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

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Abstract

We estimate the impact of robot adoption on the within- and across-firm distributions of income in Canada, focusing on the division between workers and individual owners. Using detailed information on firms' robot imports, comprehensive matched individual-firm-level data that allows for the identification of individuals who own private corporations, and employment income paid to individuals affiliated with each firm, we find that robot adoption is associated with sizable increases in firm revenues, value added, employment, and worker payroll. Contrary to common concerns, after reallocating employment income owners pay to themselves, we find little evidence of a decline in the labor share of value added for robot adopters; if anything, it tends to increase slightly, and particularly so for smaller employers, while the total owner income share remains flat or even falls. Our results underscore the importance of accounting for firm owners' different sources of income in understanding the effects of labor demand shocks on workers.

JEL Codes: J23, J30, E22, O33, D22

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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 or who work for firms that compete with adopters of these technologies.[1] This broad transformation could exacerbate economic inequality (Acemoglu and Restrepo, 2022; Moll et al., 2022). Given the potential benefits of automation,

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[1]See, for example, Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019)

it is important to understand how the rewards of increased adoption will be distributed throughout the economy, both within and between firms as well as across different individuals. 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.

This paper examines one dimension through which automation may influence the distribution of income: its impact on the earnings of workers and business owners. We evaluate how firm-, worker-, and owner-level outcomes respond to adoption of industrial robots, an automation technology whose use throughout the global economy continues to expand, both for firms that adopt robots and for firms that compete in product and labor markets with adopters, and assess the implications of these responses for income inequality.

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] Moreover, data on ownership shares allows us to infer the income owners receive from each private corporation they own and implement an individual-firm-level design to compare the effects of robot adoption on the incomes of workers and owners.

We begin our examination of the extent to which robot adoption affects inequality by shifting the distribution of income between business owners and workers using a firm-level analysis leveraging our panel data. We estimate the direct impacts of adoption on adopters and indirect effects on non-adopters using four groups of outcomes. The first group includes measures of the scale of firms including their revenues, value added, employment, payroll, and

[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]In the Canadian context, there is little-to-no incentive for owners with high levels of total individual-level income to favor taking income out of their private corporations through either dividends or employment income because of the ultimately similar tax treatment of the two income sources (Wolfson et al., 2016).

total owner income. We find consistent evidence using both panel and event study regressions that robot adoption is associated with increases in a firm's scale. Second, we evaluate the impacts of robot adoption on measures of labor productivity including per-worker payroll, value added and revenues and show 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 firm-level measure of employment to net out individual owners who pay themselves employment income.

Our third group of firm-level 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 robot adopters increase the labor share of value added by 1.4 percentage points, which stands in contrast to results from other settings, while the owner income share of value added declines by 1.7 percentage points.[4] As with our findings for firm-level labor productivity, the reallocation of owners' employment income from payroll to total owner income accounts for these effects; absent this adjustment, the labor share and owner income share are both estimated to be unaffected by robot adoption, and the decrease in the owner income share is not driven by changes in dividend payments, as there is no effect of adoption on the dividend share of value added. This absence of an effect on dividends is confirmed in our final group of firm-level results, where we find that robot adoption affects the total income of owners primarily though its impact on their employment income.

We next estimate the spillover effects on non-adopters by constructing measures of the degree of robot adoption in the industries and locations firms operate in. As our results are not yet approved for release from Statistics Canada, we omit a discussion of our findings.

Firm-level results tend to average out individual disparities, potentially masking differences in how robot adoption impacts the distribution of income within firms. Our data allow us to evaluate the effects of robot adoption on individual workers and business owners. Using panel regressions with a rich set of fixed effects, we estimate how robot adoption influences both the employment and business income each individual receives from a firm, and whether the effects on employment income differ on average for workers and owners. Additionally, we evaluate the effects of robot adoption on income changes for individuals who enter and exit a firm over time. As with our firm-level spillover results, our results have not yet been approved for release from Statistics Canada.

Our paper contributes to the literature on the firm-level effects of adoption of automation technologies. Although existing studies of the impacts of robot adoption use data from multiple different settings and varied empirical designs (e.g., Acemoglu et al., 2020; Dixon

[4]Other firm-level estimates from France (Acemoglu et al., 2020), Spain (Koch et al., 2021), and the Netherlands (Acemoglu et al., 2023) find negative impacts on the labor share of value added.

et al., 2021; Humlum, 2021; Koch et al., 2021; Bonfiglioli et al., 2024; Dinlersoz and Wolf, 2024; Acemoglu et al., 2025), a consistent finding that is confirmed by our analysis is that adoption is associated with an increase in the scale of firms.[5] Our study is the first to estimate the impacts of adoption on payroll and employment after netting out the impact of individual owners who receive employment income on these measures.

In focusing on the importance of employment income paid to owners on the distribution of firm-level surplus between workers and owner, our paper contributes to the literature on the effects of automation on the labor share. Earlier work estimating effects at the plant (Dinlersoz and Wolf, 2024), firm (Koch et al., 2021; Acemoglu et al., 2023) and industry or location levels (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Acemoglu et al., 2025) typically find negative impacts of automation on the labor share. We find that after reallocating owners' employment income from worker payroll to total owner income that the labor share, if anything, increases following adoption.

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 firm-level 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-, individual-, 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

[5] Other work examines the impact of a broader classification of automation technologies (Bessen, 2019; Aghion et al., 2021; Bessen et al., 2025).

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.[6] 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.[7] 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.[8]

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

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

[7] 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.

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

Services Agency. Industrial robots are identified through detailed Harmonized System (HS) codes that are comparable with classifications defined by the International Federation of Robotics (IFR).[9] 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.[10] 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.[11]

[9] 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.

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

[11] 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%

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.[12] 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 Individual-Level Data

Individual-level data that are not specific to the firms with which an individual is affiliated are taken from the annual T1 Income Tax and Benefit Returns. In our affiliation-level analysis, we use information on the individual's birth year, sex, and the SAC within which they reside. We calculate an individual's age at December 31 of each year using their reported birth year.

2.4 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 samples. 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.

2.4.1 Firm Level

Our firm-level analysis evaluates the effects of robot adoption on four groups of outcomes: scale, labor productivity, 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.[13] To supplement this discrete measure of adoption, we follow Dixon et al. (2021) and construct

of firm-owner-year observations, respectively. The average year-to-year change in an owner's share is just 0.2 percentage points.

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

[13]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.

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 labor productivity 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.[14] We calculate firm-level value added as the sum of before-tax net 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. Labor productivity measures include payroll per worker, revenues per worker, and value added per worker.

Other important outcome variables for our firm-level 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. In addition, we examine effects on owner payout (which we define as the sum of dividends and owner employment income) as a share of total income paid out by the firm (i.e., dividends plus total employment income).

The final set of firm-level 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.

We restrict our firm-level 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).

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

2.4.2 Affiliation Level

At the affiliation level, we evaluate how robot adoption affects both workers and owners affiliated with the firms included in our firm-level analysis. We focus on the differential impacts of robot adoption on the employment and comprehensive income of an individual within an affiliation, where comprehensive income is the total of the individual's employment income and their income obtained from their ownership of a firm. While employment income is observed at the affiliation level, both dividends and retained earnings are observed at the firm level. We distribute reported dividends and retained earnings to owners using the observed affiliation-level imputed ownership shares described in Section 2.2. We also examine the effects on the probability with which workers and owners remain with the firm or are displaced by robot adoption.

Our affiliation-level analysis results are pending release approval from Statistics Canada and we therefore omit a more detailed variable and sample description in this section.

2.5 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%).[15] 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 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).

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

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

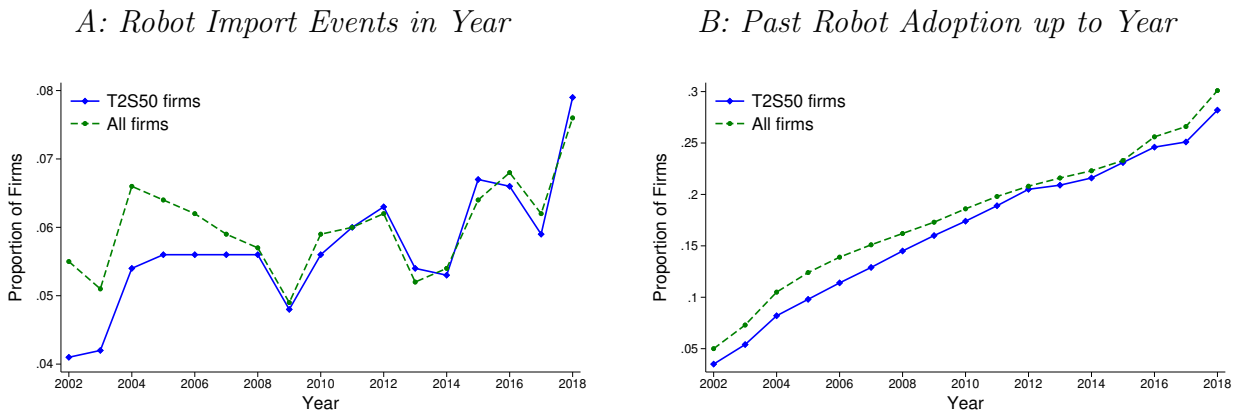


Figure 1: Prevalence of Robot Adoption in the Broad Manufacturing Sector

Notes: Figure depicts the prevalence of robot import events 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 a robot import event 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.

sector had imported robots.[16] By 2018, this proportion had increased to 0.282%.[17]

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 revenues per worker. For both robot adopters and non-adopters, the median firm does not pay out any dividends, but, despite this, dividends account for a substantial proportion of owner payout (dividends plus owner employment income) on average for both types of firms.

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

[16]The proportion in Panel A is higher than in Panel B in 2002 because, as explained in Section 2.4.1, 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.

[17]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 2.4.1 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.

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.[18] 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

Our empirical analysis proceeds in three parts. We begin with a firm-level analysis to estimate the direct effects of robot adoption on firm-level outcomes. We then examine spillover effects on non-adopting firms operating in the same industries and locations as adopters. Finally, we conduct an affiliation-level analysis that links firms to their workers and owners to study how the gains and losses from robot adoption are distributed across individuals within a firm.

3.1 Firm-Level Analysis

We estimate the direct firm-level effects of robot adoption on adopters, their workers, and their owners using both panel and event-study specifications. We then construct measures of the degree of adoption within industries and locations over time and assess how non-adopters are impacted by increases in adoption by their competitors.

3.1.1 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 2.4.1.

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 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,

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

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.

3.1.2 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:

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

where $D_{f,t}^{h}$ 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.

3.1.3 Spillovers

We examine the effect of robot adoption by a non-adopting firm's competitors by constructing two measures of the degree of robot adoption by other firms in that firm's industry and location. Specifically, we compute industry and location robot adoption measures, $r_{f,t}^{CS}$ and $r_{f,t}^{CL}$, respectively, as

$$r_{f,t}^{CS} = \frac{\sum_{f'\in s(f), f'\neq f} q_{f',t} r_{f',t}}{\sum_{f'\in s(f), f'\neq f} q_{f',t}} \tag{3}$$

$$r_{f,t}^{CL} = \frac{\sum_{f'\in l(f), f'\neq f} p_{f',t} r_{f',t}}{\sum_{f'\in l(f), f'\neq f} p_{f',t}}, \tag{4}$$

where $q_{f,t}$ are revenues and $p_{f,t}$ is payroll. We consider both the discrete and continuous measures of robot adoption and estimate effects on non-adopters using the following specification:

$$y_{f,t} = \beta^{CS} r^{CS}_{f,t} + \beta^{CL} r^{CL}_{f,t} + \gamma_t X_{f,\tilde{t}(f)} + \alpha_f + \delta_{\hat{s}(f),t} + \zeta_{\hat{l}(f),t} + \epsilon_{f,t}. \tag{5}$$

Because much of the variation in the competitor robot adoption measures originates from differences between 4-digit NAICS industries for $r^{CS}_{f,t}$ and SAC locations for $r^{CL}_{f,t}$, we control for 3-digit NAICS industry-by-year fixed effects, $\delta_{\hat{s}(f),t}$, and province-by year fixed effects, $\zeta_{\hat{l}(f),t}$, for the province of the firm's headquarters location. For all of the spillover regressions, standard errors are clustered at the 4-digit NAICS industry-by-year and SAC location-by-year levels.

Our firm-level robot adoption spillover analysis results are pending release approval from Statistics Canada.

3.2 Affiliation-Level Analysis

We estimate affiliation-level regressions of the form:

$$y_{i,f,t} = \beta^n r_{f,t} n_{i,f,t} + \beta^o r_{f,t} o_{i,f,t} + \gamma X_{i,t} + \alpha_f + \eta_i + \delta_{s(f),t} + \zeta_{l(f),t} + \epsilon_{i,f,t}, \tag{6}$$

where firm f now denotes a firm with which individual i is affiliated in year t, η_i is an individual fixed effect, $n_{i,f,t}$ is an indicator for if the individual is a worker at the firm, $o_{i,f,t}$ is an indicator for if the individual is an owner of the firm, and $X_{i,t}$ includes controls for the individuals' characteristics including their age. Our affiliation-level regressions include standard errors clustered by firm-year and individual levels.

Our affiliation-level analysis results are pending release approval from Statistics Canada.

4 Firm-Level Results

In this section, we present and discuss our baseline set of firm-level results. We begin in Section 4.1 by reporting how robot adoption affects each of the four groups of firm-level outcomes on firm scale, labor productivity, the allocation of firm-level surplus across workers and owners, and the composition of owner income. 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.

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: Robot adoption by present					
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: Continuous stock of robots					
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

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. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 this automation technology affects owners relative to workers, we show how robot adoption affects the four groups of firm-level outcomes described above.

4.1.1 Firm Scale

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

In Panel A, we use a binary measure of adoption that is equal to one for a firm starting in the first year they import robots and in all subsequent years and zero otherwise. 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.[19]

[19]Because the change in retained earnings can be negative (such as when a firm has negative after-tax net income), we use an inverse-hyperbolic-sine transformation of owner income to estimate the effects of robot

Our estimates imply that revenues, value added, and employment increase by approximately (exp(0.45)-1)×100% = 57% on average following the onset of adoption while worker payroll increases by a larger proportion (71%). For value added, this increase is larger than that reported by Acemoglu et al. (2023) for Dutch firms in a comparable set of industries, while we find a higher boost to revenues and employment than the main results emphasized by Koch et al. (2021) for a sample of Spanish firms in a more narrow manufacturing sector.[20]

To allow for the scale effects of robot adoption to vary by the amount of robots in use at a firm, Panel B shows estimates 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 results, we transform this stock measure using the inverse hyperbolic sine. Our results 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 continue to be positive and statistically significant. 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 can not be used to identify owners separately from workers).[21]

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.

As a final look at the direct scale effects of robot adoption on adopters, we estimate the same set of regressions as those in Table 2 but where relevant variables are redefined using an alternative definition of workers as any individual receiving employment income from the firm and so ignore the availability of information on individual owners. These results are reported in Table A3. The pattern of results is qualitatively unchanged, but the effects on employment and payroll are somewhat smaller while those for owner income (which no longer

adoption.

[20] Unlike Acemoglu et al. (2023), we do not weight observations by a measure of initial employment. In addition, the specification in Equation (1) is not entirely comparable to that used by Koch et al. (2021). We also note that our revenues and employment results are qualitatively similar though larger in magnitude for the direct effects of robot adoption reported in Table 1 of Bonfiglioli et al. (2024).

[21] Acemoglu et al. (2023) also find a positive and significant effect of the cumulative value of robot imports on value added and total hours worked.

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: Robot adoption by present			
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: Continuous stock of robots			
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

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. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

includes owners' employment income) are larger.

4.1.2 Labor Productivity

The second group of outcomes we examine are the three accounting-based measures of labor productivity. Estimates are provided in Table 3. We find that robot adoption, whether measured using the binary or continuous adoption variable, has a positive and significant effect on payroll per worker but no effect on either the value added or revenues per worker.[22]

The impact of accounting for individual owners in the firm-level measure of employment emerges when comparing these results with those using the alternative definition of workers that includes owners receiving employment income. In Table A4, we now estimate a positive and statistically significant impact of robot adoption on value added and revenues per worker. This finding suggests that ignoring that owners can chose to withdraw earnings from their

[22]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 after adoption.

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

	Labor share	Owner income share	Dividend share	Owner payout share
	(1)	(2)	(3)	(4)
Panel A: Robot adoption by present				
Robot adopter	0.014**	-0.017***	-0.000	-0.014**
	(0.006)	(0.006)	(0.004)	(0.005)
Adjusted R^2	0.681	0.666	0.479	0.625
No. Obs.	2,839,340	2,721,070	3,026,820	2,930,510
No. Firms	382,800	375,690	398,645	390,720
Panel B: Continuous stock of robots				
ihs robot stock	0.001**	-0.002***	-0.000	-0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.681	0.666	0.479	0.625
No. Obs.	2,839,340	2,721,070	3,026,820	2,930,510
No. Firms	382,800	375,690	398,645	390,720

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. All dependent variables are measured as shares of value added. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

firms both through employment income and dividends may lead to an overstatement of the degree to which robot adoption affects labor productivity in adopters.

4.1.3 Allocation of Surplus

We now turn to the group of outcomes that highlights the implications of robot adoption for the proportion of firm-level surplus that is distributed to workers and individual owners. Table 4 presents results for the shares of value added that are allocated to workers as payroll, owner income, as dividends, and as owner payout (dividends and owners' employment income).

The first notable finding in this table, as shown in column (1), is that robot adoption leads to a statistically significant increase in the worker payroll share of value added of 1.4 percentage points. This contrasts with the results found by Koch et al. (2021) and Acemoglu et al. (2023), who estimate a statistically significant negative impact of adoption on the labor share. As we show in Table A5, the removal of employment income received by owners from the firms' total payroll gives rise to our positive estimate, as we find no statistically significant effect on the labor share when we include this amount in a firm's payroll.

Comparing the remaining columns of Table 4 and Table A5, we find that accounting for employment income received by individual owners in total firm-level owner income leads us to estimate a negative effect of robot adoption on the owner income share of value added equal to 1.7 percentage points, while there is no statistically significant effect without such an adjustment. The results for the dividend and owner payout shares of value added suggest that this negative impact on the owner income share is not generated by a change in the dividend share but is in large part due to a decrease in the share of value added that owners pay to themselves as employment income.

4.1.4 Owner Income Composition

Our final group of firm-level outcomes digs deeper into the impact of robot adoption on firm owners and their sources of income. In Table 5, we show results for estimates of Equation (1) for dividends and owner payout both in terms of the inverse-hyperbolic-sine transformation (to account for the descriptive facts reported in Table 1 regarding the prevalence of zeros for these metrics) and as shares of the total income paid out by firms in a year. The results confirm that robot adoption has a positive and statistically significant impact on owner payout but that this is not accounted for by an increase in dividend payments to owners. As is the case for the dividend and owner payout shares of value added, owner payout as a share of total payout decreases following robot adoption.

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, owner payout, and non-negative values of total owner income in Table 5, where we use a log transformation of each of these variables. The results suggest that owner income increases following robot adoption (both for the baseline definition that includes employment income received by individual owners in column (1) and the alternative definition that omits this component in column (4)). Moreover, adoption continues to have a positive and statistically significant impact on owner payout.

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 ownership shares. For this comparison, we use the adjusted 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 we focus on estimates using the binary measure of robot adoption.

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

	ihs dividends	ihs Owner payout	Dividend share (TP)	Owner payout share (TP)
	(1)	(2)	(3)	(4)
Panel A: Robot adoption by present				
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
Panel B: Continuous stock of robots				
ihs robot stock	0.027	0.061***	-0.001	-0.002***
	(0.022)	(0.013)	(0.000)	(0.001)
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. Shares are relative to total income paid out by the firm (TP). Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. Columns (1) and (2) 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

For the enlarged sample of firms, we continue to find positive and statistically significant effects of adoption on total payroll.[23] In the sample of all firms in the broad manufacturing sector, adoption has a more pronounced impact on total owner income (dividends and retained earnings) than in the T2S50-firm sample. We also continue to find a positive impact of robot adoption on payroll per worker, though the estimated effect is considerably smaller when all firms are included in the regression.

the principal difference in results between the two samples can be found in column (4) 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 individual owner's employment income was included in 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.

[23]Estimates for other firm scale measures including revenues, value added, and employment are also positive, 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	Labor share	Owner income share
	(1)	(2)	(3)	(4)	(5)
Panel A: T2S50 Firms					
Robot adopter	0.481***	0.807*	0.072***	0.007	-0.006
	(0.039)	(0.427)	(0.012)	(0.006)	(0.005)
Adjusted R^2	0.823	0.271	0.681	0.601	0.556
No. Obs.	3,137,200	3,137,080	3,137,200	2,480,695	2,188,010
No. Firms	406,710	406,700	406,710	358,645	343,165
Panel B: All firms					
Robot adopter	0.472***	1.312***	0.039***	0.012**	0.001
	(0.034)	(0.333)	(0.010)	(0.005)	(0.003)
Adjusted R^2	0.820	0.273	0.655	0.598	0.659
No. Obs.	5,506,105	5,505,080	5,506,105	4,295,045	3,839,410
No. Firms	690,130	690,090	690,130	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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 the T2S50 firm has at least 10 workers (i.e., individuals who are never observed to be an owner of the firm). We show a comparison of some of the main results from our baseline analysis 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 labor productivity as measured using payroll per worker (in column (3)). 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.

We draw two conclusions from this comparison. First, the results suggest that the effect of robot adoption on the shift in the allocation of value added from owners to workers may be

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

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

Notes: Table presents estimates of Equation (1) or the sample of T2S50 firm-year observations with 1 or more employeea 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 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.

5 Conclusion

This paper estimates the impacts of robot adoption on firms, their workers, and their individual owners. We find evidence that robot adoption leads to increases in firm scale, whether measured by output or employment, and payroll per worker at firms that adopt robots. Using information on the individual owners of firms, we find that effects on labor productivity measures based on output per worker may be overstated if those owners are included in the number of workers employed by firms.

Our main contribution is the finding that robot adoption leads to an increase in the labor share of value added received by workers but a decrease in the owner income share of value

added after accounting for the employment income received by individual owners, particularly for smaller employers. This decrease in the owner share of value added cannot be accounted for by changes in the dividends paid out to owners.

References

Acemoglu, Daron, Gary Anderson, David Beede et al. (2025) "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey," in Basu, Susanto, Lucy Eldridge, John Haltiwanger, and Erich Strassner eds. *Technology, Productivity, and Economic Growth*, Vol. 83 of Studies in Income and Wealth, Chap. 1, 13–56: University of Chicago Press.

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.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel (2021) "What Are the Labor and Product Market Effects of Automation? New Evidence from France," Working Paper.

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

Bessen, James (2019) "Automation and Jobs: When Technology Boosts Employment," *Economic Policy*, 34 (100), 589–626.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2025) "What Happens to Workers at Firms that Automate?" *Review of Economics and Statistics*, 107 (1), 125–141.

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

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.

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

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

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

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.

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.

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

Appendix A Additional Figures and Tables

A: Robot Import Events in Year



B: Past Robot Adoption up to Year

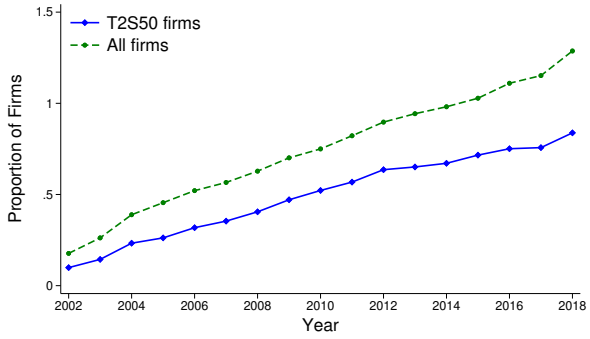


Figure A1: Prevalence of Robot Adoption for Firms with 10 or More Workers

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 a robot import event 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 2.4.1 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 2.4.1 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.

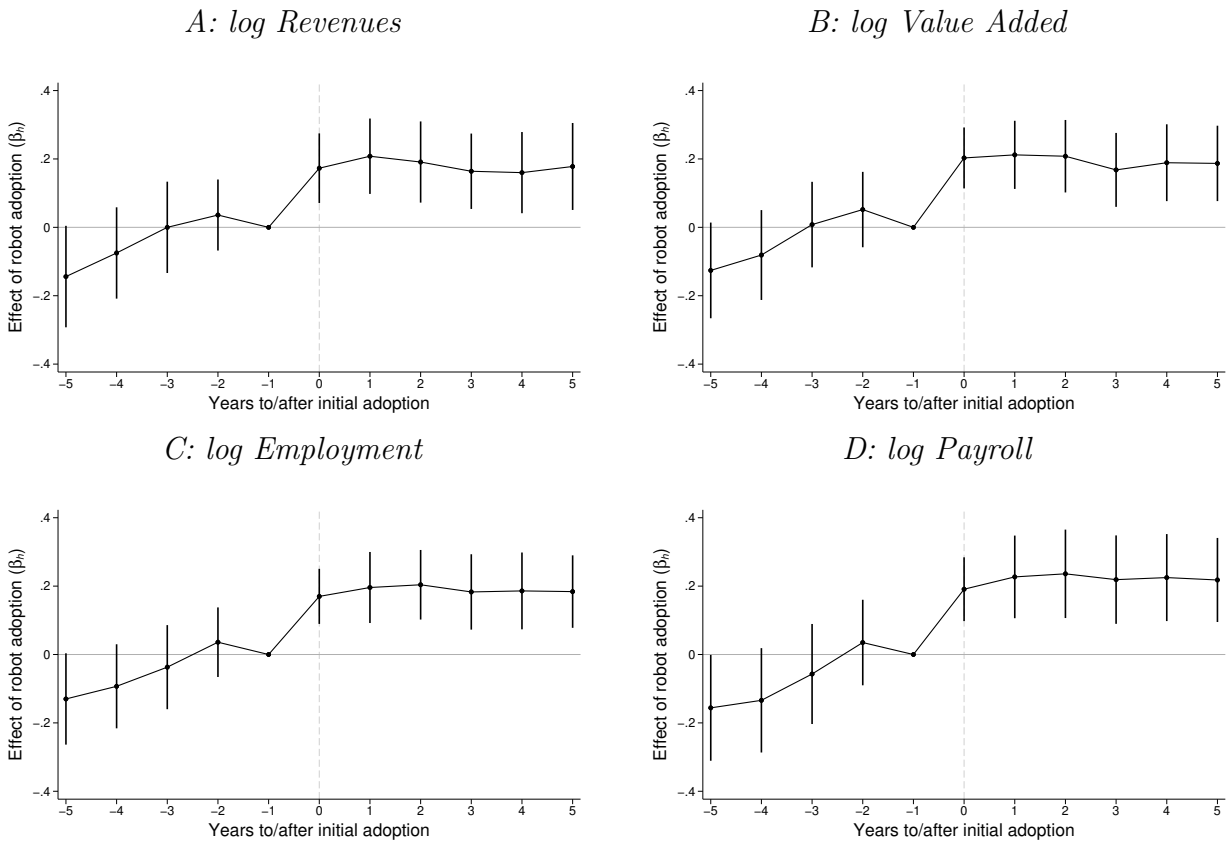


Figure A2: Firm-Level Scale-Effect Event Studies

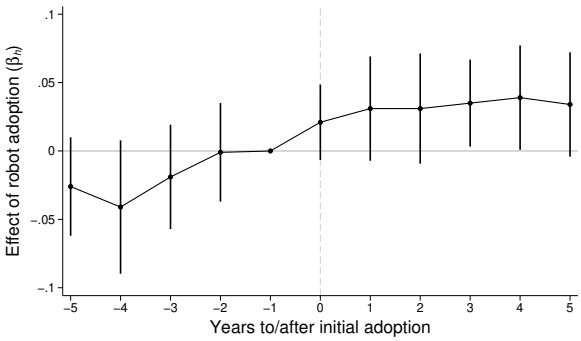
Notes: Figure plots event-study coefficents and 95% confidence intervals estimated using Equation (2) for the T2S50-firm sample. Effects are normalized relative to each variable measured one year before initial adoption.

Table A3: Firm Scale Effects without Accounting for Observed Individual Owners

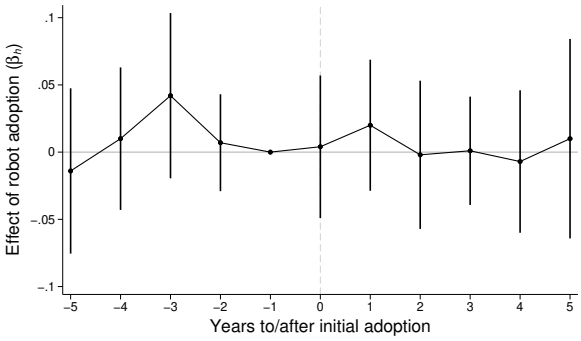
	log revenues	log value added	log employment	log payroll	ihs owner income
	(1)	(2)	(3)	(4)	(5)
Panel A: Robot adoption by present					
Robot adopter	0.451***	0.457***	0.409***	0.481***	0.807*
	(0.038)	(0.036)	(0.036)	(0.039)	(0.427)
Adjusted R^2	0.861	0.815	0.867	0.823	0.271
No. Obs.	3,137,200	3,075,020	3,137,200	3,137,200	3,137,080
No. Firms	406,710	402,110	406,710	406,710	406,700
Panel B: Continuous stock of robots					
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 the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A: log Payroll per Worker



B: log Value Added per Worker



C: log Revenues per Worker

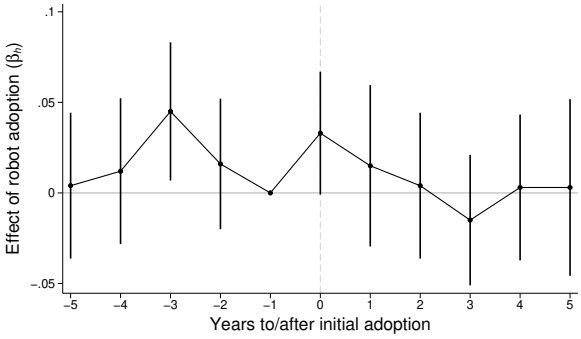


Figure A3: Firm-Level Labor Productivity Event Studies

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 A4: Labor Productivity Effects without Accounting for Observed Individual Owners

	log payroll per worker	log value added per worker	log revenues per worker
	(1)	(2)	(3)
Panel A: Robot adoption by present			
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
Panel B: Continuous stock of robots			
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 the alternative definition of workers as individuals who receive any employment income from the firm. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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 A5: Surplus Allocation Effects without Accounting for Observed Individual Owners

	Labor share (1)	Owner income share (2)	Dividend share (3)
Panel A: Robot adoption by present			
Robot adopter	0.007	-0.006	-0.000
	(0.006)	(0.005)	(0.004)
Adjusted R^2	0.601	0.556	0.479
No. Obs.	2,480,695	2,188,010	3,026,820
No. Firms	358,645	343,165	398,645
Panel B: Continuous stock of robots			
ihs robot stock	0.001	-0.001	-0.000
	(0.001)	(0.000)	(0.000)
Adjusted R^2	0.601	0.556	0.479
No. Obs.	2,480,695	2,188,010	3,026,820
No. Firms	358,645	343,165	398,645

Notes: Table presents estimates of Equation (1) for the T2S50-firm sample using the alternative definition of workers as individuals who receive any employment income from the firm and owner income nets out owner employment income. All dependent variables are measured as shares of value added. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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 Adoption on Owner Income Composition

	log owner income (base.)	log dividends	log owner payout	log owner income (adj.)
	(1)	(2)	(3)	(4)
Panel A: Robot adoption by present				
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
Panel B: Continuous stock of robots				
ihs robot stock	0.037***	0.014*	0.028***	0.035***
	(0.004)	(0.008)	(0.004)	(0.004)
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. Panel A reports estimates for the discrete measure of robot adoption equal to one in the first year a firm imports robots and all subsequent years and zero otherwise. Panel B uses the 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. 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. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.10$.