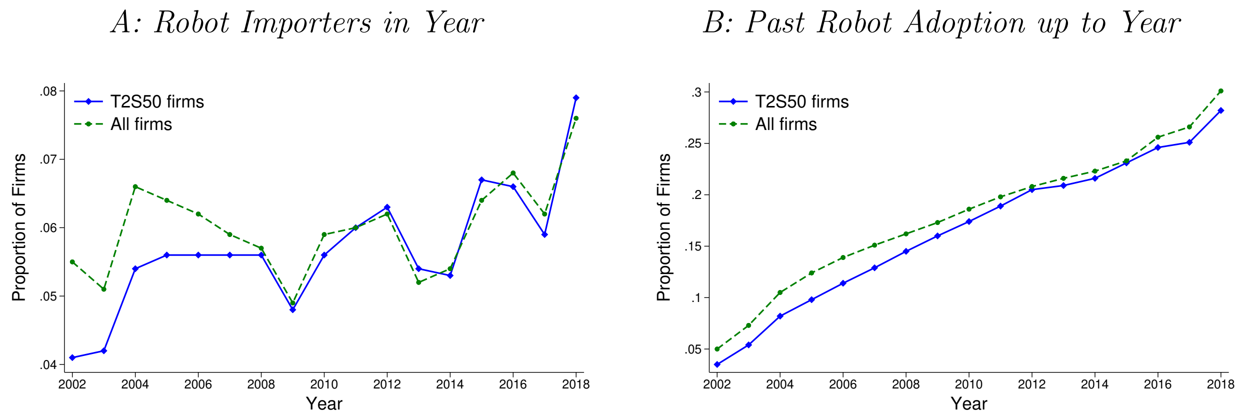


Figure 1: Prevalence of Robot Adoption in the Broad Manufacturing Sector

Notes: Figure depicts the prevalence of robot adoption in the broad manufacturing sector for the T2S50-firm sample and the all-firm sample. Panel A plots the ratio of the number of firms ever in the sample with robot imports in a year to the number of firms in the sample in that year. Panel B displays the share of firms in the sample in each year that have adopted a robot up to and including that year.

As we focus on examining the effects of initial robot adoption on our outcomes of interest in our empirical analysis, Panel B depicts the proportion of firms in each sample that have adopted robots up to and including each year of our sample. Since a firm is labeled as a past adopter once they have imported a robot for the first time, this proportion is increasing throughout the period. In 2002, only 0.035% of T2S50 firms in the broad manufacturing sector had imported robots.[18] By 2018, this proportion had increased to 0.282%.[19]

Table 1 reports summary statistics for our firm-level variables separately for firms that ever adopt robots and non-adopters, pooling all firm-year observations from 2002 to 2018. Robot adopters are, on average, substantially larger than non-adopters in terms of employment, payroll, revenues, value added, and owner income. They also exhibit a higher payroll per worker and labor share of value added, but the various measures of earnings of owners as a share of value added and total income paid out by the firm are smaller both on average and for the median observation. The descriptive statistics also suggest that robot adopters have lower value added per worker and assets per worker than non-adopters, on average, but this ranking is reversed for the median observation for both these measures as well as for

[18]The proportion in Panel A is higher than in Panel B in 2002 because, as explained in Section 2.3, we use *all* robot import data to measure robot adoption for firms that are ever in the sample and some firms in the T2S50-firm sample in later years but not in 2002 imported robots in 2002. This can occur, for example, when such a firm was not in the broad manufacturing sector in 2002. The increasing trend in Panel A remains when restricting robot importers to those that are in the T2S50-firm sample in a given year.

[19]This proportion in 2018 is larger than the share of distinct firms ever in the sample that ever adopt a robot because of attrition in our unbalanced panel.

Table 1: Summary Statistics of T2S50-Firm Sample

Variables	Mean	Std. dev.	5th perc.	Median	95th perc.	Obs.
Panel A: Robot adopters						
Revenues (millions of $)	124.739	1,395.585	0.467	6.181	152.054	9,860
Value added (millions of $)	34.277	339.748	0.169	2.269	43.404	9,740
Number of workers	394	4,058	4	56	745	9,860
Payroll (millions of $)	13.384	101.954	0.074	1.423	28.117	9,860
Owner income (millions of $)	13.068	179.050	-0.534	0.383	8.610	9,860
Dividends (millions of $)	11.422	164.329	0.000	0.000	3.912	9,860
Owner payout (millions of $)	11.781	164.350	0.000	0.210	5.368	9,860
Payroll per worker ($)	28,845	14,598	10,252	27,184	52,541	9,860
Value added per worker ($)	61,848	509,739	14,491	42,953	119,503	9,740
Assets per worker ($)	198,626	1,439,779	21,786	79,394	381,601	9,860
Revenues per worker ($)	178,077	1,108,067	41,909	116,162	399,483	9,860
Labor share (VA)	0.60	0.20	0.22	0.63	0.91	8,925
Owner income share (VA)	0.28	0.18	0.04	0.25	0.64	8,405
Dividends share (VA)	0.06	0.14	0.00	0.00	0.36	9,670
Owner payout share (VA)	0.18	0.19	0.00	0.12	0.57	9,570
Dividends share (TP)	0.07	0.15	0.00	0.00	0.42	9,860
Owner payout share (TP)	0.22	0.21	0.00	0.16	0.66	9,860
Robot import event	0.14	0.35	0.00	0.00	1.00	9,860
Robot adoption by present	0.55	0.50	0.00	1.00	1.00	9,860
Panel B: Non-adopters						
Revenues (millions of $)	2.144	41.788	0.056	0.431	6.797	3,127,340
Value added (millions of $)	0.728	15.138	0.020	0.175	2.242	3,069,880
Number of workers	17	182	1	4	57	3,127,340
Payroll (millions of $)	0.401	5.278	0.004	0.070	1.378	3,127,340
Owner income (millions of $)	0.223	13.472	-0.030	0.061	0.620	3,127,340
Dividends (millions of $)	0.094	8.263	0.000	0.000	0.190	3,127,340
Owner payout (millions of $)	0.176	8.282	0.000	0.051	0.450	3,127,340
Payroll per worker ($)	19,870	27,010	2,579	16,621	45,960	3,127,340
Value added per worker ($)	68,467	646,234	7,479	37,207	174,829	3,069,880
Assets per worker ($)	221,254	3,924,327	5,161	47,940	547,767	3,127,340
Revenues per worker ($)	178,387	980,980	21,293	95,593	496,737	3,127,340
Labor share (VA)	0.46	0.26	0.05	0.45	0.89	2,846,800
Owner income share (VA)	0.44	0.24	0.06	0.43	0.85	2,734,535
Dividends share (VA)	0.08	0.17	0.00	0.00	0.46	3,024,530
Owner payout share (VA)	0.32	0.26	0.00	0.29	0.81	2,934,355
Dividends share (TP)	0.11	0.20	0.00	0.00	0.61	3,127,340
Owner payout share (TP)	0.41	0.29	0.00	0.39	0.92	3,127,340
Robot import event	0.00	0.00	0.00	0.00	0.00	3,127,340
Robot adoption by present	0.00	0.00	0.00	0.00	0.00	3,127,340

Notes: Table reports summary statistics of firm-year-level variables defined in Section 2.3 for the T2S50-firm sample. All variables are measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel A includes all observations for firms that ever import robots over the 2002–2018 period. Panel B includes all observations for firms that did not import robots during that time. For share variables, (VA) and (TP) indicate that value added and total income paid out as employment income or dividends is the denominator, respectively. Robot import event denotes observations with positive robot imports. Robot adoption by present denotes whether the firm has imported a robot up to and including the year of the observation. Observation counts are rounded pursuant to Statistics Canada confidentiality rules.

revenues per worker.

The summary statistics also reveal important facts regarding the sources of owner income. For both robot adopters and non-adopters, the median firm does not pay out any dividends. While, for the average firm, dividends account for a not insignificant proportion of value added or total payout (dividends, owner employment income, and worker payroll), total owner payout (dividends and owner employment income) is roughly three times larger for robot adopters and four times larger for non-adopters. Consequently, owner employment income is a far more important and far more frequently used means through which owners extract income from their firms than are dividends. Finally, comparing the owner payout share of value added with the owner income share of value added (which includes retained earnings) indicates that retained earnings are also an important source of owner income on average.

To give a first look at how the availability of information identifying individual owners affects comparisons of robot adopters and non-adopters, Table A2 presents summary statistics for comparable variables where we do not account for individual owners and instead treat them as if they were workers when they receive employment income. Robot adopters remain larger than non-adopters in terms of the number of workers, payroll, and owner income (which no longer includes employment income received by individual owners), and continue to have higher payroll per worker. However, adjusting the treatment of individual owners leads to robot adopters having higher per worker measures of value added, assets, and revenues, on average. The most striking impact of this adjustment is that robot adopters and non-adopters have much more similar labor and owner income shares of value added.

These patterns provide initial descriptive evidence of systematic differences between adopting and non-adopting firms in the T2S50-firm sample.[20] However, they do not account for time-invariant firm characteristics, and conditions in firms' industries and locations that may change over time. We address these considerations in our empirical analysis.

3 Empirical Approach

We estimate the direct firm-level effects of robot adoption on adopters, their workers, and their owners using both panel and event-study specifications.

3.1 Panel Regressions

We first estimate the impact of robot adoption, $r_{f,t}$, on outcome $y_{f,t}$ for firm f in year t for the four groups of outcome variables described in Section 2.3.

To measure robot adoption, we use both a discrete and continuous approach. The former treats a firm as a robot adopter if they have imported robots in any year up to and including year t, while the latter uses the robot imports data to construct a firm-level measure of the

[20] In Table A1, we show summary statistics of our main variables for all firms in the broad manufacturing sector.

stock of robots. Our panel regression specification for the direct effect of robot adoption is:

$$y_{f,t} = \beta r_{f,t} + \gamma_t X_{f,\tilde{t}(f)} + \alpha_f + \delta_{s(f),t} + \zeta_{l(f),t} + \epsilon_{f,t}. \tag{1}$$

We include firm-level baseline characteristics, $X_{f,\tilde{t}(f)}$, using data from the first year a firm is observed in our sample, $\tilde{t}(f)$, including the log of the number of workers, the log of assets per worker, and the log of value added per worker, and interact them with year dummies to allow their effects on outcomes to be time varying. We also control for firm fixed effects, α_f, 4-digit NAICS industry-by-year fixed effects, $\delta_{s(f),t}$, and location-by-year fixed effects, $\zeta_{l(f),t}$, where the locations are the SAC within which a firm's headquarters are located. In each of these firm-level panel regressions, standard errors are clustered at the firm and year levels.

3.2 Event Studies

To examine dynamic effects and assess the validity of the parallel trends assumption underlying the identification of β in Equation (1), we estimate an event-study specification as follows:

$$y_{f,t} = \sum_{h=-5,\, h\neq -1}^{5} \beta_h D^h_{f,t} + \gamma_t X_{f,\tilde{t}(f)} + \alpha_f + \delta_{s(f),t} + \zeta_{l(f),t} + \epsilon_{f,t}, \tag{2}$$

where $D^h_{f,t}$ is an indicator equal to one if year t is h years away from the first year in which firm f adopted robots, and zero otherwise. We set $h = -1$ (the year prior to adoption) as the omitted category, and measure effects in other years relative to that year. Coefficients β_h for $h < 0$ capture pre-adoption differences between future adopters and non-adopters, while β_h for $h > 0$ trace the evolution of firms' outcomes up to five years following adoption. We estimate standard errors clustered at the firm and year levels.

We exploit both variation in timing among adopters and cross-sectional differences between adopters and non-adopters by setting the event-time variable to zero for all non-adopters, as is consistent with the hybrid event-study design described by Miller (2023). This approach increases efficiency in the estimation of the industry-year and location-year fixed effects and the time-varying coefficients on the initial-year covariates while retaining a pre- and post-adoption interpretation of the event-study coefficients.

4 Firm-Level Results

In this section, we present and discuss estimates of the firm-level effects of robot adoption, focusing in particular on the discrete measure of adoption in or before a given year. We begin in Section 4.1 by reporting how robot adoption affects outcomes for adopting firms with identified individual owners and the impact of the treatment of owners with employment income on the magnitude of these results. Section 4.2 describes how results contrast between the T2S50-firm sample and the sample of all firms that are not restricted to having information on individual owners. In Section 4.3 we evaluate how restricting our sample to firm-year observations with at least 10 employees affects our results.

4.1 Effects of Adoption

To compare the firm-level effects of robot adoption in Canada with existing evidence from other countries and document the novel insights that can be gained into how adoption affects owners relative to workers, we show how robot adoption affects each of the four groups of outcomes described above on firm scale, per-worker outcomes, the allocation of firm-level surplus across workers and owners, and the composition of total owner income.

4.1.1 Firm Scale

Table 2 presents estimates of the main coefficient of interest, β, in Equation (1) for outcomes that measure how the scale of firms is affected by robot adoption.

In Panel A, we use our baseline treatment of owners with employment income to measure outcome variables, so that employment counts do not include those owners and owners' employment income is allocated to total owner income and not to a firm's payroll. For each of the five measures of firm scale, robot adoption has a positive effect on firm size, and this effect is highly statistically significant for all but the measure of owner income.[21] Our estimates imply that revenues, value added, and employment increase by approximately (exp(0.45)-1)$\times$100% = 57% on average following the onset of adoption while worker payroll increases by a larger proportion (71%).

For the first four scale effect outcomes, we can compare our results to those estimated in other settings. Considering similar panel fixed-effect specifications using binary measures of robot adoption, the increase in value added is larger than that reported by Acemoglu et al. (2023) for Dutch firms in a comparable set of industries, while we estimate a higher boost to revenues and employment than what Koch et al. (2021) and Bonfiglioli et al. (2024) find for Spanish and French firms, respectively, in a more narrow manufacturing sector. Our results

[21] Because the change in retained earnings can be negative (such as when a firm has negative after-tax net income), owner income can be non-positive. To retain these not infrequent observations in the estimation sample, we report here results using an inverse-hyperbolic-sine transformation of owner income. In Table A3, we show that the effect using a log transformation in the sample of strictly positive observations yields a positive and statistically significant estimate with a magnitude that is comparable to, though smaller than, those found for the other measures of firm scale.

Table 2: Firm Scale Effects of Robot Adoption

	log revenues	log value added	log employment	log payroll	ihs owner income
	(1)	(2)	(3)	(4)	(5)
Panel A: baseline treatment of owners					
Robot adopter	0.451***	0.457***	0.449***	0.538***	0.696*
	(0.038)	(0.036)	(0.038)	(0.044)	(0.354)
Adjusted R^2	0.861	0.815	0.868	0.829	0.323
No. Obs.	3,137,200	3,075,020	3,137,200	3,137,200	3,137,085
No. Firms	406,710	402,110	406,710	406,710	406,700
Panel B: unadjusted treatment of owners					
Robot adopter	0.451***	0.457***	0.409***	0.481***	0.807*
	(0.038)	(0.036)	(0.036)	(0.039)	(0.427)
Adjusted R^2	0.861	0.815	0.867	0.823	0.271
No. Obs.	3,137,200	3,075,020	3,137,200	3,137,200	3,137,080
No. Firms	406,710	402,110	406,710	406,710	406,700

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. Column (5) uses an inverse-hyperbolic-sine (ihs) transformation. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.10$.

are also consistent with the robust direct evidence of positive scale effects associated with robot adoption found in Acemoglu et al. (2020), Dixon et al. (2021), Humlum (2021), and Benmelech and Zator (2025).

These scale effects could in part reflect unobserved factors varying over time within firms that lead to robot adoption being endogenous. To the extent that these factors pre-date robot adoption events, we investigate this possibility by estimating our event-study specification, Equation (2), for each of the first four dependent variables reported in Table 2 and plot the estimates and confidence intervals of the event-study coefficients in Figure A2. We find no statistically significant evidence of pre-trends for robot adopters (with the sole exception of the effect five years before adoption on payroll), but find that adoption is associated with immediate and persistent positive effects on firm scale for adopters.

Panel B of Table 2 demonstrates the impact of reclassifying owners who pay themselves employment income as workers and including this income in measures of worker payroll on the effects of robot adoption on firm scale. As this adjustment plays no role in the calculation of revenues or value added, the estimated coefficients in columns (1) and (2) are identical.

However, for employment and payroll our estimates imply that effects are understated by 11% and 13%, respectively (from 57% to 51% for employment and 71% to 62% for payroll). The differential impact suggests that total worker compensation increases proportionately more than does employment income paid to owners. The effect of robot adoption on owner income, which is now exclusive of owners' employment income, remains positive, but the imprecision of the estimates in column (5) prevents us from drawing conclusions on the relative magnitudes of the coefficients for owner income.[22]

As a final look at the direct scale effects of robot adoption, we estimate the same set of regressions as those in Table 2 but allow for the scale effects of robot adoption to vary by the amount of robots in use at a firm. Table A4 shows results using the stock of robots in a firm each year. Because, for most firm-year observations, the stock of robots is zero and to maintain comparability with the binary adoption specification, we transform this stock measure using the inverse hyperbolic sine. Our findings indicate that the qualitative pattern of scale effects are unchanged by using this continuous measure of robot adoption, as effects on revenues, value added, employment, and payroll remain positive and statistically significant, while the effect on owner income is positive though relatively imprecisely estimated.[23] Furthermore, we continue to find smaller effects for employment and payroll when we do not account for owners with employment income.

4.1.2 Per-Worker Outcomes

The second group of outcomes includes per-worker payroll, value added, and revenues. Estimates are provided in Table 3. In Panel A, which uses the baseline treatment of owners that excludes them from the count of workers and calculation of payroll, we find that robot adoption has a positive and statistically significant effect on payroll per worker but no significant effect on either value added or revenues per worker.[24] Quantitatively, average pay received by workers rises by 9% in adopting firms following initial robot adoption.

The consequences of including owners paying themselves employment income in the firm-level measure of employment for the per-worker impacts of robot adoption emerges when comparing these results with those using the alternative definition of workers, which we

[22]Coefficients estimated on the samples with strictly positive values of owner income (see Table A3), which are much more precise, are similar in size though somewhat larger using the baseline treatment of owner employment income.

[23]Reassuringly, our estimate of the effect on employment is consistent with that reported by Dixon et al. (2021) who use the same source of Canadian robot adoption data (though they use a distinct measure of employment that cannot be used to identify owners separately from workers). Acemoglu et al. (2023) also find a positive and significant effect of the cumulative value of robot imports on value added.

[24]The corresponding event study results are depicted in Figure A3. We find no evidence of pre-trends but a statistically significant effect on payroll per worker beginning three years after initial adoption that becomes weaker and only significant at the 10% level by the fifth year following adoption.

Table 3: Firm-Level Labor Productivity Effects of Robot Adoption

	log payroll per worker	log value added per worker	log revenues per worker
	(1)	(2)	(3)
Panel A: baseline treatment of owners			
Robot adopter	0.089***	0.021	0.002
	(0.013)	(0.016)	(0.015)
Adjusted R^2	0.650	0.674	0.719
No. Obs.	3,137,200	3,075,020	3,137,200
No. Firms	406,710	402,110	406,710
Panel B: unadjusted treatment of owners			
Robot adopter	0.072***	0.061***	0.042**
	(0.012)	(0.015)	(0.015)
Adjusted R^2	0.681	0.659	0.727
No. Obs.	3,137,200	3,075,020	3,137,200
No. Firms	406,710	402,110	406,710

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

present in Panel B. As discussed in the previous subsection, employment and payroll grow more slowly following adoption when including such owners in these measures. On net, we find that the these adjustments lead to a similar though slightly smaller estimate of the effect of robot adoption on average pay per employee. More importantly, using this alternative classification of owners with employment income, we now estimate positive and statistically significant impacts of robot adoption on value added and revenues per worker. These findings suggest that ignoring that owners can choose to withdraw earnings from their firms both through employment income and dividends may lead to an overstatement of the degree to which robot adoption affects value added per worker in adopters.

Evidence on direct effects on comparable firm-level average compensation and value added and sales per worker measures in the literature on robot adoption is limited. Koch et al. (2021) find no impact of robot adoption on labor costs per worker in Spain. Acemoglu et al. (2020) estimate positive effects on sales per worker and value added per worker for French manufacturing firms, the latter of which is also found to be positively associated with robot adoption in Bonfiglioli et al. (2024).[25] In the wider literature on the impacts of firms' use of

[25] In their unweighted estimates, Acemoglu et al. (2020) find a positive impact on hourly wages, sales per

industrial machinery relevant for automation, Aghion et al. (2025) find that value added per worker increases following spikes in investment in such machines in French manufacturing firms (though with no impact on average hourly wages), while Hirvonen et al. (2025) find that the reward of subsidies for investing in advanced machinery had no impact on revenues per worker on average wages for Finnish manufacturing firms.[26]

In Table A5, we report estimates of the effects of robot adoption using the continuous measure of robot stocks. The results are analogous to those obtained using the binary measure of robot adoption: payroll per worker increases with the stock of robots, but impacts on value added and revenues per worker are positive and statistically significant only when owners with employment income are included in the count of workers.

4.1.3 Distribution of Surplus Between Workers and Owners

We now turn to the outcomes that highlight the implications of robot adoption for the proportion of firm-level surplus that is distributed to workers and individual owners. Panel A of Table 4 presents results for the shares of value added that are allocated to workers as payroll and to owners as total owner income.[27]

The first notable finding in this table, as shown in column (1), is that robot adoption is associated with a statistically significant increase in the worker payroll share of value added of 1.4 percentage points. This contrasts with the results found by Acemoglu et al. (2023) who estimate a statistically significant negative impact of adoption on the labor share for firms in a similar set of industries in the Netherlands.[28] As we show in Panel B, we continue to find no evidence of a negative impact of adoption on the labor share after including owners' employment income in the measure of total labor compensation. The contrasting results in column (1) suggest that, in our setting, total worker payroll increases faster than owner employment income following robot adoption.

Second, the share of value added accruing to owners does not increase following robot adoption; instead, we find that after accounting for owners employment income in total owner

hour, and value added per hour, while Acemoglu et al. (2023) find no effect on hourly wages but results consistent with an increase in value added per hour for Dutch firms in the broad manufacturing sector.

[26] Using imports of a broader set of automation-related capital goods than industrial robots in France, Domini et al. (2022) find that average hourly wages increase and value added per hour decreases following automation import spikes.

[27] Results for estimates using the continuous stock of robots, which are consistent with those discussed here that use the binary adoption measure, are presented in Table A6 for completeness.

[28] Acemoglu et al. (2020) also find a negative effect in a shorter sample using a long-differences specification. Koch et al. (2021) find a negative impact on the labor cost share of output but do not report estimates for the labor share of value added. Using a more general set of automation-related capital investments, Aghion et al. (2025) estimate that the labor share of value added decreases following large increases in investment.

Table 4: Firm-Level Effects of Robot Adoption on Surplus Allocation

	Labor share (1)	Owner income share (2)
Panel A: baseline treatment of owners		
Robot adopter	0.014**	-0.017***
	(0.006)	(0.006)
Adjusted R^2	0.681	0.666
No. Obs.	2,839,340	2,721,070
No. Firms	382,800	375,690
Panel B: unadjusted treatment of owners		
Robot adopter	0.007	-0.006
	(0.006)	(0.005)
Adjusted R^2	0.601	0.556
No. Obs.	2,480,695	2,188,010
No. Firms	358,645	343,165

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. All dependent variables are measured as shares of value added. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

income, the owner income share of value added decreases by 1.7 percentage points.[29] The negative (or zero) impact on the owner income share does not imply that owners do not benefit from robot adoption. As discussed in Section 4.1.1, we find a positive association between adoption and owner income, particularly for firms with non-negative owner income.

Taken together, the results in Tables 2 to 4 indicate that the potential negative impacts of automation on workers through the adoption of industrial robots have been relatively more benign in private corporations in the broad manufacturing sector in Canada than in empirical settings used in related work. While adoption may indeed displace labor performing a range of tasks to which robots are well suited, the scale effect on total employment, which is consistent with most results in the literature, combined with the impacts on payroll per worker and the labor share of value added suggest that displacement is not the dominant force driving the impacts of robots on workers in Canadian firms.

[29]The contrasting effects on labor and owner income shares of value added in Panel A is not mechanical: the residual includes depreciation and taxes on net income.

Table 5: Firm-Level Effects of Robot Adoption on Owner Income Composition

	ihs dividends (1)	ihs Owner payout (2)	Dividend share (TP) (3)	Owner payout share (TP) (4)
Robot adopter	0.286	0.648***	-0.005	-0.023***
	(0.234)	(0.136)	(0.005)	(0.006)
Adjusted R^2	0.540	0.638	0.565	0.715
No. Obs.	3,137,200	3,137,200	3,137,200	3,137,200
No. Firms	406,710	406,710	406,710	406,710

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Robot adoption is a discrete measure equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Columns (1) and (2) use an inverse-hyperbolic-sine (ihs) transformation. Shares in columns (3) and (4) are relative to total income paid out by the firm to affiliated individuals (TP). All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.1.4 Owner Income Composition

Our final group of firm-level outcomes leverages the availability of information on owners' employment income to examine the impact of robot adoption on the sources of income owners can use to extract surplus from their firms. In Table 5, we show results for estimates of Equation (1) for dividends and owner payout (dividends plus owner employment income) in columns (1) and (2), respectively, and for each of these measures relative to a firms' total flow payout (owner payout plus worker payroll) in columns (3) and (4).[30] We cannot reject that robot adoption has no impact on the dividends paid out by the firm (though the point estimate is positive). However, the effect is positive and highly statistically significant when including owners' employment income in the total value that owners pay out from their firms. When expressed as a share of total payout of the firm, the dividends share is found to change little following adoption because dividends account for only a small proportion of total payout on average, but the owner payout share decreases by 2.3 percentage points. This implies that robot adoption leads compensation paid out to workers to rise at a faster rate than compensation taken out of the firm by owners.

Because many firms do not pay dividends or employment income to their owners in a given year, we also examine the intensive-margin impact of robot adoption on dividends and owner payout in Table A3. Our findings are unchanged: we find little evidence that dividends increase among firms that pay them out while total owner payout increases by nearly 34%

[30] To account for the descriptive facts reported in Table 1 regarding the prevalence of zeros for these metrics and to retain the largest possible sample, we express results for dividends and owner payout in terms of the inverse-hyperbolic-sine transformation in columns (1) and (2).

among firms with realized flow payments to owners.

That total owner payout increase following robot adoption while dividends remain unchanged implies that owners primarily extract surplus from adoption through employment income. This has important consequences both for interpreting the impacts of robot adoption on owners and for measuring aggregate distributional effects of firm-level shocks more generally.

For interpretation, the increase in owners' employment income could reflect higher returns to human capital supplied by owners. For example, the increase in the scale of the firm could require enhanced managerial inputs provided by firm owners that would be compensated for through higher employment income. At the same time, the finding that dividends do not respond to robot adoption suggests that some of the profits that owners are residual claimants may be earned as employment income.[31]

For measurement, our results demonstrate the importance of the response of owners employment income for estimating the impact of firm-level shocks on workers and owners, which is a point echoed in Wang and Young (2026). While we focus on within-firm outcomes, the findings suggest we would reach very different conclusions regarding the aggregate impact of these shocks on workers relative to owners were we to allocate owners' employment income in private corporations to workers.

4.2 Comparison with All Firms

As a first robustness test of our main results discussed in the previous section, we show how our results are affected when we do not restrict the sample to include firm-year observations with observed individual owners. By necessity, for this comparison, we use the alternative definition of employment and payroll that treats individual owners with employment income as workers and removes owners' employment income from total owner income. Results are reported in Table 6, where Panel A repeats the relevant estimates for the T2S50 firms from Tables 2 to 4 for ease of comparison.

For the enlarged sample of firms, we continue to find positive and statistically significant effects of adoption on total payroll.[32] In the sample of all firms in the broad manufacturing sector, adoption has a more pronounced impact on total owner income (dividends plus retained earnings) than in the T2S50-firm sample. We also continue to find a positive impact of robot adoption on payroll and value added per worker, though the estimated effects are

[31]It is also possible that owners defer the realization of capital income from their private corporations through capital gains on the sale of their businesses, but we are unable to evaluate this channel in our data.

[32]Estimates for other firm scale measures including revenues, value added, and employment are also positive, statistically significant, and similar in magnitude for both samples.

Table 6: Effects of Robot Adoption on All Firms in Broad Manufacturing

	log payroll	ihs owner income	log payroll per worker	log value added per worker	Labor share	Owner income share
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: T2S50 Firms						
Robot adopter	0.481***	0.807*	0.072***	0.061***	0.007	-0.006
	(0.039)	(0.427)	(0.012)	(0.015)	(0.006)	(0.005)
Adjusted R^2	0.823	0.271	0.681	0.659	0.601	0.556
No. Obs.	3,137,200	3,137,080	3,137,200	3,075,020	2,480,695	2,188,010
No. Firms	406,710	406,700	406,710	402,110	358,645	343,165
Panel B: All firms						
Robot adopter	0.472***	1.312***	0.039***	0.044**	0.012**	0.001
	(0.034)	(0.333)	(0.010)	(0.016)	(0.005)	(0.003)
Adjusted R^2	0.820	0.273	0.655	0.657	0.598	0.659
No. Obs.	5,506,105	5,505,080	5,506,105	5,375,910	4,295,045	3,839,410
No. Firms	690,130	690,090	690,130	682,630	612,570	594,370

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample in Panel (A) and the all-firm sample in Panel (B) using the alternative definition of workers as individuals who receive any employment income from the firm and owner income is net of owner employment income. Column (2) uses an inverse-hyperbolic-sine (ihs) transformation. Labor and owner income shares are measured relative to value added. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

smaller when all firms are included in the regression.

The principal difference in results between the two samples can be found in column (5) for the impact on the labor share of value added. Whereas we found no statistically significant impact of adoption on this measure for the T2S50-firm sample once owners' employment income is included in the firms' payroll, we now find a positive and significant impact on the labor share for the all-firm sample. By contrast, we continue to find no detectable effect on the owner income share of value added.

4.3 Comparison with Large Employers

Because most other firm-level studies of the impact of robot adoption use samples that are restricted in the size of firms included either because the information on robots and/or firm-level accounting data is drawn from surveys that sample disproportionately from large employers or by choice, we also evaluate how our results are robust to a minimum employment size restriction. In particular, we estimate Equation (1) on the sample of firm-year observations for which a T2S50 firm has at least 10 workers (i.e., individuals who are never observed to be

Table 7: Effects of Robot Adoption on T2S50-Firms with 10 or more Employees

	log payroll	ihs owner income	log payroll per worker	log value added per worker	Labor share	Owner income share
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firm-Years with one or more Employees						
Robot adopter	0.538***	0.696*	0.089***	0.021	0.014**	-0.017***
	(0.044)	(0.354)	(0.013)	(0.016)	(0.006)	(0.006)
Adjusted R^2	0.829	0.323	0.650	0.674	0.681	0.666
No. Obs.	3,137,200	3,137,085	3,137,200	3,075,020	2,839,340	2,721,070
No. Firms	406,710	406,700	406,710	402,110	382,800	375,690
Panel B: Firm-Years with 10 or more Employees						
Robot adopter	0.299***	0.518	0.034***	0.030	0.002	-0.007
	(0.032)	(0.399)	(0.010)	(0.017)	(0.006)	(0.005)
Adjusted R^2	0.884	0.311	0.846	0.765	0.639	0.581
No. Obs.	956,890	956,780	956,890	950,135	863,590	819,840
No. Firms	127,400	127,390	127,400	126,775	118,400	115,575

Notes: Table presents estimates of Equation (1) or the sample of T2S50 firm-year observations with 1 or more employees in Panel (A) and with 10 or more employees in Panel (B) using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Column (2) uses an inverse-hyperbolic-sine (ihs) transformation. Labor and owner income shares are measured relative to value added. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

an owner of the firm). We show a comparison of some of the main results from our baseline analysis on firm scale, average payroll, value added per worker, and the surplus split for this alternative sample of large employers in Table 7.

When restricted to using larger employers, we continue to find a positive and significant effect of robot adoption on measures of firm scale including payroll (as shown in column (1)) and payroll per worker (in column (3)), though the coefficient magnitudes are smaller.[33] Furthermore, we find no impact of robot adoption on value added per worker. However, the finding that robot adoption leads to positive impacts on the labor share and a negative effect on the owner income share is no longer present in this sample, as we cannot reject that adoption has no impact on either share.

We draw two conclusions from this comparison. First, the results suggest that the effect of robot adoption on the shift in the distribution of value added from owners to workers may be larger for smaller employers than for larger employers for which these shares are, on average, more stable in general. Second, given the consistent finding of scale effects of

[33]Unlike the baseline sample, where payroll increases more than revenues or value added, the growth rates of these three scale measures are essentially identical in the restricted sample.

adoption for employment, payroll, and value added, the omission of small employers from an evaluation of the impacts of robot adoption may give rise to the possibility of compositional bias in the estimated effects.

As for the impact on the source composition of owners' income, we find results that are consistent with the evidence for the full sample of firms.[34] Owners in larger private corporations tend to extract income from the firm following robot adoption not through dividends but instead through employment income.

5 Conclusion

This paper estimates the direct impacts of robot adoption on non-owner workers and owners within adopting firms. We find that robot adoption increases firm scale, whether measured using output outcomes such as value added and revenues or labor-based input outcomes such as employment and payroll. However, the estimated effects on worker employment, payroll, and per-worker outcomes differ materially depending on whether owner-employees and owner employment income are included in these measures. In our estimates, measures that treat these owners as ordinary workers understate the increase in non-owner employment and payroll. In addition, we find no evidence that adoption increases value added per non-owner worker, while the estimated effect on value added per worker becomes positive when owners with employment income are included in the worker count. This distinction shows that measured productivity can change because of how these owners are classified, not only because of changes in output.

Unlike much of the firm-level robot-adoption literature, we find no evidence that adoption decreases the labor share of value added. When owner employment income is included in labor compensation, adoption has no detectable impact on the conventionally measured labor share. When owner employment income is instead separated from ordinary worker payroll, we estimate a positive and significant impact on the non-owner labor share of value added. At the same time, while the level of owner income increases following adoption, the owner income share of value added does not increase, whether or not owner employment income is included in owner income.

These findings show that owner employment income is central for measuring the incidence of firm-level technology shocks. Owners benefit from robot adoption, but primarily through increases in employment income. As a result, conventional payroll measures can partly mask owner incidence, while profit-based measures can understate the extent to which owners benefit.

[34] Estimates are presented in Table A7.

Our results are specific to the direct impacts of robot adoption on adopting firms. Important questions for future research include how robot adoption affects workers and owners at competing firms, how adoption changes the earnings dynamics of individual workers and owners, and whether these direct adopter effects aggregate to broader changes in industry-level employment, productivity, and labor shares.

The results are also specific to Canadian private corporations. In other settings, differences in legal form, tax policy, and owner compensation practices may affect whether owners receive gains from automation through employment income, dividends, retained earnings, or other channels. Accounting for these institutional differences is important for understanding how robot adoption affects workers, owners, and the distribution of income within firms.

References

Acemoglu, Daron, Hans R.A. Koster, and Ceren Ozgen (2023) "Robots and Workers: Evidence from the Netherlands," NBER Working Paper 31009, National Bureau of Economic Research.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020) "Competing with Robots: Firm-Level Evidence from France," in *AEA Papers and Proceedings*, 110, 383–388, May.

Acemoglu, Daron and Pascual Restrepo (2018) "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, 108 (6), 1488–1542.

——— (2019) "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33 (2), 3–30.

——— (2020) "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128 (6), 2188–2244.

——— (2022) "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 90 (5), 1973–2016.

——— (2024) "Automation and Rent Dissipation: Implications for Wages, Inequality, and Productivity," NBER Working Paper 32536, National Bureau of Economic Research.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel (2025) "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France," Working Paper.

Barth, Erling, Marianne Røed, Pål Schøne, and Janis Umblijs (2026) "Winners and Losers When Firms Robotize: Wage Effects Across Occupations and Education," *The Scandinavian Journal of Economics*, 128 (1), 3–32.

Bena, Jan, Andrew Ellul, Marco Pagano, and Valentina Rutigliano (2024) "Entrepreneurs' Diversification and Labor Income Risk," Working Paper.

Benmelech, Efraim and Michał Zator (2025) "Robots and Firm Invesment," *Journal of Financial Economics*, 174, 104183.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2020) "Firm-Level Automation: Evidence from the Netherlands," in *AEA papers and proceedings*, 110, 389–393, May.

——— (2025) "What Happens to Workers at Firms that Automate?" *Review of Economics and Statistics*, 107 (1), 125–141.

Bisio, Laura, Angelo Cuzzola, Marco Grazzi, and Daniele Moschella (2025) "The Dynamics of Automation Adoption: Firm-Level Heterogeneity and Aggregate Employment Effects," *European Economic Review*, 173, 104943.

Bonfiglioli, Alessandra, Rosario Crino, Harald Fadinger, and Gino Gancia (2024) "Robot Imports and Firm-Level Outcomes," *The Economic Journal*, 134 (664), 3428–3444.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021) "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 19 (6), 3104–3153.

Dinlersoz, Emin and Zoltan Wolf (2024) "Automation, Labor Share, and Productivity: Plant-Level Evidence from U.S. Manufacturing," *Economics of Innovation and New Technology*, 33 (4), 604–626.

Dixon, Jay (2020) "How to Build a Robots! Database," Analytical Studies: Methods and References 11-633-X No. 028, Statistics Canada.

Dixon, Jay, Bryan Hong, and Lynn Wu (2021) "The Robot Revolution: Managerial and Employment Consequences for Firms," *Management Science*, 67 (9), 5586–5605.

Domini, Giacomo, Marco Grazzi, Daniele Moschella, and Tania Treibich (2022) "For Whom the Bell Tolls: The Firm-Level Effects of Automation on Wage and Gender Inequality," *Research Policy*, 51 (7), 104533.

Drucker, Lev, Katya Mazirov, and David Neumark (2021) "Who Pays for and Who Benefits from Minimum Wage Increases? Evidence from Israeli Tax Data on Business Owners and Workers," *Journal of Public Economics*, 199, 104423.

Firooz, Hamid, Zheng Liu, and Yajie Wang (2025) "Automation and the Rise of Superstar Firms," *Journal of Monetary Economics*, 151, 103733.

Graetz, Georg and Guy Michaels (2018) "Robots at Work," *Review of Economics and Statistics*, 100 (5), 753–768.

Hirvonen, Johannes, Aapo Stenhammar, and Joonas Tuhkuri (2025) "Winners and Losers of Technology Grants: Evidence on Jobs and Skills," Working Paper.

Hubmer, Joachim and Pascual Restrepo (2026) "Not a Typical Firm: Capital–Labor Substitution and Firms' Labor Shares," *American Economic Journal: Macroeconomics*, 18 (2), 34–71.

Humlum, Anders (2021) "Robot Adoption and Labor Market Dynamics," Working Paper.

Kennedy, Patrick, Christine Dobridge, Paul Landefeld, and Jacob Mortenson (2026) "Corporate Tax Cuts, Firm Growth, and Workers' Earnings," Working Paper.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021) "Robots and Firms," *The Economic Journal*, 131 (638), 2553–2584.

Leduc, Sylvain and Zheng Liu (2024) "Automation, Bargaining Power, and Labor Market Fluctuations," *American Economic Journal: Macroeconomics*, 16 (4), 311–349.

Miller, Douglas (2023) "An Introductory Guide to Event Study Models," *Journal of Economic Perspectives*, 37 (2), 203–230.

Moll, Benjamin, Lukasz Rachel, and Pascual Restrepo (2022) "Uneven Growth: Automation's Impact on Income and Wealth Inequality," *Econometrica*, 90 (6), 2645–2683.

Rao, Nirupama L and Max Risch (2026) "Who's Afraid of the Minimum Wage? Measuring The Impacts on Independent Businesses Using Matched US Tax Returns," *The Quarterly Journal of Economics*, 141 (1), 373–427.

Risch, Max (2024) "Does Taxing Business Owners Affect Employees? Evidence From A Change in the Top Marginal Tax Rate," *The Quarterly Journal of Economics*, 139 (1), 637–692.

Rispoli, Luke (2009) "Measuring the Contribution of the Unincorporated Sector in the Canadian Economy, 1997 to 2002," Insights on the Canadian Economy 11-624-M No. 023, Statistics Canada.

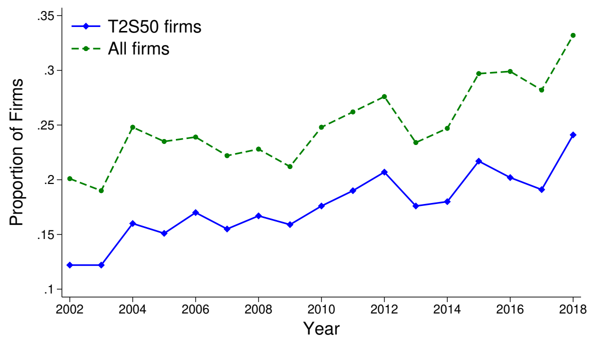
Splinter, David, Michael Love, Eric Heiser, and Jacob Mortenson (2026) "The Paycheck Protection Program: Progressivity and Tax Effects," *National Tax Journal*, 79 (2), 409–429.

Wang, Sean and Samuel Young (2026) "The Distributional Effects of Firm Demand Changes: Evidence from U.S. Worker-Owner Data," Working Paper.

Wolfson, Michael, Mike Veall, Neil Brooks, and Brian Murphy (2016) "Piercing the Veil: Private Corporations and the Income of the Affluent," *Canadian Tax Journal*, 64, 1–30.

Appendix A Additional Figures and Tables

A: Robot Importers in Year



B: Past Robot Adoption up to Year

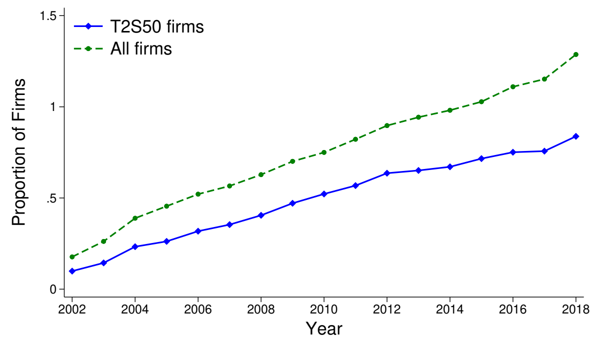


Figure A1: Prevalence of Robot Adoption for Firms with 10 or More Workers

Notes: Figure depicts the prevalence of robot adoption in the broad manufacturing sector for firm-year observations with 10 or more workers in the T2S50-firm sample and the all-firm sample. Panel A plots the ratio of the number of firms ever in the sample with robot imports in a year to the number of firms in the sample in that year. Panel B displays the share of firms in the sample in each year that have adopted a robot up to and including that year.

Table A1: Summary Statistics of All-Firm Sample

Variables	Mean	Std. dev.	5th perc.	Median	95th perc.	Obs.
Panel A: Robot adopters						
Revenues (millions of $)	341.972	1961.721	0.562	13.401	1114.269	17,930
Value added (millions of $)	90.755	513.631	0.206	4.573	338.672	17,550
Number of workers	840	3,938	6	105	3,659	17,930
Payroll (millions of $)	40.009	160.390	0.149	3.465	189.977	17,930
Owner income (millions of $)	22.932	439.027	-4.968	0.268	74.857	17,930
Dividends (millions of $)	21.452	233.957	0.000	0.000	28.384	17,930
Payroll per worker ($)	38,095	22,508	13,522	34,811	71,700	17,930
Value added per worker ($)	112,128	3,500,838	14,875	46,710	148,090	17,550
Assets per worker ($)	521,900	8,683,153	23,333	99,899	929,377	17,930
Revenues per worker ($)	291,860	3,766,568	42,267	134,533	582,645	17,930
Labor share (VA)	0.68	0.20	0.29	0.70	0.95	15,140
Owner income share (VA)	0.20	0.16	0.02	0.16	0.51	13,445
Dividends share (VA)	0.06	0.15	0.00	0.00	0.38	17,355
Dividends share (TP)	0.08	0.17	0.00	0.00	0.48	17.930
Robot import event	0.17	0.38	0.00	0.00	1.00	17,930
Robot adoption by present	0.58	0.49	0.00	1.00	1.00	17,930
Panel B: Non-adopters						
Revenues (millions of $)	2.767	76.035	0.030	0.236	5.484	5,488,180
Value added (millions of $)	0.973	30.328	0.012	0.112	1.845	5,365,855
Number of workers	16	260	1	3	48	5,488,180
Payroll (millions of $)	0.533	9.693	0.006	0.072	1.334	5,488,180
Owner income (millions of $)	0.224	26.799	-0.049	0.010	0.314	5,488,180
Dividends (millions of $)	0.178	15.523	0.000	0.000	0.140	5,488,180
Payroll per worker ($)	31,938	91,938	3,544	22,275	79,869	5,488,180
Value added per worker ($)	65,108	1,265,325	6,138	32,366	159,297	5,365,855
Assets per worker ($)	256,645	12,168,925	3,582	40,623	583,625	5,488,180
Revenues per worker ($)	148,924	1,656,592	16,023	76,961	389,794	5,488,180
Labor share (VA)	0.64	0.26	0.12	0.69	0.98	4,329,420
Owner income share (VA)	0.26	0.22	0.00	0.20	0.72	3,880,125
Dividends share (VA)	0.09	0.18	0.00	0.00	0.53	5,255,845
Dividends share (TP)	0.13	0.24	0.00	0.00	0.72	5,488,180
Robot import event	0.00	0.00	0.00	0.00	0.00	5,488,180
Robot adoption by present	0.00	0.00	0.00	0.00	0.00	5,488,180

Notes: Table reports summary statistics of firm-year-level variables defined in Section 2.3 for the sample of all firms in the broad manufacturing sector. All variables are measured using a consistent definition of workers as individuals who receive any employment income from the firm and the calculation of owner income ignores owner employment income. Panel A includes all observations for firms that ever import robots over the 2002–2018 period. Panel B includes all observations for firms that did not import robots during that time. For share variables, (VA) and (TP) indicate that value added and total income paid out as employment income or dividends is the denominator, respectively. Robot import event denotes observations with positive robot imports. Robot adoption by present denotes whether the firm has imported a robot up to and including the year of the observation. Observation counts are rounded pursuant to Statistics Canada confidentiality rules.

Table A2: Summary Statistics of T2S50-Firm Sample without Accounting for Observed Individual Owners

Variables	Mean	Std. dev.	5^{th} perc.	Median	95^{th} perc.	Obs.
Panel A: Robot adopters						
Revenues (millions of $)	124.739	1,395.585	0.467	6.181	152.054	9,860
Value added (millions of $)	34.277	339.748	0.169	2.269	43.404	9,740
Number of workers	396	4,058	5	58	747	9,860
Payroll (millions of $)	13.743	102.024	0.129	1.686	28.891	9,860
Owner income (millions of $)	12.709	179.020	-0.732	0.183	7.635	9,860
Dividends (millions of $)	11.422	164.329	0.000	0.000	3.912	9,860
Payroll per worker ($)	33,278	19,162	12,263	30,245	62,255	9,860
Value added per worker ($)	56,742	508,944	13,648	40,298	104,287	9,740
Assets per worker ($)	183,733	1,425,176	20,000	73,809	345,908	9,860
Revenues per worker ($)	164,449	1,106,060	38,985	108,554	349,267	9,860
Labor share (VA)	0.71	0.18	0.36	0.74	0.95	8,475
Owner income share (VA)	0.18	0.14	0.02	0.15	0.45	7,615
Dividends share (VA)	0.06	0.14	0.00	0.00	0.36	9,670
Dividends share (TP)	0.07	0.15	0.00	0.00	0.42	9,860
Robot import event	0.14	0.35	0.00	0.00	1.00	9,860
Robot adoption by present	0.55	0.50	0.00	1.00	1.00	9,860
Panel B: Non-adopters						
Revenues (millions of $)	2.144	41.788	0.056	0.431	6.797	3,127,340
Value added (millions of $)	0.728	15.138	0.020	0.175	2.242	3,069,880
Number of workers	18	182	1	6	59	3,127,340
Payroll (millions of $)	0.482	5.318	0.011	0.121	1.635	3,127,340
Owner income (millions of $)	0.141	13.456	-0.067	0.016	0.357	3,127,340
Dividends (millions of $)	0.094	8.263	0.000	0.000	0.190	3,127,340
Payroll per worker ($)	25,969	41,264	4,523	20,933	57,923	3,127,340
Value added per worker ($)	48,033	443,146	6,276	28,959	110,334	3,069,880
Assets per worker ($)	164,958	3,544,545	4,021	37,241	374,368	3,127,340
Revenues per worker ($)	130,108	759,730	17,569	72,775	351,200	3,127,340
Labor share (VA)	0.67	0.24	0.19	0.72	0.97	2,502,735
Owner income share (VA)	0.23	0.20	0.00	0.18	0.64	2,222,025
Dividends share (VA)	0.08	0.17	0.00	0.00	0.46	3,024,530
Dividends share (TP)	0.11	0.20	0.00	0.00	0.61	3,127,340
Robot import event	0.00	0.00	0.00	0.00	0.00	3,127,340
Robot adoption by present	0.00	0.00	0.00	0.00	0.00	3,127,340

Notes: Table reports summary statistics of firm-year-level variables defined in Section 2.3 for the T2S50-firm sample. All variables are measured using an alternative definition of workers as individuals who receive any employment income from the firm and the calculation of owner income ignores owner employment income. Panel A includes all observations for firms that ever import robots over the 2002–2018 period. Panel B includes all observations for firms that did not import robots during that time. For share variables, (VA) and (TP) indicate that value added and total income paid out as employment income or dividends is the denominator, respectively. Robot import event denotes observations with positive robot imports. Robot adoption by present denotes whether the firm has imported a robot up to and including the year of the observation. Observation counts are rounded pursuant to Statistics Canada confidentiality rules.

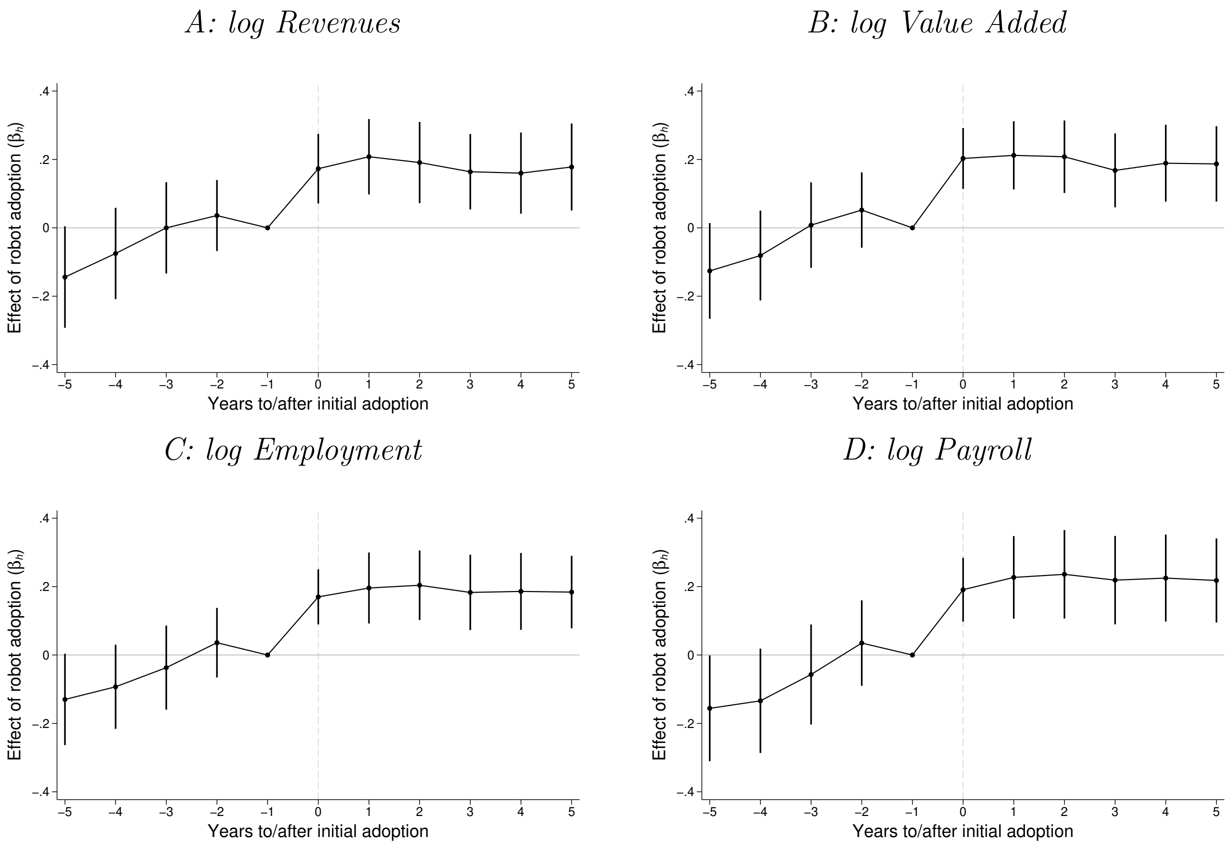


Figure A2: Firm-Level Scale-Effect Event Studies

Notes: Figure plots event-study coefficents and 95% confidence intervals estimated using Equation (2) for the T2S50-firm sample. Effects are normalized relative to each variable measured one year before initial adoption.

Table A3: Firm-Level Effects of Robot Adoption on Owner Income Composition

	log owner income (base.) (1)	log dividends (2)	log owner payout (3)	log owner income (adj.) (4)
Robot adopter	0.396***	0.150	0.292***	0.375***
	(0.043)	(0.088)	(0.042)	(0.048)
Adjusted R^2	0.682	0.593	0.703	0.642
No. Obs.	2,707,175	1,222,695	2,700,255	2,118,590
No. Firms	372,565	209,400	358,515	331,255

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using log transformations of strictly positive values of the dependent variables. Columns (1) and (3) use the baseline definition of owner income and payout that include owner employment income. Column (4) uses the adjusted definition of owner income that is net of owner employment income. Robot adoption is a discrete measure equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A4: Firm Scale Effects of Robot Stocks

	log revenues	log value added	log employment	log payroll	ihs owner income
	(1)	(2)	(3)	(4)	(5)
Panel A: baseline treatment of owners					
ihs robot stock	0.043***	0.043***	0.043***	0.051***	0.065*
	(0.004)	(0.003)	(0.003)	(0.004)	(0.033)
Adjusted R^2	0.861	0.815	0.868	0.829	0.323
No. Obs.	3,137,200	3,075,020	3,137,200	3,137,200	3,137,085
No. Firms	406,710	402,110	406,710	406,710	406,700
Panel B: unadjusted treatment of owners					
ihs robot stock	0.043***	0.043***	0.039***	0.046***	0.076*
	(0.004)	(0.003)	(0.003)	(0.004)	(0.040)
Adjusted R^2	0.861	0.815	0.867	0.823	0.271
No. Obs.	3,137,200	3,075,020	3,137,200	3,137,200	3,137,080
No. Firms	406,710	402,110	406,710	406,710	406,700

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a continuous robot stock measure calculated using the cumulative value of robot imports where imports in each year are subject to depreciation over a 12-year useful life. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. Column (5) and the robot stock use an inverse-hyperbolic-sine (ihs) transformation. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.10$.

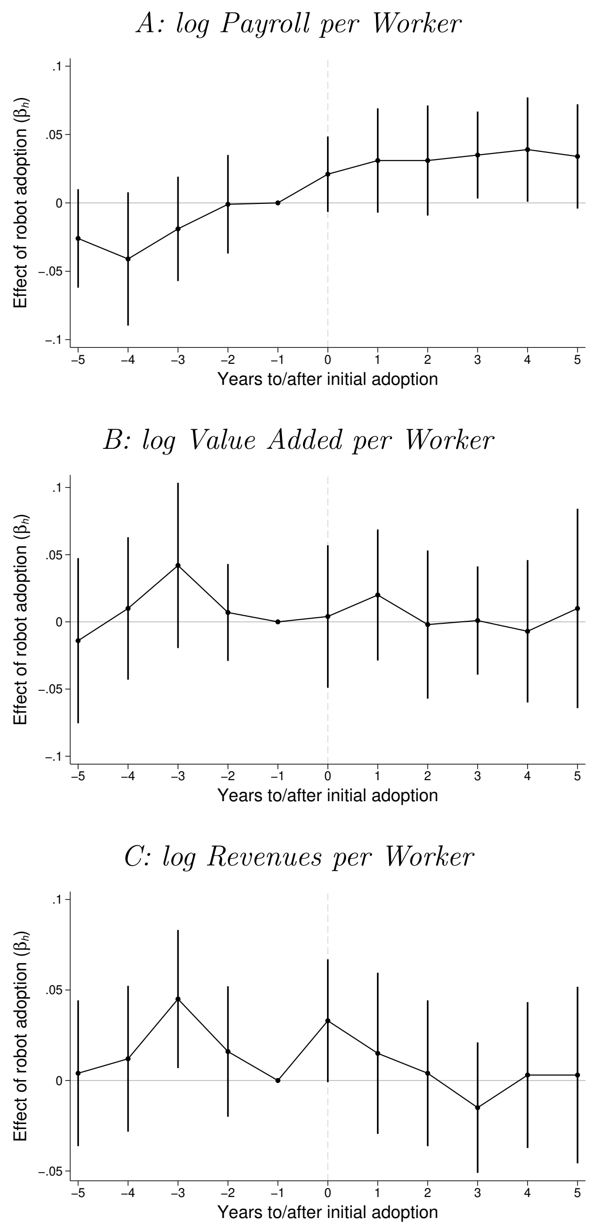


Figure A3: Firm-Level Labor Productivity Event Studies

Notes: Figure plots event-study coefficents and 95% confidence intervals estimated using Equation (2) for the T2S50-firm sample. Effects are normalized relative to each variable measured one year before initial adoption.

Table A5: Firm-Level Labor Productivity Effects of Robot Stocks

	log payroll per worker	log value added per worker	log revenues per worker
	(1)	(2)	(3)
Panel A: baseline treatment of owners			
ihs robot stock	0.009***	0.002	0.000
	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.650	0.674	0.719
No. Obs.	3,137,200	3,075,020	3,137,200
No. Firms	406,710	402,110	406,710
Panel B: unadjusted treatment of owners			
ihs robot stock	0.007***	0.006***	0.004**
	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.681	0.659	0.727
No. Obs.	3,137,200	3,075,020	3,137,200
No. Firms	406,710	402,110	406,710

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a continuous robot stock measure calculated using the cumulative value of robot imports where imports in each year are subject to depreciation over a 12-year useful life. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm. The robot stock uses an inverse-hyperbolic-sine (ihs) transformation. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A6: Firm-Level Effects of Robot Stocks on Surplus Allocation

	Labor share	Owner income share
	(1)	(2)
Panel A: baseline treatment of owners		
ihs robot stock	0.001**	-0.002***
	(0.001)	(0.000)
Adjusted R^2	0.681	0.666
No. Obs.	2,839,340	2,721,070
No. Firms	382,800	375,690
Panel B: unadjusted treatment of owners		
ihs robot stock	0.001	-0.001
	(0.001)	(0.000)
Adjusted R^2	0.601	0.556
No. Obs.	2,480,695	2,188,010
No. Firms	358,645	343,165

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using a continuous robot stock measure calculated using the cumulative value of robot imports where imports in each year are subject to depreciation over a 12-year useful life. All dependent variables are measured as shares of value added. Panel A reports estimates for outcomes measured using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Panel B uses the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. The robot stock uses an inverse-hyperbolic-sine (ihs) transformation. All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.10$.

Table A7: Robot Adoption and Owner Income Composition in Large Employers

	ihs dividends	ihs Owner payout	Dividend share (TP)	Owner payout share (TP)
	(1)	(2)	(3)	(4)
Robot adopter	0.015	0.429***	-0.002	-0.008
	(0.224)	(0.140)	(0.004)	(0.005)
Adjusted R^2	0.501	0.667	0.433	0.639
No. Obs.	956,890	956,890	956,890	956,890
No. Firms	127,400	127,400	127,400	127,400

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample with 10 or more employees using the baseline definition of workers as individuals affiliated with a firm that are never observed to be an owner of the firm. Robot adoption is a discrete measure equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Columns (1) and (2) use an inverse-hyperbolic-sine (ihs) transformation. Shares in columns (3) and (4) are relative to total income paid out by the firm to affiliated individuals (TP). All regressions include firm fixed effects, 4-digit NAICS×year fixed effects, SAC location×year fixed effects, and time-varying effects of initially observed log employment, log value added per worker, and log assets per worker. Observations and firm counts are rounded to comply with Statistics Canada confidentiality rules. Standard errors clustered at the firm and year levels are in parentheses. $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.10$.